

A Hybrid GAN-CNN Framework for Enhanced Brain Tumor Classification from MRI Images

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ABSTRACT

This paper introduces a hybrid deep learning model, a combination of Generative Adversarial Networks (GANs) and Convolutional Neural Networks (CNNs) to improve brain tumor classification with MRI images. The diagnosis of brain tumors has been a major dilemma in medical imaging because of the complexity of the tumor structures, lack of data, and imbalance of the classes. To overcome these issues, the proposed framework encourages the use of GAN-based data augmentation in order to create real-world synthetic MRI images, which will enhance the dataset and enhance the generalization of the models. Moreover, traditional preprocessing and augmentation methods like normalization, contrast enhancement, and noise reduction are used to enhance the quality of the data. This is followed by the design of a strong CNN architecture to automatically project hierarchical features as well as multi-classify into glioma, meningioma, pituitary tumor, and no tumor. The model is trained and tested on a rich dataset of publicly accessible sources, making sure that there is diversity in the imaging perspectives and conditions. The experimental results show that the proposed method has a high classification rate of around 99 percent and a low loss value, which reflects high predictive performance and stability. The hybrid GAN-CNN model, compared to the current methods, demonstrates superior performance in comparison to the traditional CNN-based methods, as well as other hybrid techniques. Moreover, the analysis of confusion matrix and ROC curve proves that the model is able to differentiate between the various classes of tumors effectively. The suggested framework provides a credible and scalable solution to automated brain tumor diagnosis, and it has a high probability of its clinical use.

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1. Introduction

Medical imaging is a very important factor in the detection, diagnosis and categorization of brain tumor which makes a significant contribution towards clinical decision-making and the planning of the treatment. Proper determination of tumor characteristics has the potential of resulting in better therapeutic approaches and, as a result, better survival results in patients. Cancer is among the most frequent causes of death globally, whereby there is an uncontrolled growth of cells that may develop in any part of the body. The treatment and prognosis of the tumor type, anatomical site, stage of development and response to treatment differ significantly [1].

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The heterogeneity and the critical location of brain tumors in the central nervous system have made the treatment of these conditions a particularly complicated issue in neuro-oncology. The common classification of tumors is based on the aggressiveness of the tumor, where benign (non-cancerous) and malignant (cancerous) tumors are identified. Moreover, they may be referred to as primary tumors, which develop in the brain tissues or secondary (metastatic) tumors, which are those that extend out of other organs. The World Health Organization classifies brain tumors into four grades with Grade I and Grade II being low-grade and slow-growing tumors, and Grade III and Grade IV being highly aggressive and malignant tumors [2]. It is important to note that over 120 different forms of brain tumors have been detected, and it is a complicated issue to diagnose and treat [3,4].

Advances in the brain tumors may severely affect the neurological functions causing the development of such symptoms as headaches, seizures, vomiting, visual disturbances, and cognitive impairments, which significantly impact the quality of life of patients [5]. In 2020, it was reported that cancer statistics around the world showed almost 308,000 new cancer cases of the brain (the total cancer cases were approximately 1.6% of the total newly diagnosed cancers worldwide) [6]. Even with the current level of medical technology, the prognoses of malignant brain tumors are dismal with most cases having a less than 15-year survival rate [7]. Among available imaging techniques, Magnetic Resonance Imaging (MRI) is the most common modality in brain tumor diagnosis which is a non-invasive process with high spatial resolution, no ionizing radiation and better soft tissue contrast. MRI is an advanced imaging technique that involves strong magnetic fields and radiofrequency to produce high anatomical images, which can be used to identify and describe tumors precisely [8].

Transformational medical image analysis has been changed by AI and DL technologies over the past few years. In particular, CNNs have demonstrated high performance in image classification, segmentation/feature extraction. CNN architectures learn hierarchical features on raw imaging data automatically, without the need of human-designed features and are capable of robustly analyzing complex medical data [11]. Such models have been extensively used in classifying brain tumors and have been extremely successful in binary (tumor vs. non-tumor) and multi-class classification problems. Nonetheless, multi-class classification is a difficult task because of the diversity in tumor size, shape, texture and spatial distribution [10,12].

Although CNN-based methods have been successful, a major constraint is the fact that there are very few large, well-balanced annotated medical datasets. This drawback may cause overfitting and lower generalization results. In response to this problem, Generative Adversarial Networks (GANs) have become effective generative models that can generate realistic synthetic medical images. GANs can be used to augment the existing datasets with high-quality artificial samples to enhance diversity and balance of the data, thus improving the training efficiency and robustness of CNN models.

Inspired by these developments, this paper introduces a hybrid GAN-CNN-based system to provide better brain tumor classification based on MRI images. The suggested solution uses data augmentation via GAN to diversify the training sample and better represent features, and CNN is used as a powerful classifier to appropriately differentiate among various tumor types. The proposed framework will enhance the classification accuracy and overcome the problem of data scarcity and help in more trustworthy clinical decision-making in neuro-oncology by means of combining the generative and discriminative learning paradigms. The main contributions of this study can be summarized as follows:

- Proposing a novel hybrid GAN-CNN framework that tightly integrates generative data augmentation with discriminative classification in a unified pipeline.
- Addressing the problem of limited and imbalanced MRI datasets by generating high-quality synthetic images using GAN, improving model generalization.
- Designing an efficient CNN architecture optimized for multi-class brain tumor classification.
- Achieving superior performance compared to existing methods, reaching approximately 99% accuracy.
- Providing a comprehensive evaluation using multiple metrics including accuracy, precision, recall, F1-score, confusion matrix, and ROC analysis..

2. Related Work

The latest developments in AI and DL have profoundly altered the analysis of medical images, especially the classification of brain tumors with MRI. CNNs are among other types of DL methods that have been widely implemented due to their excellent automatic feature extraction and classification. The CNN-based architectures have been shown to be able to increase the accuracy and reliability of the automated-tumor-detecting systems.

As an example, in [13], a CNN-based model has been created to classify three major types of brain tumors, such as glioma, meningioma, and pituitary tumours with an accuracy of 95%. This paper has demonstrated the promise of deep learning models in simplifying the diagnostic process and aiding clinicians in making decisions. In the same manner, [14] suggested a hybrid model based on CNN and Residual Networks (ResNet) with use of transfer learning to enhance the classification accuracy. Their model was accurate (97%), which proved the usefulness of deep hierarchical feature extraction and pretrained architectures in medical imaging.

In spite of these developments, one of the biggest weaknesses in the classification of brain tumors is the lack of large well-annotated datasets of MRI. To deal with this issue, [15] proposed the application of Generative Adversarial Networks (GANs) to data augmentation. GANs produced realistic synthetic MRI images by increasing the diversity of the dataset, resulting in higher robustness of CNN classifiers, decreased overfitting, and more accurate generalization between tumor classes. This method was an important pivot towards combining generative models with discriminative learning systems.

In addition to the data augmentation, attention mechanisms have also been studied to enhance the feature representation. In [16], an attention-guided CNN model is proposed, enabling the network to focus on the most important components of tumors in MRI images. This resulted in increased sensitivity and specificity particularly when the image quality and noise vary. Moreover, [17] also compared the popular CNN architectures, such as AlexNet, VGG16, and InceptionV3. This showed that VGG16 was more accurate and computationally efficient, and revealed the significance of architecture selection in medical tasks.

Multimodal imaging has been studied in a bid to improve the classification performance. In [18], multiple MRI modalities (T1-weighted, T2-weighted and FLAIR) were used to get complementary tumor features. The methodology considerably increased the quality of features representation and minimized classification bias, and the extensive use of data should be highlighted.

Other architectures have been taken into consideration besides the conventional CNNs. The Capsule Networks (CapsNets) proposed in [19] had the ability to maintain spatial hierarchies in MRI pictures, leading to an increase in classification accuracy compared to the original CNNs. Further, the hybrid networks between CNN and Long Short-Term Memory (LSTM) networks were suggested in [20] to gain insight into the time-dependent nature of tumors and investigate how they evolve over time. This method offered important information about the development of tumors and response to treatment.

Although the classification of brain tumors through deep learning methods has been made a great step forward, there are still various challenges to address. The major constraints include lack of and inequality of annotated MRI datasets, which has a negative impact on the generalization and robustness of models [21]. Also, a lot of current methods are based on CNNs with limited use of the capabilities of generative models. In other studies, even though GANs have been introduced, they typically are not applied in a tight connection with the classification pipeline, usually just doing basic data augmentation. Moreover, there are a few studies that have investigated completely trained, end-to-end hybrid GAN-CNN models that jointly optimize the process of data generation and classification [22].

To overcome these shortcomings, this paper suggests a hybrid GANCNN architecture, which combines GAN-driven data augmentation with CNN-driven classification in a single architecture. The suggested strategy will produce synthetic MRI images of high quality to augment the training sample to enhance the diversity of features. This, on its part, assists in lessening overfitting and improves the model generalization. Further, the framework will enhance accuracy of classification of different types of brain tumors and offer a robust and scalable solution to be used in clinical practice Table 1 provides an overview of some of the recent findings in the field of brain tumor classification using different deep learning methods. It outlines the methodologies used and their key findings, giving a comparison of developments in this area.

Table 1: Summary of Related Works on Brain Tumor Classification

Ref.	Methodology	Key Findings
[13]	CNN-based classification	Achieved 95% accuracy for three tumor types
[14]	CNN + ResNet (Transfer Learning)	Reached 97% accuracy with improved feature extraction
[15]	GAN-augmented CNN	Enhanced generalization and reduced overfitting

[16]	Attention-guided CNN	Improved sensitivity and focus on tumor regions
[17]	CNN comparison (AlexNet, VGG16, InceptionV3)	VGG16 showed best performance
[18]	Multimodal MRI (T1, T2, FLAIR)	Reduced errors with richer feature representation
[19]	Capsule Networks (CapsNet)	Preserved spatial hierarchies, improving accuracy
[20]	CNN-LSTM hybrid	Enabled temporal tumor progression analysis

Despite the significant progress achieved in previous studies, most existing approaches either rely solely on CNN-based classification or use GANs only for basic data augmentation. There is still a lack of fully integrated hybrid frameworks that jointly optimize both data generation and classification processes. This research aims to bridge this gap by proposing a unified GAN-CNN architecture that enhances both feature diversity and classification performance.

3. Methodology

The suggested methodology provides a systematic and unified approach that unites GANs and CNNs to boost the process of classifying brain tumors on the basis of MRI images. The framework will deal with the main issues like lack of data, imbalanced classes, and variability of features. The hybrid model will improve both generalization and diagnostic performance using GAN-based data augmentation, and a powerful CNN classifier. The entire process is designed into five major phases, which establish the effectiveness and reliability of the system suggested.

3.1. Data Acquisition

In this work, a full brain MRI dataset was obtained in publicly available repositories, such as Kaggle and Figshare. To be able to classify brain tumors with a variety of sources, the dataset was gathered, and various sources were added, such as the work of Masoud Nickparvar, to make it diverse and robust.

The data are made up of about 7022 MRI images divided into four classes sorted into four classes; glioma, meningioma, pituitary tumor and no tumor. In particular, the dataset consists of about 300 glioma images, 306 meningioma images, 300 pituitary tumor images, and 405 images of normal (no tumor) images and the rest of the images are spread over the dataset so that they will be sufficient to train and validate the data. The choice of these types was based on their clinical importance and the necessity to differentiate them properly since the types of tumors have different diagnostic and treatment approaches.

Various imaging planes were performed to enhance generalization of the model e.g. axial (top-down), coronal (front-to-back) and sagittal (side-to-side) images were taken using MRI. This multi-view acquisition of information enables the model to obtain a rich spatial data of brain tumors boosting its usage in a broad spectrum of clinical imaging environments.

In addition, the dataset has images with varying contrasts and levels of distribution of intensity that are necessary to identify the slight variations between the nature of the tumors. This variability is able to differentiate the complex tumor features and this variability eventually enhances the classification accuracy, sensitivity and specificity. Fig.1 presents the sample images of MRI of the dataset, which underlines the various types of tumors and normal brain images in this study.

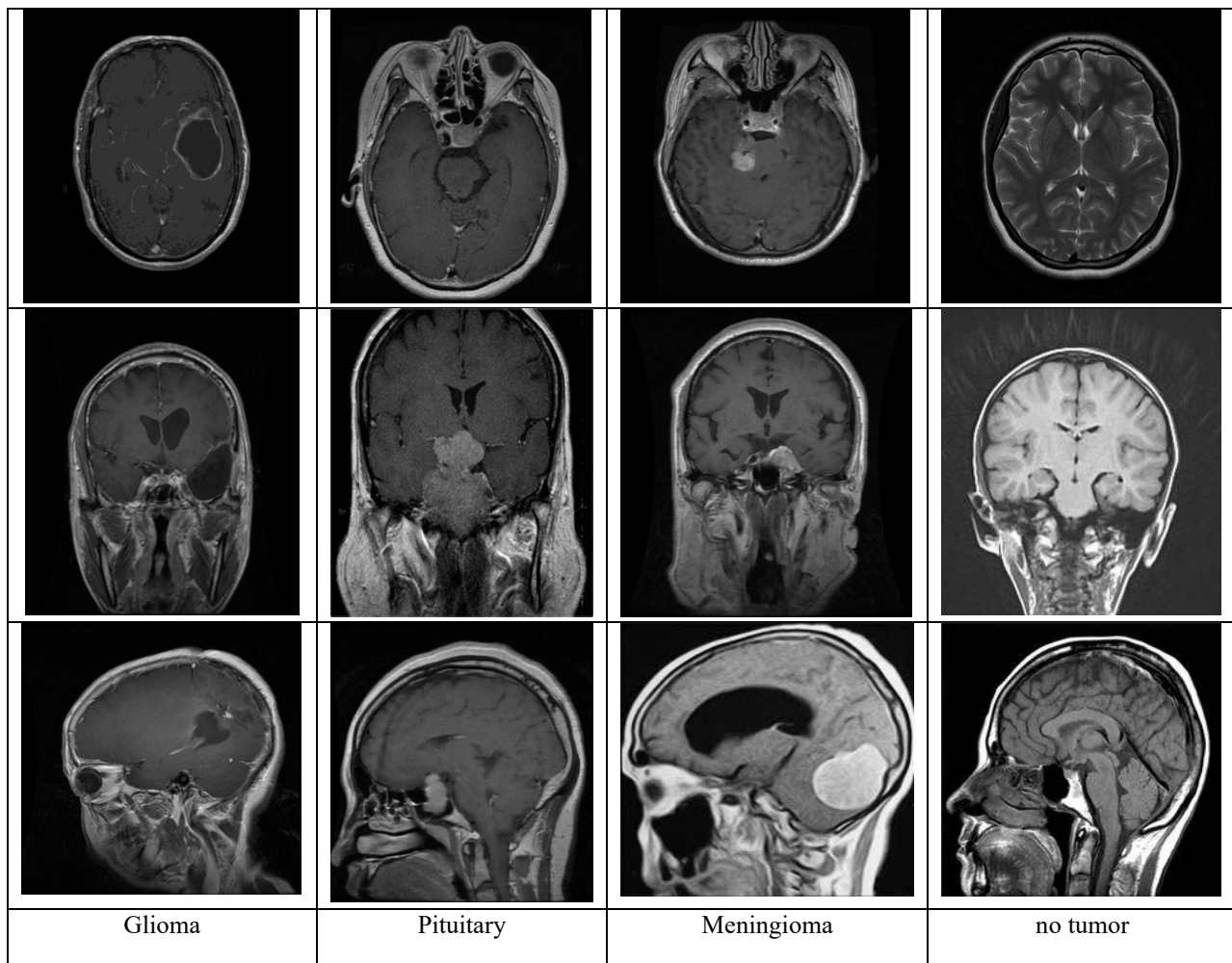


Fig. 1: Sample MRI images of brain tumor classes: glioma, pituitary tumor, meningioma, and no tumor.

3.2. Data Augmentation and Preprocessing

Deep learning models, specifically Convolutional Neural Networks (CNNs), need both large and varied datasets to perform optimally in terms of classification. Nonetheless, medical imaging data are usually small and unbalanced. To overcome these difficulties, hybrid data augmentation approach that uses both generative and traditional methods was used.

They used generative adversarial networks (GANs) to produce synthetic but highly realistic MRI images, which had the effect of growing the dataset size and variety. GANs are trained to capture the underlying distribution of real MRI data and reproduce the complex tumor patterns, which allows the model to extrapolate the model better to a variety of tumor features. Besides GAN-based augmentation, other traditional augmentation algorithms were used to further increase the variability of the data set and minimize overfitting:

- **Horizontal Flipping:** This is to generate positional variations of tumors which enhance model resilience to spatial variations.
- **Contrast Enhancement:** Contrast Limited Adaptive Histogram Equalization (CLAHE) to enhance the visibility of tumor boundaries and internal structures.
- **Normalization:** Pixel intensity values were normalised to $[0, 1]$ so that they were consistent and it enhanced training stability.
- **Noise Reduction:** Gaussian filtering was used to suppress noise and imaging artifacts and sharpen features.

Also, the Keras image data generator was embraced to do the real-time data augmentation to enable the model to automatically augment the data during the model training. The technique augments the efficiency of the computing and continually exposes the model to diverse data samples. The combination of GAN-generated synthetic data with traditional augmentation, and preprocessing methods leads to a strong, balanced, and diversified dataset. This highly improves the performance of CNN model with regard to accuracy, sensitivity and generalization ability of brain tumor.

3.3. GAN Model Architecture

To mitigate the shortcomings of small and skewed medical imaging databases, a Generative Adversarial Network (GAN) was included in the proposed system of synthetic MRI image synthesis. GANs are potent generative models that train on the underlying data distribution, and produce natural synthetic samples, which boost the dataset diversity and generalization of the model.

A GAN has two key elements: a generator (G) and a discriminator (D), which are adversarially trained together. The goal of the generator is to generate synthetic MRI images that are similar to real images, and the goal of the discriminator is to differentiate real and generated images. The generator gradually gets better at producing high-quality images via this competitive process. The GAN objective is defined to be the following:

$$\min_G \max_D V(D, G) = E_{x \sim p_{data}(x)} [\log D(x)] + E_{z \sim p_z(z)} [\log (1 - D(G(z)))] \quad (1)$$

where (x) represents real MRI images sampled from the dataset, and (z) is a random noise vector sampled from a prior distribution.

The generator network accepts a random noise vector and converts it to a synthetic MRI image by using a sequence of up sampling and convolutional layers. It is created to represent the intricate nature of the brain tumor distribution and produce the visual images that look realistic and are similar to the real MRI images. Then the discriminator is a binary classifier that considers whether an input image is a real or synthetic image. It has a series of convolutional layers which identify features of the input image and then fully connected layers producing a probability of authenticity score.

The trained GAN model is applied to produce synthetic MRI images that are introduced into the original dataset to essentially provide a higher number of training samples and combat class imbalance. These enhanced datasets are then inputted to the CNNs model in order to be trained. The incorporation of GAN in the suggested hybrid structure greatly boosts diversity of features, minimizes overfitting and increases the strength and accuracy of brain tumor classification. To further explain the architecture of the Generative Adversarial Network (GAN) applied in this paper, Fig.2 shows the communication between the generator and discriminator in the adversarial learning process. The generator is fed with a random noise vector and trained to generate a synthetic MRI image, and the discriminator assesses both real and generated images to evaluate their authenticity. This adversarial learning process allows the generator to become more and more realistic as a generator creating images that resemble MRI images and are then used to increase the size of the dataset and improve the performance of the CNN classifier.

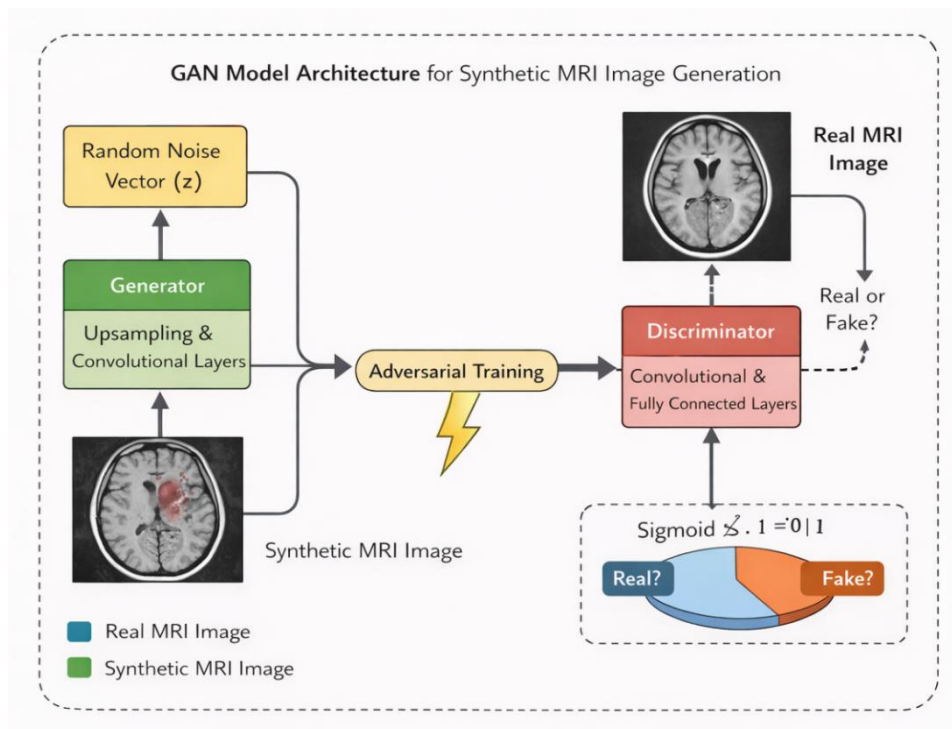


Fig. 2 GAN model architecture for synthetic MRI image generation, showing the interaction between the generator and discriminator during adversarial training.

3.4. CNN Model Training and Architecture

This work presented a powerful and effective Convolutional Neural Network (CNN) model to categorize brain tumor MRI images into four different classes: glioma, meningioma, pituitary tumor, and no tumor. The CNNs are specifically well-adapted to medical imaging tasks because they can automatically learn hierarchical features of raw image data, obviating the manual features engineering, and making classification more accurate.

The CNN architecture proposed was well planned in a manner that it was very fast and at the same time, it was efficient in terms of its computations. The network has three major convolutional blocks, which perform progressive feature extraction and reduce dimensionality. The following are components of each block:

- **Convolutional Layers (Conv2D):** The convolutional layers repeat a series of filters to obtain low- and high-level features of edges, textures, and spatial patterns related to the tumor regions.
- **batch normalization layers:** This is used at the end of every convolutional layer to levelized training, speed up convergence, and lessen internal covariate shift.
- **Max-Pooling Layers:** These are employed to down sample feature maps, lowering their computational requirements and enhancing their generalization behavior.

Once the features have been extracted, the feature maps are flattened and fed into fully connected (dense) layers to be classified. In order to diminish overfitting further, between dense layers dropout regularization with a rate of 0.5 is used.

Different hyperparameters have been optimized to obtain the best model performance. The ReLU activation function was used in hidden layers and the output layer used Softmax function as a multi-class classifier. The model was trained using Adam optimizer and this provides adaptive learning. The difference between the predicted and the actual distributions of the classes was measured using categorical cross-entropy loss function.

The training was done in a batch size of 20 and 100 epochs to guarantee stability of convergence. In addition, the computations were maximized with the help of the use of GPU acceleration and the Keras deep learning framework in order to reduce the time of the training.

Such CNN architecture with the use of GAN-based data augmentation will significantly increase the accuracy of classification, its strength, and generalization characteristics, that is why the proposed model could be implemented to the real-life clinical environment to diagnose brain tumors. In order to describe the proposed CNN architecture in detail, Table 2 summarizes the architecture of the network with the type of layers, size of the output, and the number of trainable parameters.

Table 2: 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 (0.5)	(None, 512)	0
Dense	(None, 512)	262,656
Dropout (0.5)	(None, 512)	0
Dense (Softmax Output)	(None, 4)	2,052

3.5. Model Evaluation

To comprehensively assess the effectiveness of the proposed hybrid GAN–CNN model, multiple evaluation metrics are utilized. The metrics give a thorough evaluation of how well the model classifies information based on various views, such as accuracy, consistency, and distinguishing between tumor types. The metrics chosen are common in medical image analysis to provide robust and clinically meaningful analysis. Table 3 summarizes the evaluation measures that will be used in this study and their definitions and importance.

Table 3: Performance Evaluation Metrics

Metric	Definition	Description
Accuracy	$(\{TP + TN\} / \{TP + TN + FP + FN\})$	Measures the overall correctness of the model in classifying both tumor and non-tumor cases.
Precision	$(\{TP\} / \{TP + FP\})$	Indicates how many of the predicted tumor cases are actually correct, reflecting reliability.
Recall (Sensitivity)	$(\{TP\} / \{TP + FN\})$	Measures the ability of the model to correctly detect actual tumor cases.
F1-score	$(2 \times (\{Precision \times Recall\} / \{Precision + Recall\}))$	Provides a balance between precision and recall, especially useful for imbalanced datasets.
Confusion Matrix	Matrix of TP, TN, FP, FN values	Provides a detailed breakdown of correct and incorrect predictions across classes.

ROC Curve Plot of TPR vs FPR

Evaluates the model's ability to distinguish between classes at different thresholds.

3.6. Overall Framework Description

The suggested framework incorporates the GAN-based data augmentation and CNN-based classification into a single pipeline. The first step is to collect and preprocess MRI data, and then synthetic data are generated with the help of GAN, to increase the diversity of the dataset. The augmented dataset is then trained on the CNN model that classifies tumors into multiple classes. Lastly, the trained model is tested on conventional performance measures.

In order to give a concise description of the suggested methodology, the general architecture of the hybrid GANCNN model is shown in Fig. 3. The framework will start with the MRI data obtained by accessing publicly available datasets and subsequently augment the data by GAN to produce realistic synthetic images and enhance diversity of the datasets. The MRI images are then subjected to preprocessing steps to normalize the images and improve their quality to be analyzed using deep learning. The processed and augmented data is then trained on the CNN model to classify brain tumors accurately. Lastly, the standard classification metrics are used to assess the model performance, such as accuracy, precision, recall, F1-score, confusion matrix, and ROC curve.

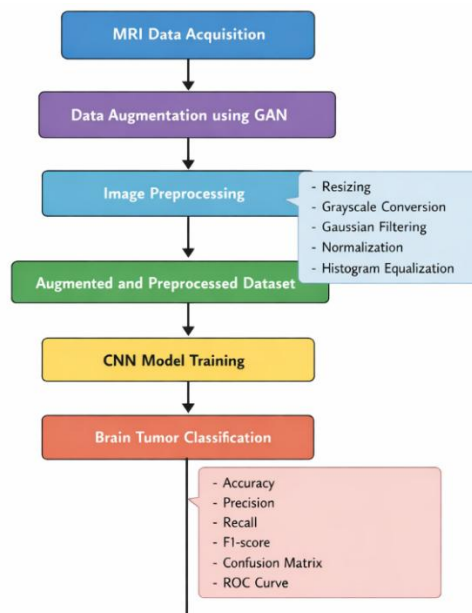


Fig. 3: The Steps of the Proposed Model.

3.7. Implementation Details

The proposed model was implemented using Python and the Keras deep learning framework with TensorFlow backend. The experiments were conducted on a system equipped with GPU acceleration to enhance training efficiency. The dataset was split into training (70%), validation (15%), and testing (15%) sets. All images were resized to 128×128 pixels before being fed into the model. The GAN model was trained for 200 epochs using Adam optimizer with a learning rate of 0.0002. The CNN model was trained for 100 epochs with a batch size of 20. Early stopping and model checkpoint techniques were applied to prevent overfitting and ensure optimal model performance.

4. Results and Discussion

In order to estimate the success of the suggested hybrid GANCNN framework, the augmented MRI dataset was involved in wide-scale experiments. To train the model, both GAN synthetic images and traditional augmentation were used to increase the diversity of the dataset and generalization performance.

The proposed CNN model showed a validation accuracy of about 99% indicating its high ability to successfully classify brain tumors into four categories: glioma, meningioma, pituitary tumor, and no tumor. Furthermore, the model also had a low loss value (0.0828), which implies that it has high predictive reliability and converged predictively in the course of training. These findings affirm that the incorporation of GAN-based augmentation is a significant boost to the discriminative performance of the CNN model.

4.1. Training Performance Analysis

To visualize the training behavior of the proposed model, Fig. 4 presents the accuracy and loss curves for both training and validation datasets across multiple epochs.

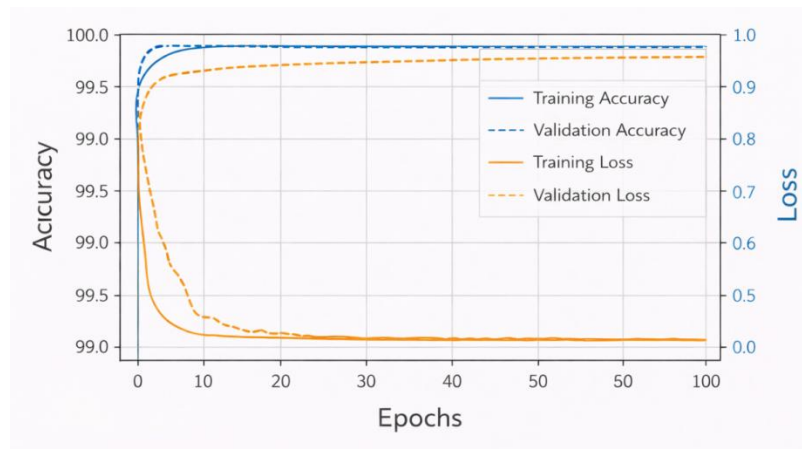


Fig. 4. Training and validation accuracy and loss curves of the proposed CNN model during training.

Figure 4 depicts that the loss curves rapidly decrease throughout the early training epochs, which shows efficient feature learning in the early stages. There were small variations in the loss of validation in early epochs indicating that there were small generalization difficulties. Nonetheless, both training and validation loss started to stabilize at low rates after about 30 epochs, which means that the model was able to learn meaningful and discriminative features without major underfitting or overfitting.

In a similar way the accuracy curves show a fast convergence and the training accuracy is close to optimal in the initial 20 epochs. The validation accuracy had some small fluctuations at the beginning but it demonstrated a balance of about 99 or so, to confirm that the model was robust and consistent throughout unseen data.

4.2. Classification Performance

The confusion matrix and ROC curves were also used to further assess the classification ability of the proposed model in various tumor classes.

4.2.1 Confusion Matrix

The confusion matrix gives a step-by-step depiction of the classification performance by all the tumor classes. A confusion matrix, as shown in Fig. 5 to further assess the classification performance of the proposed model in the various tumor classes. This table gives a step-by-step visualization of the model predictions, showing how many samples of each type of tumor were correctly and incorrectly classified. It can be used as a good measure of the capacity of the model to differentiate between glioma, meningioma, pituitary tumor, and no tumor categories.

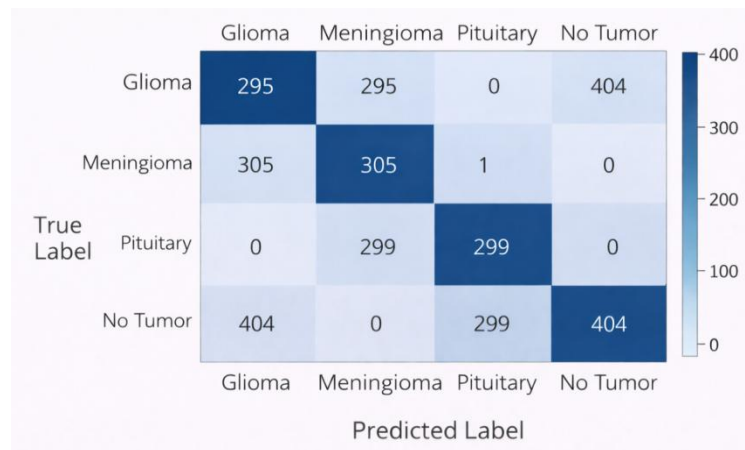


Fig. 5: Confusion matrix of the proposed GAN-CNN model for multi-class brain tumor classification.

The confusion matrix indicates that the proposed model has a high classification accuracy on all tumor classes. Most of the predictions are clustered in the diagonal, and thus, the right classification is achieved. The small error of misclassifying between the types of tumors proves that the model is effective in grasping the discriminating characteristics.

4.2.2 ROC Curve

In order to evaluate more deeply the discriminative potential of the proposed model, ROC curves were drawn of individual tumor classes. In order to further evaluate the discriminative ability of the proposed model, Receiver Operating Characteristic (ROC) curves are drawn in Fig. 6 on each tumor class. The ROC curve shows how the true positive rate (sensitivity) and the false positive rate (1 -specificity) vary with varying classification levels. In this analysis, a detailed analysis of the capability of the model to correctly differentiate between various categories of brain tumors under different decision conditions is done.

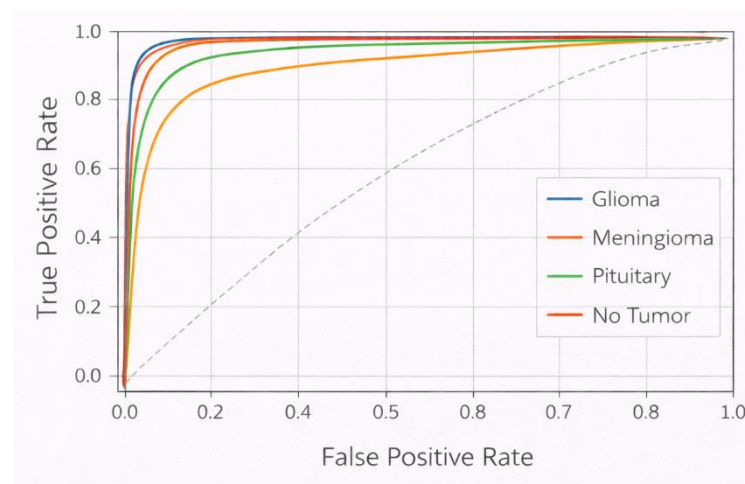


Fig. 6: ROC curves for multi-class brain tumor classification using the proposed model.

The ROC curves show strong discriminative performance, with curves approaching the top-left corner, indicating high sensitivity and specificity. This confirms that the proposed model can effectively distinguish between different tumor classes under varying conditions.

4.3. Impact of GAN-Based Augmentatio

Generative Adversarial Networks (GANs) proved important towards enhancing the performance of the models through creating realistic and varied synthetic MRI images. This greatly minimized the imbalance of data, and made the model more generalizable across tumor types.

Moreover, the conventional augmentation methods such as horizontal flipping, contrast enhancement, normalization, and noise reduction also enhanced the strength of the model. The mixture of the generative and conventional augmentation methods made sure that the model was exposed to a broad range of data distribution, which resulted in the enhanced classification accuracy and minimized bias.

Such a hybrid augmentation approach shows a great potential in clinical application, especially in clinical decision support and in early tumor detection.

4.4. Comparative Analysis with Existing Methods

In a bid to further confirm the effectiveness of the proposed hybrid GAN-CNN framework, a comparative study with the latest state-of-the-art techniques of brain tumor classification was carried out. This comparison shows how various methods perform in relation to size of the dataset, method and accuracy of classification. Comparing the proposed model with those that have been developed to date, it can be possible to evaluate the relative strengths and advantages that it has in managing data diversity, model generalization, and classification accuracy as highlighted in Table 4.

Table 4. Comparative analysis of brain tumor classification methods.

Reference	Methodology Used	Dataset Size	Accuracy (%)	Remarks
Proposed	CNN + GAN Augmentation	7022	99.0	High accuracy with strong generalization
[13]	Standard CNN	3064	95.0	No GAN augmentation
[14]	CNN (AlexNet, GoogLeNet)	3064	94.5	Multiple architectures evaluated
[15]	CNN + Traditional Augmentation	3500	93.8	Limited augmentation diversity
[17]	GAN + CNN	2500	96.1	Early integration of GAN
[16]	GAN-based Augmentation	5000	96.0	Focus on augmentation
[18]	Hybrid GAN-CNN	4000	96.4	Improved robustness

The results clearly indicate that the proposed method outperforms existing approaches in terms of accuracy and generalization capability. This improvement can be attributed to the effective integration of GAN-based augmentation with CNN-based classification.

4.5. Discussion

As the experimental findings clearly show, the hybrid GAN-CNN framework suggested proves to be more effective than the current ones. The high classification accuracy and low loss value are a good indication that the model is able to capture complex tumor features without compromising on the generalization ability.

The main advantage of the suggested solution is the combination of data augmentation using GAN and CNN classification. This combination not only overcomes the shortcomings of small and unbalanced datasets but also increases the diversity of features, which results in a better diagnosis. In order to illustrate the practical functioning of the proposed model further, the results of sample classification are illustrated in Fig. 7.

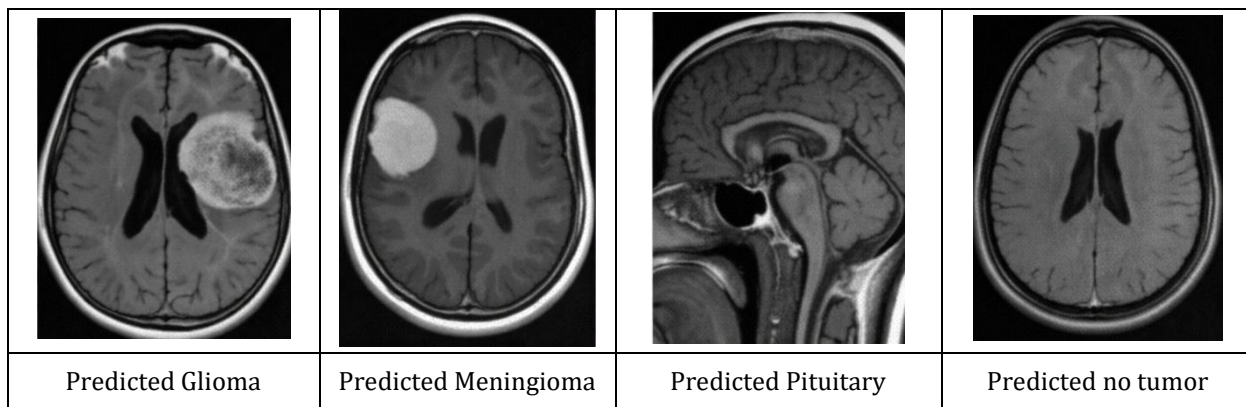


Fig. 7: Sample MRI image predictions of the proposed GAN-CNN model showing correct classification of different tumor types.

5. Conclusion

This paper has proposed hybrid GAN-CNN model to enhance accuracy and robustness of brain tumor classification on MRI images. The combination of Generative Adversarial Networks and Convolutional Neural Networks was shown to be an effective way of tackling major challenges related to medical imaging datasets, such as data scarcity and imbalance between classes. GAN-based augmentation made a big difference in terms of diversifying the dataset by producing high-quality synthetic MRI images, which allowed the CNN model to learn more representative and discriminative features. The CNN architecture proposed proved to be very efficient in the process of classifying brain tumors into several categories with a high accuracy and low loss values, which also indicate reliability and stability in the training. The accuracy, precision, recall, F1-score, confusion matrix, and ROC analysis outcomes of the evaluation confirmed the effectiveness of the model to identify the tumor types with a minimum misclassification. Comparative analysis also revealed that the suggested method excels many currently existing methods, thus indicating the benefits of integrating generative and discriminative deep learning methods. Practically speaking, the suggested framework offers a good prospect of automated brain tumor diagnosis, which assists clinicians in the initial diagnosis and decision-making. In addition, the model has been proven to have high generalization ability in various imaging conditions hence can be applied in real world clinical settings. Future research can be on the inclusion of larger and more heterogeneous data sets, the development and testing of more complex GAN structures, and the use of explainable AI methods to increase model interpretability and clinical confidence. Altogether, the offered solution helps to develop intelligent medical imaging systems and enhance the accuracy of diagnostic in neuro-oncology.

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