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Research Paper

Enhancing Brain Tumor MRI Classification Using Dual-GAN Data Augmentation and Deep Ensemble Feature Extraction

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ABSTRACT

Background: Accurate computer-assisted classification of brain tumors from magnetic resonance imaging (MRI) remains difficult because medical imaging datasets are often imbalanced. Deep learning algorithms tend to over-represent majority classes, with fewer samples available for under-represented tumor classes, making it less reliable to diagnose clinically important minority cases. To address class imbalance and enhance discriminative feature representation and model interpretability, the authors propose a DualGAN–DeepEFE framework.

Methods: The proposed framework combines the dual-stage generative augmentation with deep ensemble feature extraction. Two complementary generative adversarial networks (GANs) are used to synthesize realistic MRI samples for under-represented tumor classes without altering anatomical structure or fine-grained lesion characteristics. The enhanced, balanced dataset is then fed into the pre-trained ResNet50 and VGG16 networks. Both backbones are used for feature extraction, and their features are concatenated to provide a complete representation of the tumor, which is then passed to a fully connected classifier for four-class prediction. To improve visual interpretability, Grad-CAM is used to highlight image regions that influence each prediction.

Results: Using an open four-class brain MRI dataset, the model achieved a validation accuracy of 94.16%, a test accuracy of ~94%, and a macro F1-score of 94.5%. The class-wise ROC-AUC values were all above 0.96, indicating good discrimination across all tumor classes.

Conclusion: It can be inferred from the findings that the use of dual-stage synthetic augmentation with complementary deep feature fusion is effective in minimizing the effect of class imbalance and can maintain classification performance well. Furthermore, the Grad-CAM algorithm was used to localize regions associated with diagnostic information, which can be interpreted, thus aiding in the potential clinical use of the proposed DualGAN–DeepEFE framework.

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Introduction

The automatic classification of brain tumors using Magnetic resonance imaging (MRI) remains very sensitive to the quality and variety of training data.One subject that remains sensitive to the quality and variety of training data is classification of brain tumors with Magnetic resonance imaging (MRI). Tumors may differ in appearance, some imaging characteristics may be identical and the number of tumors per class may vary making identification difficult. To address the aforementioned issues, complementary feature extraction and Generative augmentation are solutions. To explore the possibility of synthetic samples and multiple representations for brain tumor classification, Roy et al. [1] came up with a Dual-GAN mechanism as well as deep ensemble feature extraction (DeepEFE) and visual explanations. In the initial research, it was demonstrated how generative learning can be combined with classification. Ghassemi et al. [2] applied generative adversarial network (GAN) pre-training to get the initial weights of a deep neural network for brain MRI classification. To overcome limitations due to available imaging modalities, Ge et al. [3] came up with the idea of using pairwise GANs to expand training sets for molecular-based tumor classification. They then scaled up to semi-supervised learning with the use of labeled and unlabeled images [4]. Depending on the degree of supervision provided, the improvement on data utilization could be in the form of synthetic image generation, representation learning or both, in the above studies.

A number of synthesis methods were subsequently explored. Gab Allah et al. [5] investigated the progressive growing GAN augmentation in brain MRI tumor classification and Ahmad et al. [6] applied variational autoencoders with GANs. Mukherkjee et al. [7] compiled a number of GAN models to generate tumor images by style transfer. Huang et al. [8] proposed the common feature learning from MRI modalities, with an adversarial synthesis applied to the context-aware. Yurtsever et al. [9] conducted tests with augmentation on Gazi Brains dataset using radiogenomic classification via GAN. Melekoodappattu et al. [10] have also explored the use of multistage ensemble for classification of brain cancer. These all encourage us to consider synthetic data in terms of their contribution to classification and not just on the basis of their visual appearance. Representation learning is an alternative. Kang et al. [11] concatenated the deep features learned by the pre-trained networks with the machine learning classifiers. Celik et al. [12] studied Ensemble attention and Ullah and Kim [13] studied Hierarchical feature fusion and Ensemble learning. Patro et al. [14] investigated a set of deep learning techniques and Kaya et al. [15] presented the Fusion-Brain-Net approach for deep representation fusion. As a methodological reference point, convolutional neural network (CNN) classification, as in the case of Badža and Barjaktarović [16] has been studied, as well as isolated deep feature extraction followed by shallow classification as studied by Almalki et al. [17] have been studied. This literature can be used to appraise the impact of feature combination on the classification, as well as the impact of augmentation. Although of these progressions, the significance of synthesis and feature fusion is still subject to the dataset and evaluation circumstances. The more samples the greater the variation that can be diagnostically useful, but the more features streams that are combined the more redundant they can be. Additionally, the overall accuracy may be a reflection of the differences in sensitivity across tumor type. These two considerations make one think of the augmentation and feature extraction in tandem; and look at the errors and explanations of predictions in each class separately. This evaluation should be conducted in an unambiguous way, with a clear separation between the development and the testing of the model, which is not possible with a synthetic image to prove the generalization to other patients and institutions. Dual-GAN and DeepEFE concept is not new, the current study will be conducted in a defined four-class application and evaluation scenario.

This study, therefore, explores the sequential image generation and refinement of DualGAN–DeepEFE, and then the complementary feature extraction of pretrained ResNet50 and VGG16 networks. The representation of an image by a fully connected softmax classifier overlaid on all the images in the world is done by global average pooling and concatenation. Gradient-weighted class activation mapping (Grad-CAM) is a visualisation technique that is qualitative and can be used to identify regions that can influence predictions. There are 7,023 images in public dataset with mild class imbalance and accuracy, precision, recall, macro F1-score, ROC-AUC and confusion matrix analysis are performed. We compare the effectiveness of the integrated configuration with the conventional CNNs to show that the integrated configuration can outperform the single-GAN augmentation. The aim is to evaluate the usefulness of the classification in this sample, and to interpret its performance; again, however, it is necessary to validate its usefulness in wider clinical use.In sum, the DualGAN–DeepEFE pipeline combines two-stage GAN augmentation, multi-backbone feature fusion, fully connected classification and Grad-CAM explainability into a unified pipeline.

These parameters are used to evaluate the performance: accuracy, precision, recall, macro F1, ROC-AUC, confusion matrix and training–validation convergence. The above reported results show test accuracy of ~94%, macro F1 score of 94.5%, and the class-wise ROC-AUC above 0.96 with a better performance than the traditional augmentation and single-backbone baselines. These advantages of integrated design directly address the issues of data scarcity, feature diversity and interpretability, but not in the way of adding more data and then, in a later step of the diagnostic process, classifying the data.

Materials and Methods

This proposed framework is intended to tackle the issues of class imbalance and training set in brain tumor classification tasks. Here, we suggest a Dual-GAN + Deep Feature Ensemble (DeepEFE) pipeline, consisting of high-quality synthetic data augmentation, deep ensemble feature extraction and interpretable classification. The whole framework of DualGAN-DeepEFE model is shown in Figure 1. For standardization, all the MRI images are resized to 224×224 and normalized to [0,1] to facilitate the model convergence and to standardize MRI intensities. The data is split using stratified partitioning of 80% training set and 20% testing set while maintaining a balance in class distribution. The image data for this work is a publicly available dataset of MRIs of four classes (glioma, meningioma, pituitary tumor, and no-tumor) from the brain. This dataset contains 7023 MRI images and during the pre-processing, images. The distribution is imbalanced with a slight over-representation of cases with glioma or pituitary tumors compared with meningioma. The augmented data set was divided into 80% training set and 20% test set by the stratified data sampling method which preserved the class distribution for both training set and test set.

Data Pre-processing and Feature Selection

To classify the brain tumors correctly, an integrated preprocessing, feature extraction and implicit feature selection strategy is incorporated into the DualGAN-DeepEFE framework to effectively tackle the imbalanced MRI inputs. The intensities of the pixels are mapped to the range [0,1] to minimise the difference between the intensities of the images, and stabilise the gradients optimisation. Data quality screening is applied and stratification used to divide the data into training and testing sets while keeping the distribution of the glioma, meningioma, pituitary tumor and no-tumor classes unchanged [19]. In this work, the focus is on the classification of brain magnetic resonance imaging (MRI) images in four classes namely gliomas, meningiomas, pituitary tumors, and no tumor. Overall, there are 7023 images, including 1621 glioma, 1645 meningioma, 1757 pituitary tumor and 2000 no tumor images. Glioma is, therefore, the smallest and no-tumor the largest. Class ratio is fairly moderate (Class ratio ~ 1.23). Because, the study does not take the stand of assuming that the dataset is heavily imbalanced; instead, it looks into synthetic augmentation as an alternative to that. Data were obtained from [verified repository, author, version of the data set, and citation]. The first training and testing partitions contained objects, respectively, [verified counts] respectively. The Dual-GAN module is designed to tackle the class imbalance issue and intelligently create more samples from the minority tumor classes. The first GAN is used to learn the global tumor morphology, while the second one is used to learn the image-to-image GAN to add the local tumor texture, boundary continuity, and

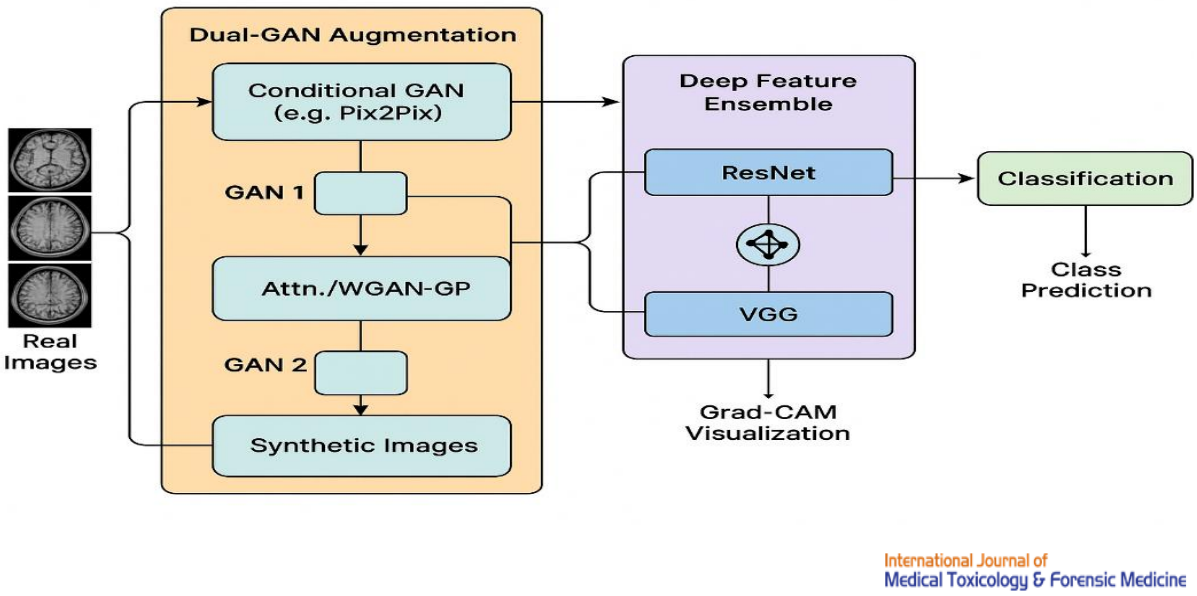
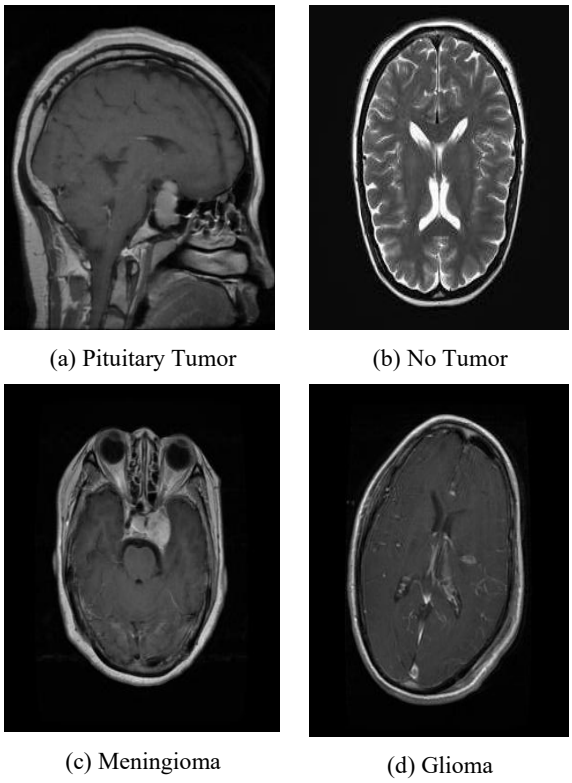


Figure 1. Shows the overall block diagram of proposed model.

anatomical plausibility to enhance the generated images. This synthetic imaging creates a more balanced training set which decreases the risks of majority-class bias and increases the exposure to variations in the minority class, and is combined with the original MRI scans. The MRI images of DualGAN-DeepEFE framework is shown in Figure 2.



(a) Pituitary Tumor (b) No Tumor

(c) Meningioma (d) Glioma

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Figure 2. Representative MRI images from the brain tumor dataset illustrating four classes: (a) Pituitary tumor, (b) No Tumor, (c) Meningioma, and (d) Glioma.

The framework is developed by using the discriminative representation learning using complementary pre-trained feature extractors ResNet50 and VGG16. While VGG16 is learning detailed local-texture, edge and tumor-boundary patterns by sequential convolutional blocks, ResNet50 is learning high level semantic and global structural patterns by residual learning. To reduce dimensionality of networks, and to pick the most relevant activations from the last convolutional feature maps of both networks, global average pooling (GAP) is employed. Then take the output from ResNet50 2048 dimensions and the output from VGG16 (512 dimensions) and concatenate to form a DeepEFE 2560-dimensional representation. This proposed model is end to end supervised learning, without requiring the use of any handcrafted feature selection algorithm. Before and after the augmentation by Dual-GAN, the distribution of the data sets is given in Table 1.

Dual-GAN Data Augmentation

The proposed DualGAN–DeepEFE framework is capable of alleviating the class imbalance by synthesizing anatomically consistent MRI samples using Noise-to-Image and Image-to-Image GANs. Visual and FID evaluation of the synthetic images are performed and used to join the original data. The image features are extracted by ImageNet-pretrained ResNet50 and VGG16, then fused by GAP, fully connected classification and softmax prediction. Optimizing training is done using Adam and categorical cross-entropy and interpretability is achieved using Grad-CAM. The performance is measured by comparing the following metrics to baseline models: Accuracy, Precision, Recall, F1-score, ROC-AUC and confusion matrix. The Architecture diagram of the proposed model is shown in Figure 3.

Results

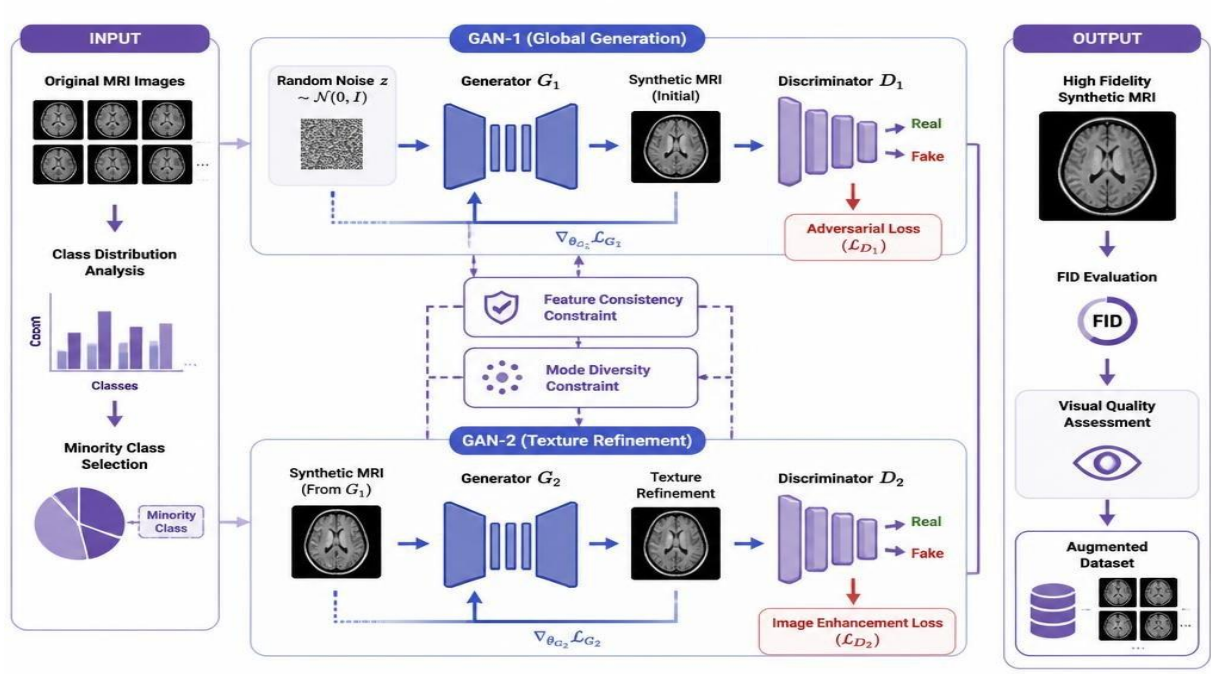
Training and Validation Performance

The convergence behavior of the proposed model is shown in Figure 4. The training accuracy improves from 82.4% at epoch 1 to 98.29% at epoch 10, reflecting the successful learning of feature representations. Likewise, the validation accuracy also is enhanced from 81.6% to 94.16% and the best value is obtained at the 7th epoch, which is 96.51%. This optimal performance indicates that this model achieves the best level of generalization before some slight stabilization in the later epochs.

Table 1. Dataset distribution before and after Dual-GAN augmentation.

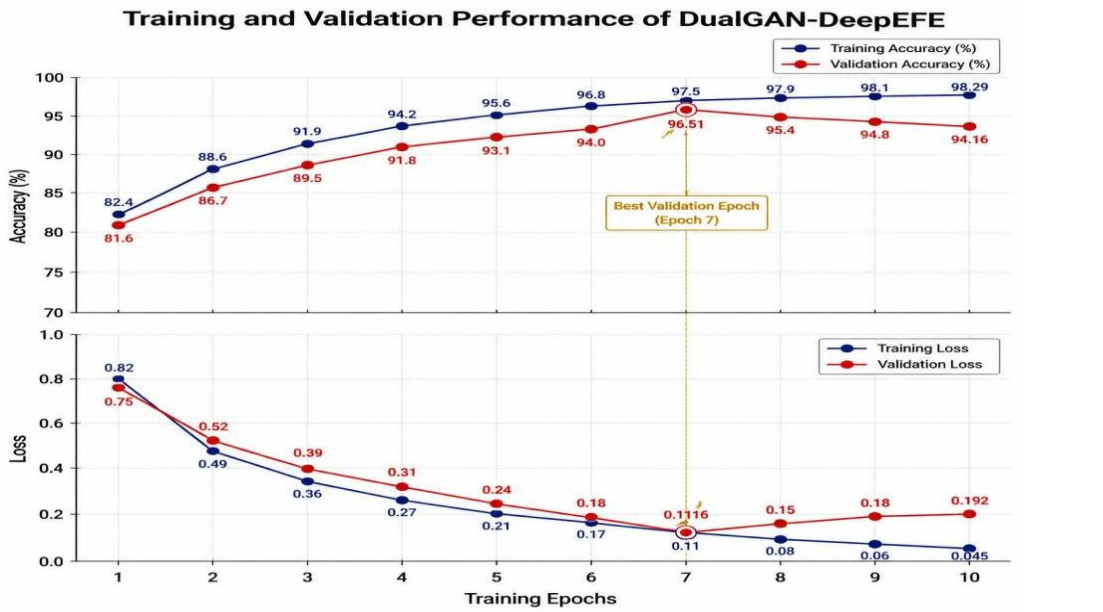
Class	Original Images	Augmented Images (Dual-GAN)	Total After Augmentation	Train Samples	Test Samples
No-Tumor	2000	0	2000	1600	400
Pituitary	1757	+400	2157	1725	432
Meningioma	1645	+500	2145	1716	429
Glioma	1621	+500	2121	1697	424
Total	**7023**	**+1400**	**8423**	**6738**	**1685**

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Figure 3. Architecture diagram of the proposed framework.



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Figure 4. Training and Validation Performance of the Proposed model.

This is confirmed by the loss curves. The training loss falls drastically from 0.82 to 0.045 and the validation loss dips at a minimum of 0.1116 at epoch 7 and slightly rises. A slight increase suggests a mild overfitting, but the difference between the training curve and the validation curve is not significant, indicating that the Dual-GAN augmentation approach has a good regularization effect, and it can better regularize the learning process and improve the generalization ability.

Class-wise Performance Analysis

As shown in Figure 5, the class-wise performance of the model depicts the model's good predictive ability for all the tumor classes. The model has Precision values of 98%, 91%, 97%, and 96% for glioma, meningioma, no-tumor and pituitary classes, respectively. Its Recall indicates that the model has a higher ratio for no-tumor cases, with a near-perfect value of 99%, showing it to be effective in identifying no-tumor cases.

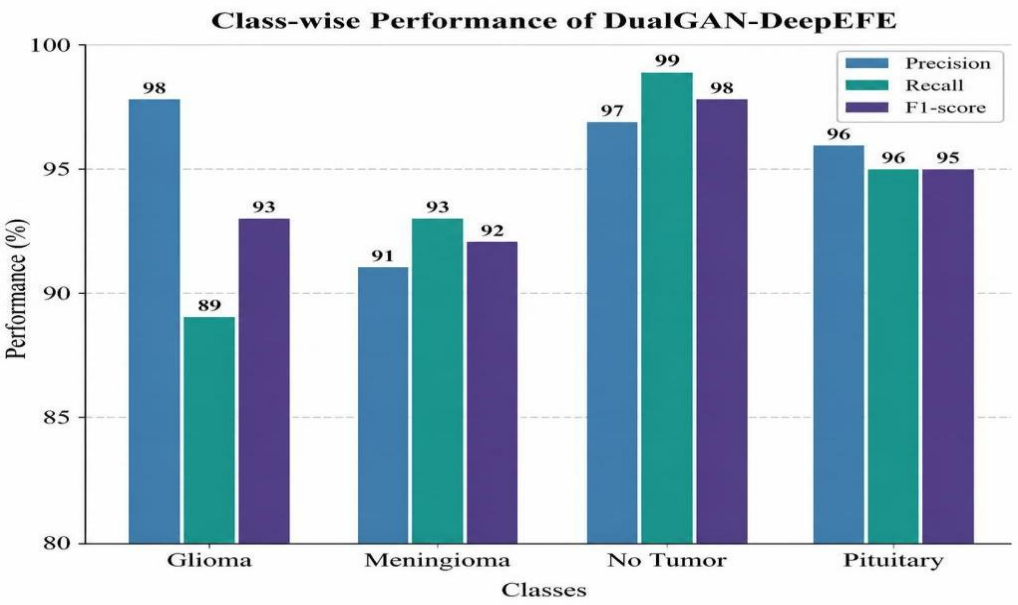


Figure 5. Class-wise performance.

Balanced trade-off between Precision and Recall is confirmed by the resulting F1-scores, of 93% (glioma), 92% (meningioma), 98% (no-tumor), and 95% (pituitary). The slight reduction in the Recall for glioma may result from some confusion with meningioma, which is not unexpected as both tumors have similar visual features on MRI images. However, the macro F1 score is 94.5% which shows that the model is robust in all the classes, including minority tumor classes.

Comparative Accuracy Evaluation

The comparative Accuracy of proposed method with baseline models is shown in Figure 6. The conventional CNN gives 84.2% Accuracy, ResNet50 gives 86.0% Accuracy and VGG16 gives 87.0% Accuracy. Adding augmentation using the GAN approach boosts performance, the Single-GAN + CNN model attains 91.8% Accuracy.

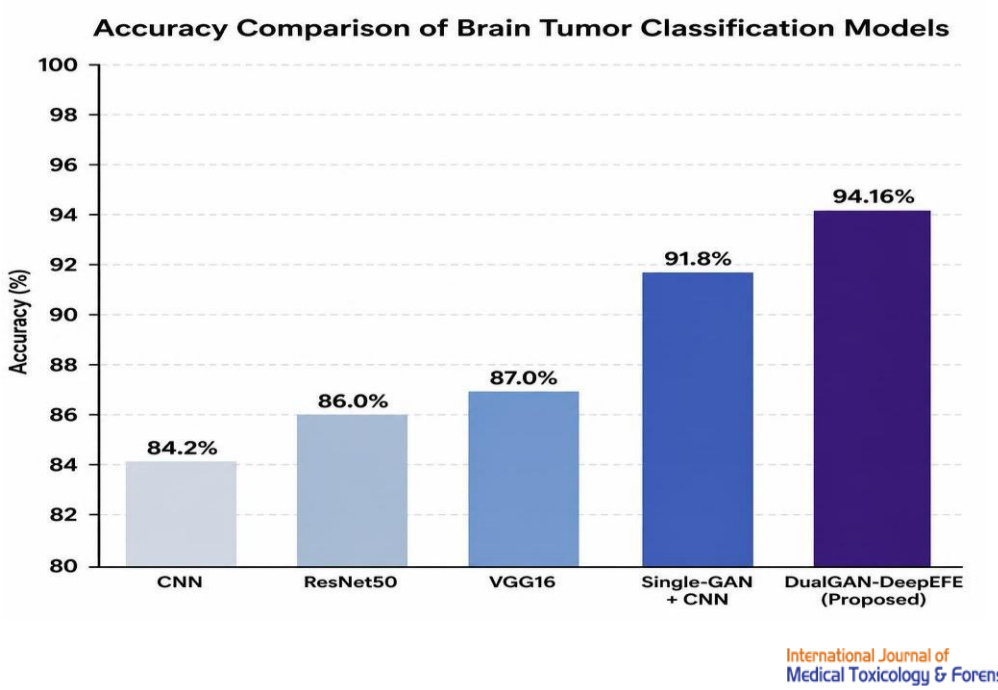


Figure 6. Accuracy comparison.

But the DualGAN-DeepEFE framework achieves the Accuracy of 94.16% as compared to CNN, ResNet50 and Single-GAN frameworks with an Accuracy gap of around 10%, 8.16% and 2.36% respectively. This improvement clearly shows that dual-stage augmentation with feature ensemble learning yields more discriminative representation than single-model or single-GAN.

ROC Curve and Discriminative Capability

Figure 7 also shows the ROC curves, which further verify the classification performance of the model. All the curves are tightly grouped in the upper left corner of the graph, showing high TPR and low FPR. The AUC values are 0.97 (glioma), 0.96 (meningioma), 0.99 (no-tumor), and 0.98 (pituitary). These high AUC values validate the good separability between the classes as obtained in the proposed model, with a near-perfect discrimination for the no-tumor class. This is particularly important in clinical use where the false positive and the false negative can affect the diagnosis.

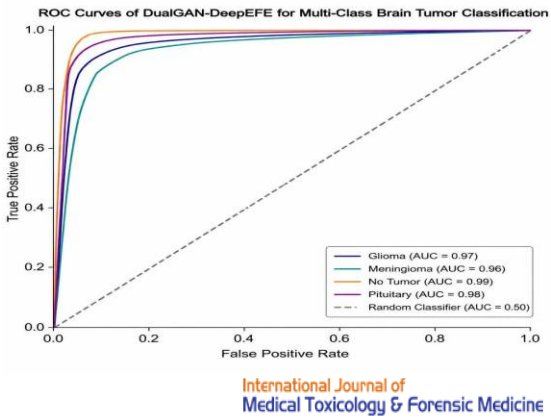


Figure 7. ROC curve.

Confusion Matrix Interpretation

A detailed insight of the detailed classification Accuracy at the class level is given by the row-normalized confusion matrix in Figure 8. The model achieves high Accuracy in the classification of glioma (88.34%), meningioma (90.41%), no-tumor (98.01%) and pituitary (94.59%).

Misclassification is most often seen between glioma and meningioma with approximately 10.80% of those with glioma being misclassified as meningioma, and this is likely to be due to the fact that there are inherent visual similarities between the two tumor types. But the no tumour class exhibits very little confusion with less than 2% of misclassification highlighting the good separation from pathological classes. The Precision values also corroborate this with all the classes having Precision values above 91% indicating the reliability of the predicted labels. The balanced confusion matrix shows that the model has performed well in handling class imbalance and is performing well on each class.

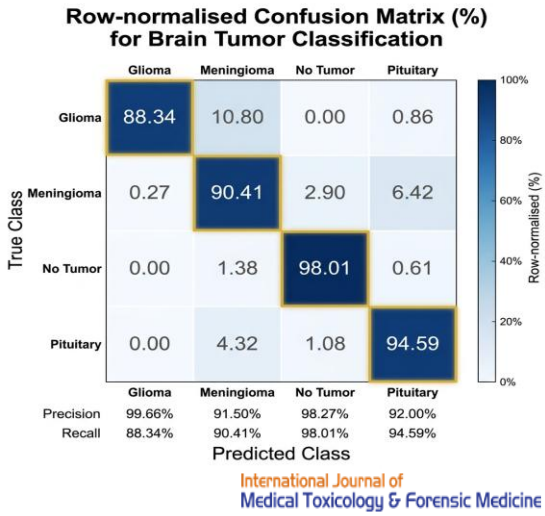


Figure 8. Confusion matrix.

Comprehensive Metric Comparison

Figure 9 presents an overall performance comparison of the proposed model which shows that the proposed model outperforms in several performance measures. The DualGAN-DeepEFE framework can attain 94.16% Accuracy, 96.0% Precision, 94.0% Recall and 94.5% macro F1 score, which is better than all baseline models. The proposed model achieves better generalization and robustness when compared with VGG16 and ResNet50, which have lower Recall and F1-scores. The results are consistent across all metrics, showing that the dual-GAN augmentation and deep feature extraction based on feature ensemble can improve the sensitivity and specificity of the classification system.

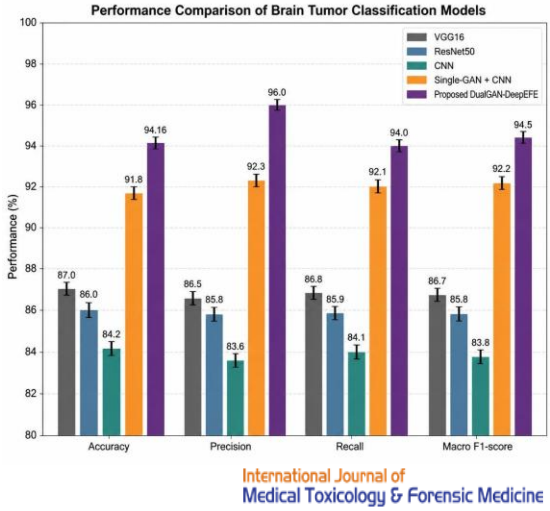


Figure 9. Overall performance comparison of brain tumor classification models.

Discussion

The results should be interpreted with the following limitations. The framework was validated based on 2D MRI images from a single public dataset, and hence, generalizations about the performance on full volumetric examinations and/or images acquired under different clinical conditions are limited. Patient independent generalization is not possible with image-level partitioning if patient identifiers are not available. The class imbalance is mild in the original class and the conclusions made for more severe class imbalance are based on controlled experiments. Synthetic augmentation can lead to artifacts or artefacts can be a replica of the patterns seen in the training images but not necessarily diagnostic. Furthermore, the sensitivity of gliomas is of particular interest, where errors could have a clinical impact. Furthermore, Grad-CAM provides qualitative explanations and is not a pathological; correct. Prior to considering clinical deployment external, patient level, and prospective validation, as well as expert assessment, is required.

Conclusion

The experimental results demonstrate the effectiveness of the proposed DualGAN-DeepEFE framework in tackling problems of class imbalance and small sample size in brain tumor MRI classification. The dual-GAN framework brings benefits of generating high-quality synthetic samples, boosting data diversity, and combining complementary strengths of ResNet50 and VGG16 into the DeepEFE module for further enriching feature representation. Based on these results, the DualGAN-DeepEFE model could be used as a powerful and clinically useful tool for automatic brain tumor diagnosis. The proposed method can well solve the problem of class imbalance and other key issues of small samples and weak feature representation through dual-stage GAN-based augmentation and deep ensemble feature extraction. Both the high-quality synthetic MRI samples generated by Dual-GAN mechanism to increase minority-class representation and the global and fine-grained anatomical features captured by DeepEFE module (combining ResNet50 and VGG16) are well leveraged. Experimental results show the effectiveness of the proposed method in terms of various performances. It was able to obtain a validation Accuracy of 94.16% with a maximum Accuracy of 96.51% at epoch 7 showing good generalization ability. In addition, the framework achieves a macro F1-score of 94.5%, Precision of 96.0%, and Recall of 94.0%, indicating that the performance is more balanced among the tumor classes. The ROC-AUC values greater than 0.96 for all the categories validate the good discriminative ability and the confusion matrix analysis reveals good class-wise Accuracy (98.01% for no-tumor class, 94.59% for pituitary tumor). The comparison results show that the proposed method significantly outperforms the baseline models in terms of classification Accuracy, achieving around 7-10% Accuracy improvement on conventional CNN architectures and 2-3% Accuracy improvement on single-GAN based methods. This integration of Grad-CAM not only boosts quantitative Accuracy but also improves interpretability by highlighting tumor-relevant regions, leading to further increases in the reliability of the model for clinical decision support. In conclusion, the proposed DualGAN-DeepEFE framework is a comprehensive, accurate and interpretable approach for automated brain tumor MRI classification.

Ethical Approval

Not applicable.

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Conflicts of Interest

The authors report there are no competing interests to declare.

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