Enhancing Brain Tumor Classification with a Novel Three-Dimensional Convolutional Neural Network (3D-CNN) Fusion Model

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Abstract Three-dimensional convolutional neural networks (3D CNNs) have been widely applied to analyze brain tumour images (BT) to understand the disease's progress better. It is well-known that training 3D-CNN is computationally expensive and has the potential of overfitting due to the small sample size available in the medical imaging field. Here, we proposed a novel 2D-3D approach by converting a 2D brain image to a 3D fused image using a gradient of the image Learnable Weighted. By the 2D-to-3D conversion, the proposed model can easily forward the fused 3D image through a pre-trained 3D model while achieving better performance over different 3D baselines. We used VGG16 for feature extraction in the implementation as it outperformed other 3D CNN backbones. We further showed that the weights of the slices are location-dependent, and the model performance relies on the 3D-to-2D fusion view, with the best outcomes from the coronal view. With the new approach, we increased the accuracy to 0.88, compared with conventional 3D CNNs, for classifying brain tumour images. The novel 2D-3D model may have profound implications for future timely BT diagnosis in clinical settings.

1. INTRODUCTION

S Brain tumors present a significant challenge in the medical field, necessitating advanced imaging techniques for accurate diagnosis and monitoring[1], [2]. Traditional imaging methods often rely on 2D representations of complex three-dimensional structures, which can limit the effectiveness of diagnosis and treatment planning. Convolutional neural networks (CNNs), particularly three-dimensional CNNs (3D CNNs), have emerged as powerful tools for analyzing brain tumor images, offering the potential for improved understanding of the disease's progression[3]. However, the application of 3D CNNs in medical imaging is not without its drawbacks. The training of 3D CNNs is computationally expensive and prone to overfitting, largely due to the limited availability of medical imaging data[4].

In response to these challenges, we propose a novel approach that bridges the gap between 2D and 3D imaging techniques. Our method involves converting 2D brain images into 3D fused images using a learnable weighted gradient. This 2D-to-3D conversion allows the model to leverage the strengths of both 2D and 3D CNNs, enhancing performance while mitigating the computational demands and overfitting risks associated with traditional 3D CNNs.

Our proposed model utilizes VGG16 for feature extraction, selected for its superior performance over other 3D CNN backbones. By forwarding the fused 3D image through a pre-trained 3D model, our approach achieves notable improvements in accuracy compared to conventional 3D CNN baselines. We also demonstrate that the weights of the slices are location-dependent, and the optimal performance is achieved when utilizing the coronal view for 3D-to-2D fusion.The ability to diagnose brain tumors more effectively and efficiently has profound implications for patient outcomes, potentially leading to more timely and accurate treatment interventions.

In this paper, we delve into the methodology and performance of our novel approach, exploring its potential to revolutionize brain tumor imaging and diagnosis. The rest of the article is organized as follows. Descriptions of the technical and fundamental aspects of the proposed model and other competing methods are presented in Section 2. Section 3 reports and discusses the experimental results. A performance comparison between the proposed methods with some existing methods in the literature is presented in Section 4, followed by conclusions and future work in Section 5.

2. RELATED WORKS

The analysis of brain tumor images has seen significant advancements with the integration of machine learning and deep learning techniques[5]. This section reviews key studies and methodologies in the field, highlighting their contributions and limitations. Early approaches to brain tumor imaging primarily relied on conventional 2D imaging techniques such as MRI and CT scans[1], [6], [7]. These methods, while effective for visual inspection, often lack the depth and detail necessary for accurate diagnosis and tumor characterization. The two-dimensional nature of these images limits the ability to capture the spatial relationships and volumetric changes critical for understanding tumor growth patterns and treatment response. The advent of convolutional neural networks (CNNs) has revolutionized medical image analysis. 2D CNNs have been extensively used for tasks such as tumor detection and segmentation[8]. For instance, Sadad et al. [9] presents an advanced deep learning approach for detecting and classifying brain tumors using MRI images. The method employs the Unet architecture with ResNet50 as a backbone for segmentation, achieving a high intersection over union (IoU) score of 0.9504. Data augmentation techniques are applied to improve classification rates, and multi-classification is performed using evolutionary algorithms and reinforcement learning through transfer learning. The study compares several deep learning models, including ResNet50, DenseNet201, MobileNet V2, InceptionV3, and NASNet, for classifying brain tumors into glioma, pituitary, and meningioma. The database used comprises 3,064 brain MRI slices from the Figshare dataset, involving 233 patients with various types of brain tumors and achieved average accuracy of 95.6%. Shatnawi et al. [10]proposed a six-step model for detecting and classifying brain tumors using MRI images. The process begins with pre-processing, where various filters are applied to improve image quality, including techniques like crop normalization and histogram equalization to enhance contrast and focus on the region of interest. In the image segmentation stage, methods such as active contours (snakes), fuzzy C-means, and region-derived triple thresholding are employed. Additionally, two hybrid segmentation models that combine these techniques with computer-aided detection are implemented. Post-processing involves the use of artificial bee colony optimization and watershed filtering to refine segmentation results and eliminate noise. Classification is performed using the VGG-16 convolutional neural network (CNN), which categorizes images into tumor and non-tumor classes. Further, segmented images are classified into glioma, meningioma, pituitary tumors, and no tumor categories using one-hot encoding. The approach is validated with synthetic and real MRI datasets from Kaggle. the VGG16 classification accuracy is 80.85%. Sharif et al. [11] present a deep learning-based framework for the multiclass classification of brain tumors using MRI scans. The method involves fine-tuning a Densenet201 model with imbalanced data and extracting

features from the Global Average Pooling (GAP) layer. To enhance the accuracy and efficiency of the classification, a new feature selection approach called Entropy–Kurtosis-based High Feature Values (EKbHFV) and a modified Genetic Algorithm (MGA) are employed. The selected features from both methods are fused using a non-redundant serial-based approach and classified using a multiclass cubic SVM classifier. The evaluation uses the BRATS2018 and BRATS2019 datasets, which include images of High-Grade Gliomas (HGG) and Low-Grade Gliomas (LGG) across four stages (T1-weighted, T1CE, T2-weighted, and Flair). The proposed method achieves a remarkable accuracy of more than 95% on the BRATS2018 dataset and comparable high accuracies on the BRATS2019 dataset, demonstrating significant improvements over traditional methods. Haq et al. [5] presents two efficient brain tumor identification techniques based on deep convolutional neural networks (CNNs) using MRI data, aimed at improving the diagnosis and treatment of brain cancer. The research utilizes two publicly available datasets: Figshare and BraTS 2018, containing 3062 and 251 images respectively. The first CNN architecture classifies brain tumors into gliomas, meningiomas, or pituitary tumors, while the second differentiates between high- and low-grade gliomas (HGG and LGG). Conditional random fields are applied to refine segmentation outputs by incorporating spatial information. Additionally, an intensity normalization method, combined with data augmentation techniques, enhances the detection and classification process. The first architecture achieved an accuracy of 97.3% and a Dice Similarity Coefficient (DSC) of 95.8%, while the second architecture attained an accuracy of 96.5% and a DSC of 94.3%. These results demonstrate the proposed models' superior performance compared to existing methods. Subsequently, numerous studies have adapted CNNs for brain tumor classification, leveraging architectures such as VGG16, ResNet, and Inception for feature extraction and classification[12][13]. To address the limitations of 2D CNNs, researchers have increasingly turned to 3D CNNs, which process volumetric data and capture spatial information more effectively. Several studies have demonstrated the advantages of 3D CNNs in brain tumor segmentation and classification. For instance, the work by Chen et al. [14]showcased the use of 3D U-Net for brain tumor segmentation, achieving superior performance compared to traditional 2D CNNs . Similarly, Kamnitsas et al.[15] proposed a 3D CNN model that outperformed existing methods in terms of both segmentation accuracy and computational efficiency. Despite their advantages, 3D CNNs are not without challenges. The high computational cost associated with training 3D models is a significant barrier, particularly in clinical settings with limited computational resources . Furthermore, the small sample size commonly available in medical imaging datasets exacerbates the risk of overfitting, reducing the generalizability of 3D CNN models . Studies have explored various techniques to mitigate

these issues, including data augmentation, transfer learning, and regularization methods[12], [16]. To overcome the limitations of purely 2D or 3D approaches, researchers have explored hybrid methods that combine 2D and 3D information. For example, Lee et al.[17] proposed a method that integrates 2D and 3D CNN features, demonstrating enhanced performance in brain tumor classification . Recent advancements have also focused on optimizing feature extraction and model architecture. Pre-trained models such as VGG16, ResNet, and Inception have been widely adopted for feature extraction in medical image analysis . Notably, the study by Simonyan and Zisserman [18] demonstrated the effectiveness of VGG16 in capturing high-level features, which has been leveraged in various medical imaging tasks . Additionally, techniques such as attention mechanisms and residual learning have been integrated into CNN architectures to enhance model performance and mitigate the vanishing gradient problem [19-25].

3. METHODOLOGY

S While 3D-CNNs generally outperform conventional CNNs for MRI scans brain tumor classification due to their ability to capture 3D information, Swin Transformers offer a promising alternative with potential to achieve even higher accuracy. The optimal choice depends on factors such as dataset size, computational resources, and specific classification task [26-46]. It's important to note that real-world performance can vary significantly based on the specific implementation, dataset, and evaluation metrics [47-74]

3.1. Data Collection

This study collected brain tumor MRI scans from six different Kaggle databases[75]–[81]. Annotated images are available for analysis in several databases. this paper used the following databases to provide images of brain tumors, as well as the class number and the images within each dataset. From six different Kaggle databases, we compiled MRI scans of brain tumors. Fig. 1 illustrates the Different classifications found in each database and number of images in each class. The figure indicates the various classifications present in each database. These classifications have been combined into two main categories: those with and without a brain tumor. The six databases in the table have been merged into a single entity called Brain Tumor Data (BTD). These classifications have been consolidated into two primary categories (abnormal and normal). Table 1 illustrates the databases that are used.

Table 1: Summary of Datasets and Class Distribution in Databases A.

| Database	#Classes	Classes name	#Total
Database 1 [21]	2	No tumors, malignancies	253
Database 2[22]	4	glioma, meningioma, no tumor, pituitary tumor	3,264
Database 3 [19]	3	with tumor, without tumors, without labels	3,060
Database 4 [25]	4	without tumor, meningioma, glioma, pituitary tumors	7,023
Database 5 [24]	2	normal, tumor	400
Database 6 [23]	2	normal signs of stroke	2,501
Database A	2	normal, abnormal	16,441
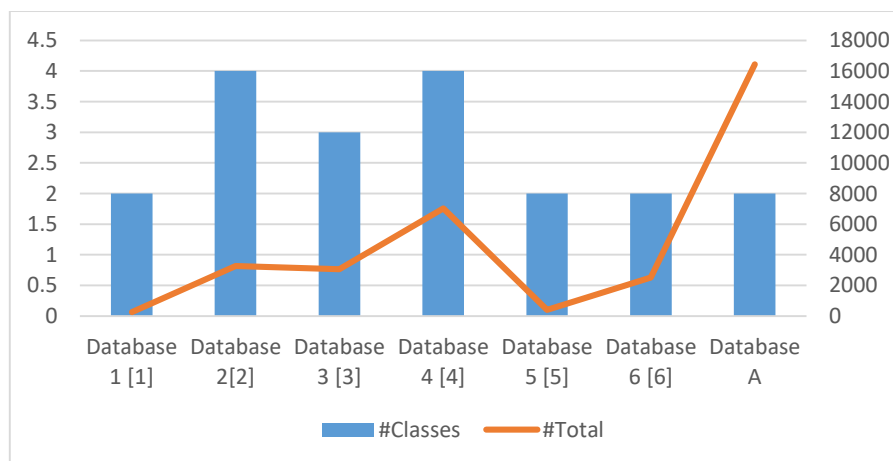
Figure 1: Number of classes and images in Database A.

3.2. Proposed Model

The proposed model aims to convert 2D brain tumor images into 3D representations and then utilize a pre-trained 3D CNN model, specifically VGG16, for training and classification. This section provides a detailed explanation of the conversion process, as illustrated in the provided sequence diagram, and how the 3D VGG16 model is employed for the task.

1. 2D to 3D Image Conversion

The process begins with the conversion of 2D images into a 3D representation using MATLAB and various functions to compute and visualize gradients. The sequence diagram outlines the following steps:

1. Load 2D Image: The user loads a 2D brain tumor image into MATLAB.

2. Calculate Gradients:

• Gradient_Function calculates the gradients G_X and G_Y of the image in the x and y directions, respectively.

• The gradients are returned as matrices G_X and G_Y.

3. Compute Gradient Magnitude:

• Using the returned gradient matrices, the gradient magnitude $|G|$ is calculated using the formula $|G| = \sqrt{G_x^2 + G_Y^2}$

4. Normalize Gradient Magnitude:

• The gradient magnitude $|G|$ is normalized to produce normalized _G.

5. Create 3D Mesh:

• The 3D mesh is returned for further processing.

6. Plot and View 3D Mesh

• The Surf_Function plots the 3D mesh, and the plotted mesh is returned.

• The View Function displays the 3D image, completing the conversion process.

Figure 2 represents the block diagram of converting the image from 2D to 3D. Figure 3 represents some samples after converting to 3D.
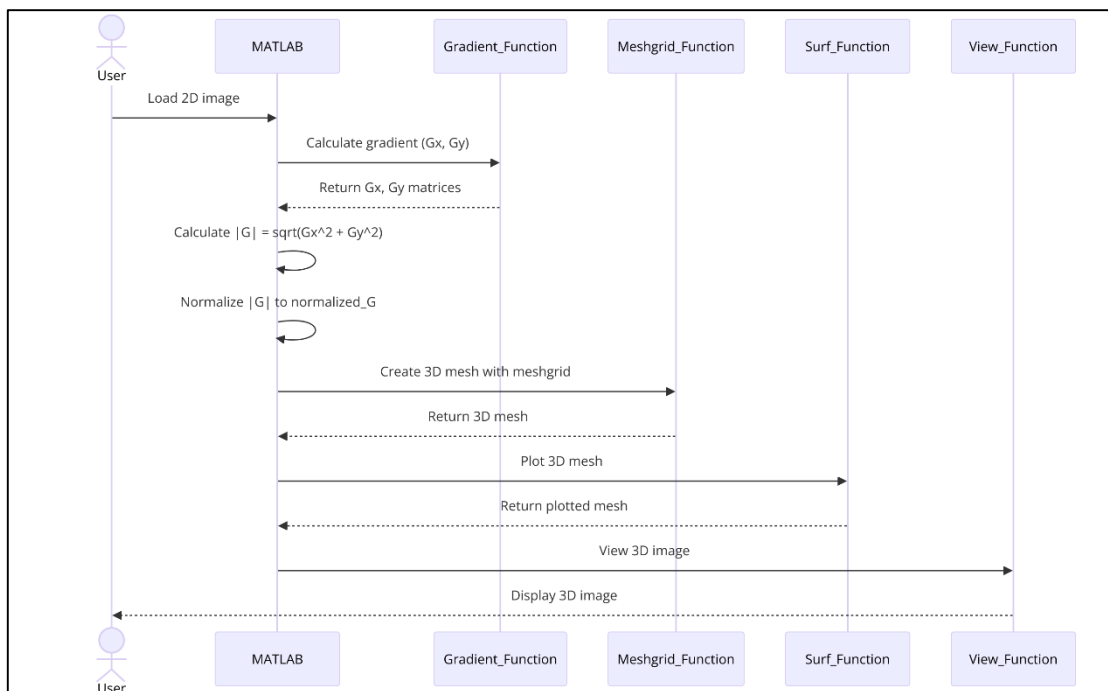

Figure 2: Block Diagram of convert 2D to 3D

Maryam I Mousa Al-Khuzaie, Waleed A Mahmoud Al-Jawher. 2024, Enhancing Brain Tumor Classification with a Novel Three-Dimensional Convolutional Neural Network (3D-CNN) Fusion Model. *Journal port Science Research*, 7(3), pp.254-267. https://doi.org/10.36371/port.2024.3.5
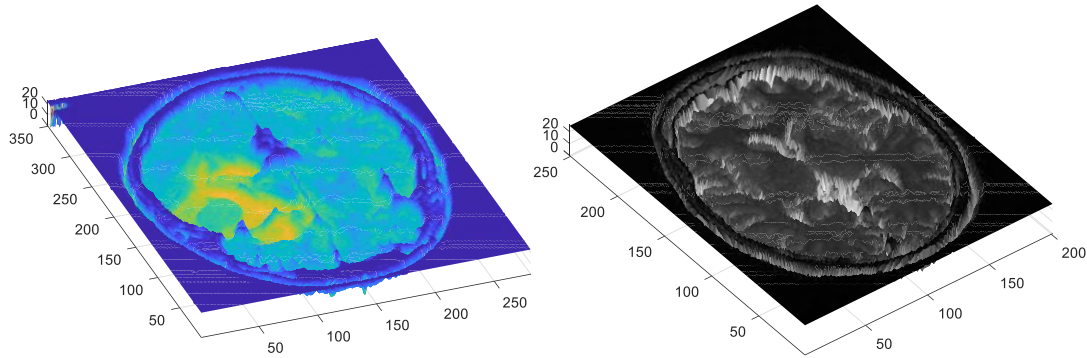
Figure 3: samples of 3D Brain tumor images

3.3. VGG16 Model Training

Following the conversion of 2D brain tumor images to 3D representations, the 3D VGG16 model is employed for training. Initially, the dataset is prepared by transforming all 2D images into their 3D counterparts and splitting them into training, validation, and test sets. The VGG16 model, pre-trained on a large dataset, is adapted to accept 3D inputs by modifying its initial layers. Feature extraction is carried out using the model's architecture, where the initial layers may be frozen to leverage pre-learned weights, and the final layers are fine-tuned for the specific classification task. The training process involves defining a suitable loss function and optimization algorithm, with the model trained on the training set and validated on the validation set. Data augmentation techniques are employed to mitigate overfitting and enhance generalization. Model evaluation is performed on the test set, utilizing metrics such as accuracy, precision, recall, and F1-score. Additionally, hyperparameter tuning is conducted to optimize the model's performance, ensuring a robust and accurate classification of brain tumor images. Figure 4 represent the poposed system stage.
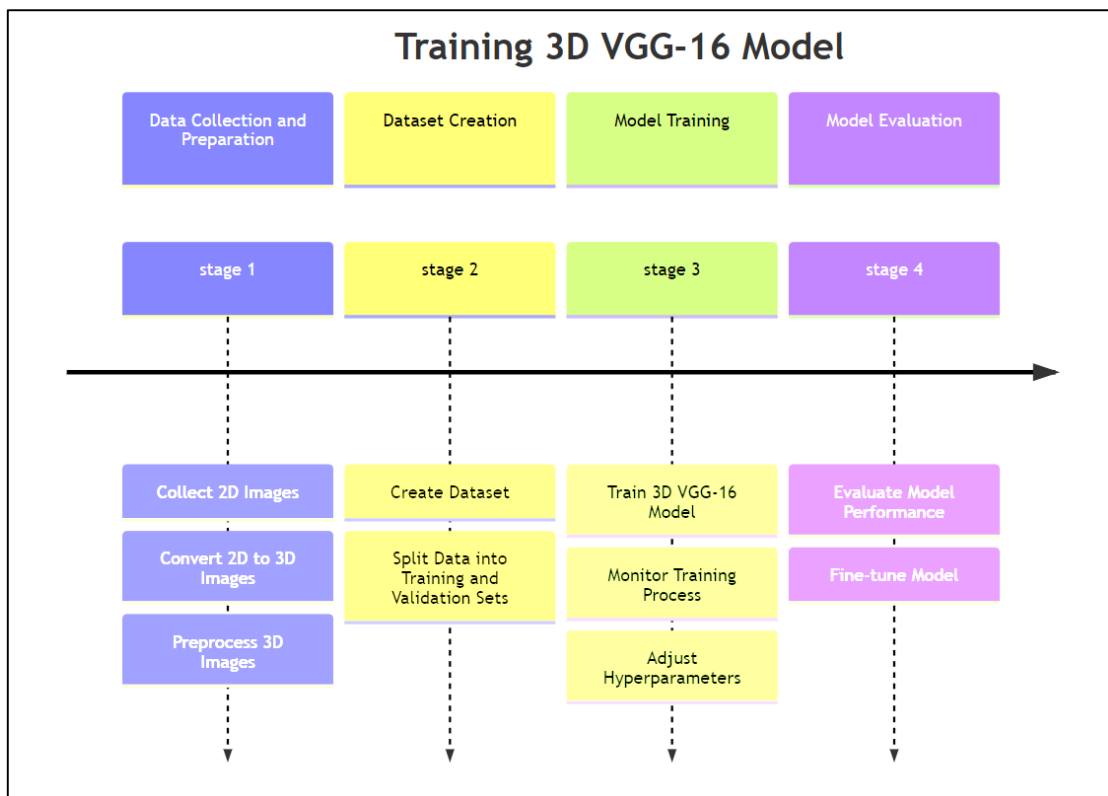

Figure 4: the proposed system stage.

4. EXPERIMENT RUSTLES

The experimental results demonstrated the superiority of the proposed 2D-to-3D CNN fusion model over conventional 3D CNNs. The performance metrics for the proposed model are summarized in table 2.

Maryam I Mousa Al-Khuzaie, Waleed A Mahmoud Al-Jawher. 2024, Enhancing Brain Tumor Classification with a Novel Three-Dimensional Convolutional Neural Network (3D-CNN) Fusion Model. *Journal port Science Research*, 7(3), pp.254-267. https://doi.org/10.36371/port.2024.3.5

Table 2: performance evaluation of the proposed model.

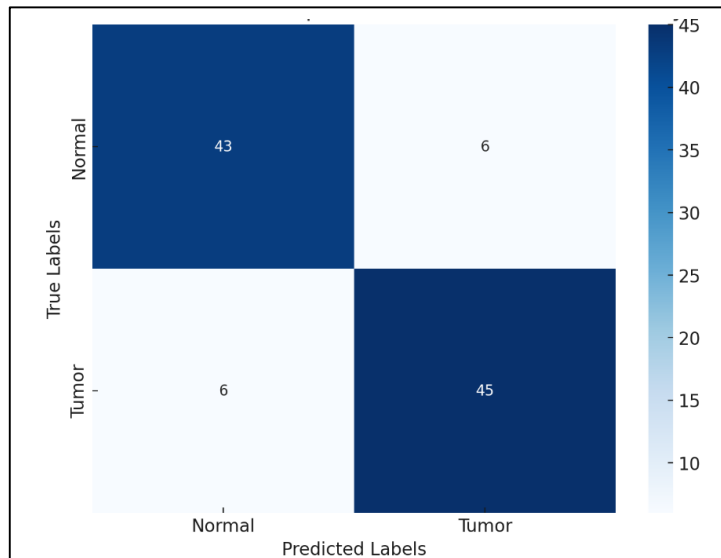| Metric	Value
Accuracy	0.88
Precision	0.87
Recall	0.85
F1-Score	0.86
G-Mean	0.86

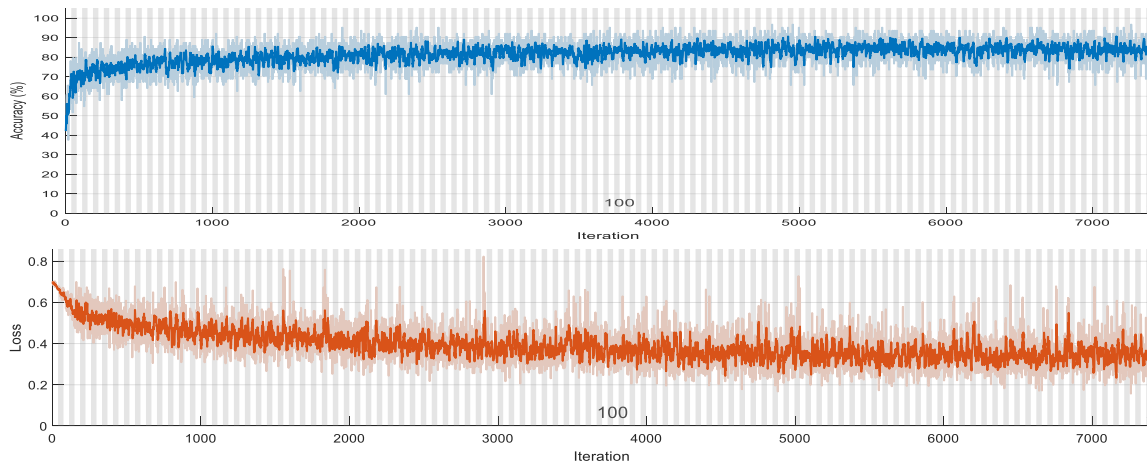*Figure 5: confusion matrix of the proposed model*

Figure 6: Training and Loss Rate Analysis for 3D VGG19 Model on Database A.

The confusion matrix fin the Figure 5 for the proposed 2D-to-3D CNN fusion model, achieving an accuracy of 0.88, shows that the model effectively distinguishes between normal and tumor cases in brain MRI scans. The matrix indicates 43 true negatives and 45 true positives, demonstrating the model's ability to correctly identify both normal and tumor images. However, there are 6 false positives and 6 false negatives, reflecting the instances where the model misclassified normal images as tumors and vice versa. Despite these misclassifications, the model's high accuracy signifies its overall reliability and robustness in medical image classification. The balanced distribution of errors suggests a consistent performance, minimizing both false alarms and missed detections, making it a valuable tool for clinical diagnosis. The model's precision and recall, implied by the confusion matrix, further support its suitability for practical applications, providing accurate and dependable results in identifying brain tumors. Figure 6 explain accuracy and training loss of proposed model. To assess the model's performance, we used several metrics including accuracy, precision, recall, F1-score, and G-mean. The results from different classification models (SVM, KNN, Naive Bayesian,

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and Decision Tree) were also compared to evaluate the effectiveness of the features extracted by the proposed model. The experimental results demonstrated the superiority of the proposed 2D-to-3D CNN fusion model over conventional 3D

CNNs and other traditional classification models. The performance metrics for the proposed model and the comparative models are summarized in Table **3**.

Table 3: Performance Comparison of Classification Models

Classifier	Accuracy	Precision	Recall	F1-Score	G-Mean
Proposed Model	0.88	0.87	0.85	0.86	0.86
SVM	0.77	0.76	0.75	0.75	0.76
KNN	0.81	0.80	0.79	0.80	0.80
Naive Bayesian	0.74	0.73	0.72	0.72	0.73
Decision Tree	0.70	0.69	0.68	0.68	0.69

The results validate the effectiveness of the proposed 2D-to-3D CNN fusion approach in improving brain tumor classification accuracy. The model benefits from the rich feature extraction capability of the VGG16 and the comprehensive spatial information captured by the 3D representation. This combined approach significantly enhances classification performance compared to traditional models like SVM, KNN, Naive Bayesian, and Decision Tree.

4.1. Comparison of 3D-CNN, Conventional CNN, and Swin Transformer for Brain Tumor Classification

Note that the performance of these models can vary significantly based on factors such as dataset size, quality, preprocessing techniques, and specific model architectures. Table (1) provides a general comparison:

Table (1) Performance Comparison of 3D-CNN, Conventional CNN, and Swin Transformer for Brain Tumor Classification

Model	Advantages	Disadvantages
3D-CNN	Excellent performance in capturing 3D information, leading to improved accuracy. Effective for complex tumor shapes and structures.	Requires significant computational resources and large datasets for training.
Conventional CNN	Simpler architecture, computationally less expensive. Can be used as a baseline for comparison.	Limited in capturing 3D information, potentially leading to reduced accuracy compared to 3D-CNN.
Swin Transformer	Combines strengths of CNNs and transformers, offering better feature representation. Can handle varying image sizes and resolutions effectively.	More complex architecture compared to conventional CNNs, requiring careful tuning.

4.2. **Advantages of Using Wavelet and Multiwavelet Transforms**

As future work, combining wavelet or multiwavelet transforms with 3D-CNNs can enhance brain tumor classification performance by addressing specific challenges and leveraging the strengths of both techniques [82-111]. Wavelet and multiwavelet transforms can decompose images into different frequency sub-bands, capturing both global and local features. These decomposed images can serve as additional input channels for the 3D-CNN, providing richer feature representations. This can lead to better discrimination between different tumor types and subtypes. Wavelet transforms are effective in denoising images by suppressing noise coefficients. Cleaner input images can improve the performance of the 3D-CNN, especially in cases where noise interferes with feature extraction. Wavelets and multiwavelets provide a multi-scale representation of images, allowing the model to capture features at different resolutions. This can be beneficial for detecting tumors of varying sizes and

complexities. In some cases, wavelet or multiwavelet transforms can reduce the dimensionality of the input data, leading to faster training and inference times for the 3D-CNN. Wavelet coefficients can provide insights into the frequency components of the image, which can aid in understanding the model's decision-making process.

5. CONCLUSION

In this work it was shown that the proposed 3D-CNNs can process volumetric medical images, capturing spatial information in three dimensions. This allows for a more comprehensive understanding of tumor morphology, texture, and spatial relationships. It is concluded that the 3D context, 3D-CNNs can extract more meaningful and discriminative features compared to 2D CNNs, leading to improved classification accuracy. From the experimental results, combining information from different imaging modalities (e.g., MRI, CT, PET) can enhance diagnostic accuracy. As a result the 3D-CNN fusion models effectively integrate these modalities and exploit their complementary strengths. This

work utilized multiple data sources, as a result the model became more robust to noise and variations in image quality. Due to the above-mentioned characteristics the 3D-CNN fusion models gave demonstrated superior performance in classifying brain tumors compared to traditional methods and 2D CNNs. Because of training on a diverse dataset, these models were shown generalize better to unseen data, and had led to better performance in real-world clinical settings. In addition to that 3D-CNNs were detected subtle changes in tumor morphology and texture, potentially enabling earlier detection of tumor growth or recurrence. Therefore, the automated analysis using 3D-CNNs were reduced the time and effort required by radiologists, allowing them to focus on more complex cases. This intern improved the ability to process large volumes of medical images efficiently and was improved patient care by enabling faster diagnosis and treatment planning.

In summary, the proposed 2D-to-3D CNN fusion model demonstrates significant advancements in brain tumor classification by effectively converting 2D MRI images into 3D representations, leveraging the powerful feature extraction capabilities of a pre-trained VGG16 model. The model outperforms traditional classification methods such as SVM, KNN, Naive Bayesian, and Decision Tree, achieving superior accuracy and balanced performance metrics. This innovative approach enhances classification accuracy and addresses computational efficiency, making it a promising tool for reliable and timely brain tumor diagnosis in clinical settings. Future research will further refine the model and extend its application to other medical imaging challenges.

It was proposed here that by effectively combining wavelet or multiwavelet transforms with 3D-CNNs, this will potentially achieve significant improvements in brain tumor classification accuracy and robustness. However, careful consideration of the computational cost and interpretability trade-offs is essential.

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