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Deep Learning in Neuroimaging: A Comparative Analysis of Models for Brain Tumor Classification using MRI Images

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Abstract. The precise classification of brain tumors is essential for timely diagnosis and effective treatment planning. This study proposes a deep learning framework for the automatic categorization of three primary brain tumour types: glioma, meningioma, and pituitary tumors using Magnetic Resonance Imaging data. A dataset publicly accessible on Mendeley, containing 6,056 labeled MRI images categorized into three tumor types, was utilized to train and assess three different models: a hybrid CNN-LSTM network, ResNet18, and VGG16. These models were chosen to investigate both temporal-sequential learning (through the CNN-LSTM) and effective convolutional feature extraction using established transfer learning frameworks (ResNet18 and VGG16). The MRI images underwent various pre-processing steps, which included resizing, normalization, and augmentation, to enhance the robustness of the models. Among the models tested, ResNet18 achieved the highest classification Accuracy of 93.50%, Precision of 93.40%, Recall of 93.40% and F1-Score of 93.40% while the CNN-LSTM following at 92.24% Accuracy, 92.00% Precision, 91.80% Recall and 91.80% F1-Score and VGG16 achieves Accuracy of 91.82%, Precision of 91.80%, Recall of 91.40% and F1-Score of 91.40%. ResNet18 demonstrated improved generalization when applied to various tumor classifications. These findings underline the potential of deep learning, especially ResNet18, as a valuable tool to support radiologists in the early and non-invasive identification of brain tumors, showcasing its importance in the progression of automated neuro-oncological diagnosis.

Keywords: Brain Tumor Classification, Magnetic Resonance Imaging, Deep Learning, Medical Image Analysis, Tumor Classification, ML in Healthcare, Brain Tumor.

1 Introduction

1.1 Background

Brain tumors are among the most critical neurological conditions and can lead to life-threatening complications if they are not detected and addressed promptly. The primary type gliomas, meningiomas, and pituitary tumors demonstrate unique biological characteristics and necessitate customized treatment strategies. Therefore, accurately identifying the type of tumor is essential for guiding clinical decisions. Magnetic Resonance Imaging (MRI) is the preferred approach for identifying brain tumors because of its non-invasive characteristics and capacity to generate high-resolution images of soft tissues. Nonetheless, distinguishing between different tumor types based solely on MRI scans can be challenging, as many tumors present similar visual characteristics. Traditionally, this distinction has primarily depended on assessments by experienced radiologists, a process that can be time-consuming and may differ among various analysts.

In the past few years, advancements in Artificial Intelligence (AI), especially in deep learning, have shown considerable potential in improving the interpretation of medical imaging. Deep learning frameworks, especially Convolutional Neural Networks (CNNs), have demonstrated considerable accuracy in the automated classification of brain tumors by identifying complex patterns within MRI data. However, a thorough assessment of different deep learning frameworks is crucial for determining the most effective methods. This research intends to examine and contrast various deep learning models to evaluate their performance, efficiency, and appropriateness for clinical use in brain tumor classification.

1.2 Problem Statement

Recognizing brain tumors in MRI scans manually is a challenging and labor-intensive endeavor that demands significant expertise in radiology. This task is vulnerable to human mistakes, particularly as various tumor types, such as gliomas, meningiomas, and pituitary tumors, can appear quite similar. The presence of these similarities can make it challenging to distinguish between different tumor types, even for experienced radiologists, increasing the risk of misdiagnosis. Mistakes or delays in diagnosis may result in unsuitable treatment strategies, which could endanger patient outcomes. Additionally, the growing demand for quick and accurate diagnoses puts further pressure on healthcare professionals and systems. Consequently, there is an urgent need for dependable automated diagnostic tools that can help accurately identify brain tumor types from MRI imagery. Such technologies could improve diagnostic reliability, decrease interpretation times, and assist in clinical decision-making, ultimately enhancing patient care and treatment strategies in neuro-oncology.

1.3 Aim and Objectives

This research focuses on developing and comparing deep learning models—CNN-LSTM, ResNet18, and VGG16—for categorizing brain tumors into several types, such as glioma, meningioma, and pituitary tumors, using MRI images. The primary objective is to assess and analyze the performance of each model to determine which one attains the highest accuracy in tumor classification. This research aims to leverage the strengths of different architectures to identify the most effective model for reliable and automated identification of brain tumors, ultimately improving diagnostic assistance in clinical neuroimaging environments.

1.4 Research Gap

Many studies into deep learning for brain tumor detection primarily focus on binary classification tasks that separate tumor instances from non-tumor ones, or they emphasize the identification of individual tumor types in isolation. While these approaches provide valuable findings, they often overlook the complexities involved in multi-class classification, which is crucial for accurately distinguishing between various tumor types such as gliomas, meningiomas, and pituitary tumors. Additionally, many research efforts either concentrate on hybrid models or pre-trained architectures independently, failing to assess or compare their performance on MRI datasets. This gap limits a comprehensive understanding of how different deep learning methods function in real-world clinical environments. Notably, there is a significant scarcity of research that systematically investigates and compares the effectiveness of hybrid models like CNN-LSTM with popular pre-trained architectures such as ResNet18 and VGG16 for multi-class brain tumor classification. Such comparative studies are crucial for determining the most effective models that maintain a balance between accuracy, efficiency, and robustness. To fill this void, the present research seeks to carry out a comprehensive comparative evaluation of these deep learning architectures using MRI data, aiming to offer clearer guidance for future applications in neuroimaging and enhance automated diagnostic support.

1.5 Scope of Research

This study can classify three categories of brain tumors—glioma, meningioma, and pituitary—by utilizing a publicly accessible MRI dataset. The study can involve several essential tasks: examining the MRI images, developing deep learning models, evaluating their performance, and comparing three distinct deep learning approaches. The models under evaluation include CNN-LSTM, ResNet18, and VGG16, chosen for their varied architectures and efficacy in image analysis. It is important to note that this study does not incorporate clinical data or involve tumor segmentation processes, as the main aim is to assess the classification performance based exclusively on imaging data. The results aim to improve and facilitate radiological processes by providing accurate, automated tools for tumor classification, which can help reduce the workload of radiologists. However, the study does not seek to replace professional medical expertise but rather intends to serve as an assistive tool that can boost diagnostic efficiency and dependability in neuroimaging.

2 Review Of Literature

Numerous research efforts have utilized both deep learning and traditional machine learning methods for classifying brain tumors through MRI images. In one particular study, a combined technique employing a single hidden layer back propagation neural network achieved flawless classification accuracy of 100% in both training and testing however this result was based on a small dataset of only 66 images (18 normal and 48 abnormal), raising concerns about over-fitting and lack of generalizability [1]. Similarly, an alternative method utilizing a back-propagation neural network achieved an impressive accuracy of 96.33% in the classification of brain images [2]. Various studies have examined Support Vector Machine (SVM) techniques, yielding different levels of effectiveness; one study showed an accuracy of 65% [3], whereas another noted an accuracy between 80% and 90% [4].

Additionally, a fully automatic heterogeneous segmentation-based SVM (FAHS-SVM) method managed to attain an impressive accuracy of 98.51% [5]. Techniques based on Convolutional Neural Networks (CNNs) have demonstrated considerable promise; for instance, one CNN classifier achieved a 96.56% accuracy in tumor classification [6]. In a different study, ResNet50 and InceptionV3 were analyzed, producing accuracies of 89% and 75% respectively [7].

Additionally, feed-forward artificial neural networks (FF-ANNs) demonstrated their effectiveness, achieving accuracies of 95.8% and 95.83% [8] [9]. Furthermore, deep transfer learning methods that leveraged Inception-V3 achieved a validation accuracy of 88.26% for brain tumor classification [10], highlighting the growing efficacy of pre-trained models in medical image analysis. In case of CNN-S, CNN-M and CNN-L correct classification rate was 97.00% of all cases and 3.00% of CNN's classifications were erroneous [11]. Similarly, a CNN model is defined which have an accuracy of 100% because dataset is small consisting of only 200 images aggregated from 8 patients [12]. When U-Net is used for Brain tumor classification achieves an accuracy of 98.56%, along with an F-score of 99%, an area under the curve of 99.8%, and recall and precision rates of 99% [13]. These diverse methods underscore the improving reliability and efficiency of AI-based techniques in clinical diagnostics.

Table 1. Comparative Analysis of Existing Brain Tumor Classification Methodologies

S.No.	Title	Author	Year	Technology Used	Performance
1	A hybrid method for MRI brain image classification	Yudong Zhang et al. [1]	2011	Principle Component Analysis incorporated with Back Propagation Neural Network (BPNN)	Accuracy on both training and test images is 100%
2	MRI brain image classification using neural networks	Walaa Hussein Ibrahim et al. [2]	2013	PCA and BPNN	Accuracy score of 96.33%
3	Image classification of brain MRI using support vector machine	Noramalina Abdullah et al. [3]	2011	Support Vector Machine	Accuracy of 65%
4	Classification of Brain MRI Tumor Images: A Hybrid Approach	Sanjeev Kumar et al. [4]	2017	SVM Classifier	Accuracy lies between 80% to 90%
5	Brain Tumor Identification and Classification of MRI images using deep learning techniques	Zheshu Jia and Deyun Chen [5]	2020	Fully Automatic Heterogeneous Segmentation using Support Vector Machine	98.51% Accuracy
6	Classification of Brain Tumors from MRI Images Using a Convolutional Neural Network	Milica M. Badža and Marko Č. Barjaktarović [6]	2020	Convolutional Neural Network (CNN)	Accuracy of 96.56%
7	Brain tumor classification in MRI image using convolutional neural network	Hassan Ali Khan et al. [7]	2021	Scratched CNN model, VGG16, ResNet50, and InceptionV3	CNN gives 100% accuracy, while VGG16 gives 96%, ResNet50 gives 89% and InceptionV3 gives 75% accuracy
8	A hybrid image enhancement based brain MRI images	Zahid Ullah et al. [8]	2020	Deep Neural Network (DNN)	95.8% Accuracy

	classification technique				
9	An Efficient Classification of MRI Brain Images	Muhammad Assam et al. [9]	2021	Feed Forward - ANN (FF-ANN)	Average Accuracy of 95.83%
10	Deep Transfer Learning Approaches in Performance Analysis of Brain Tumor Classification Using MRI Images	Chetana Srinivas et al. [10]	2022	VGG16, ResNet50, and InceptionV3	VGG16 gives 96% Accuracy, ResNet50 gives 95% Accuracy, and InceptionV3 gives 78% Accuracy

3 Methodology

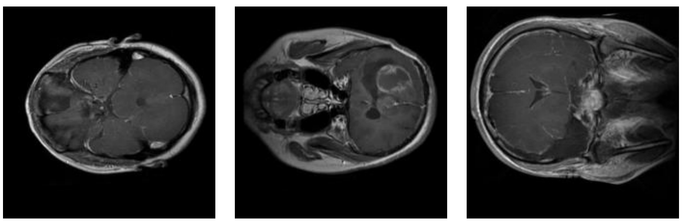
3.1 Overview of proposed system

The suggested framework utilizes a deep learning method to identify brain tumors in MRI images. It combines three robust architectures: ResNet18, VGG16, and a tailored hybrid model that merges CNN and LSTM, specifically created to capture both spatial and temporal characteristics for precise tumor detection. Key preprocessing methods are applied to the MRI images, including resizing, normalization, and data augmentation, to boost the models' generalization abilities and enhance their robustness. ResNet18 and VGG16 utilize transfer learning by fine-tuning convolutional layers pre-trained on extensive datasets, facilitating efficient feature extraction without the need to start the training process from the beginning.

On the other hand, the CNN-LSTM model integrates convolutional layers for spatial feature extraction with LSTM layers to address sequential dependencies, which helps in recognizing temporal patterns within the data. The performance of the models is assessed using widely recognized classification metrics, such as accuracy, precision, recall, and F1-score, to provide a thorough evaluation of the effectiveness of architectures. Through the use of advanced deep learning methods, the framework seeks to facilitate the prompt and accurate detection of brain tumors. This system is designed to support radiologists by increasing diagnostic accuracy and efficiency, ultimately leading to improved clinical decision-making and enhanced patient outcomes in neuro-oncology.

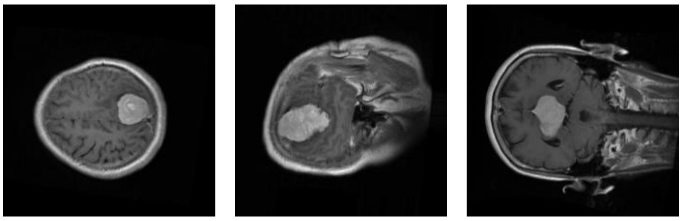
3.2 Data Collection

The information utilized for this study was sourced from a publicly accessible MRI dataset available on Mendeley, named "Brain Cancer - MRI Dataset" [14]. This dataset includes a collection of MRI images that are categorized into three types of brain tumors: Glioma tumors, Meningioma tumors, and Pituitary tumors. The MRI images are in JPG format and arranged into folders specific to each class, making it appropriate for supervised image classification tasks. In total, the dataset contains 6056 images. The processed dataset includes 2004 images of Glioma, 2004 images of Meningioma, and 2048 images of Pituitary tumors. Fig. 1-3 shows the sample MRI images of brain tumors for model training.



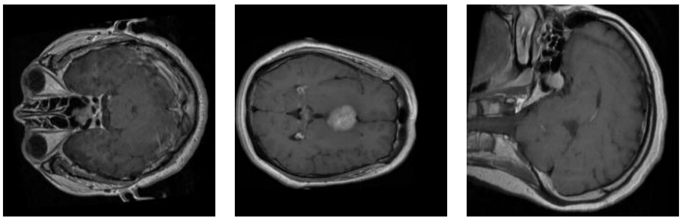
a b c

Fig. 1. Sample MRI images of glioma tumor (a,b,c) for model training



a b c

Fig. 2. Sample MRI images of meningioma tumor (a,b,c) for model training



a b c

Fig. 3. Sample MRI images of pituitary tumor (a,b,c) for model training

3.3 Data Preprocessing

For all three models: ResNet18, VGG16, and the CNN-LSTM hybrid, preparing the data was crucial for standardizing the input images and enhancing model generalization. For ResNet18 and VGG16, the RGB images were adjusted to a size of 224×224 pixels to correspond with the input dimensions required by the pre trained models. Both architectures utilized normalization strategies that incorporated the mean and standard deviation values obtained from the ImageNet dataset ([0.485, 0.456, 0.406] for the mean and [0.229, 0.224, 0.225] for the standard deviation), thereby ensuring they were compatible with their pre trained weights.

Furthermore, a variety of data augmentation methods, such as random horizontal and vertical flips, rotations of 10, and color perturbations 0.2 brightness and 0.2 contrast, were utilized to enhance the dataset's diversity. In the hybrid CNN-LSTM model, the data preprocessing process included converting images to grayscale, resizing them to 64×64 pixels, and normalizing the pixel values within the range of [0, 1]. The grayscale images were transformed into a single channel format, after which they were flattened and organized into a sequence suitable for processing by the LSTM layers.

For the purpose of training and validation pre-processed dataset is split into ratios of 15:85, 20:80, 25:75, 30:70, 35:65 and 40:60. These preprocessing steps ensured that the models received data that was properly formatted and optimized for optimal learning efficiency.

3.4 Models used in this work

ResNet18. In this research, the ResNet18 architecture serves as both a feature extractor and a classifier for identifying brain tumors from MRI images. A modified version of ResNet18, which was originally trained on the ImageNet dataset, is adapted for this specific classification objective. To preserve the learned hierarchical features, all convolutional layers are kept frozen, while the final fully connected (FC) layer is substituted with a custom classifier that includes a dense layer with 256 neurons, followed by ReLU activation, dropout for regularization, and a concluding output layer with a number of neurons corresponding to the brain tumor classes. The model utilizes cross-entropy loss during training and is optimized with the Adam optimizer along with a learning rate of 0.0005, batch size is 32 and epoch is 25. To avoid over-fitting and enhance generalization, early stopping is applied. This modified ResNet18 leverages transfer learning to effectively distinguish between various types of brain tumors using MRI images.

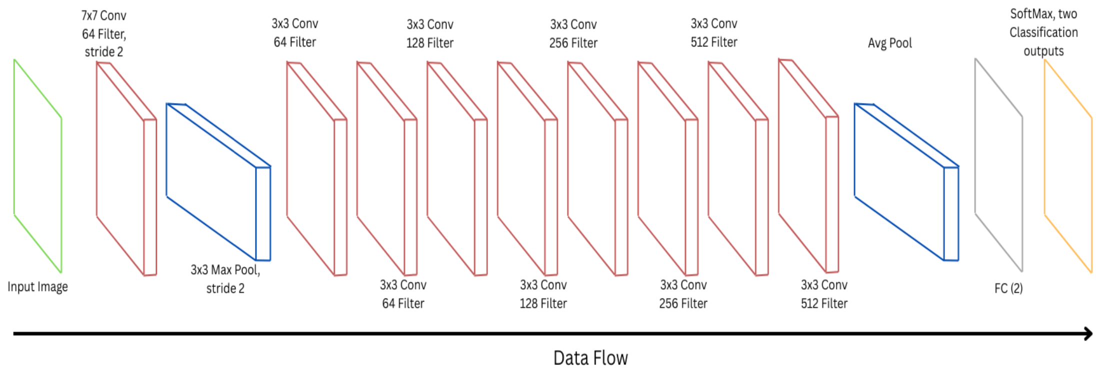


Fig. 4. Basic ResNet18 Architecture

CNN and LSTM Hybrid Model. The CNN-LSTM hybrid model utilized in this research consists of 15 layers and about 278,339 parameters that can be trained. The convolutional base starts with four Conv2D layers arranged sequentially, employing increasing filter sizes (32, 64, 128, 128) and kernel dimensions of (3×3), each followed by Batch Normalization and MaxPooling2D layers to stabilize the feature maps and reduce their spatial dimensions. After the feature maps are flattened (changing from shape 2×2×128 to 512), a Reshape layer transforms the data into a sequence with a shape of (8, 64), which facilitates temporal pattern recognition through an LSTM layer comprising 64 units. The output from the LSTM undergoes regularization via Dropout layers (0.5 and 0.3) before being forwarded through two Dense layers: the first with 64 neurons and ReLU activation and the concluding output layer containing 3 neurons with softmax activation to categorize the MRI scans into three tumor types: glioma, meningioma, and pituitary tumor. The model utilizes categorical cross-entropy loss during training and is optimized with the Adam optimizer along with a learning rate of 0.001, batch size is 32 and epoch is 15. This architecture efficiently merges spatial feature extraction with temporal modeling, improving the network's capability to detect both local and sequential patterns in medical imaging data.

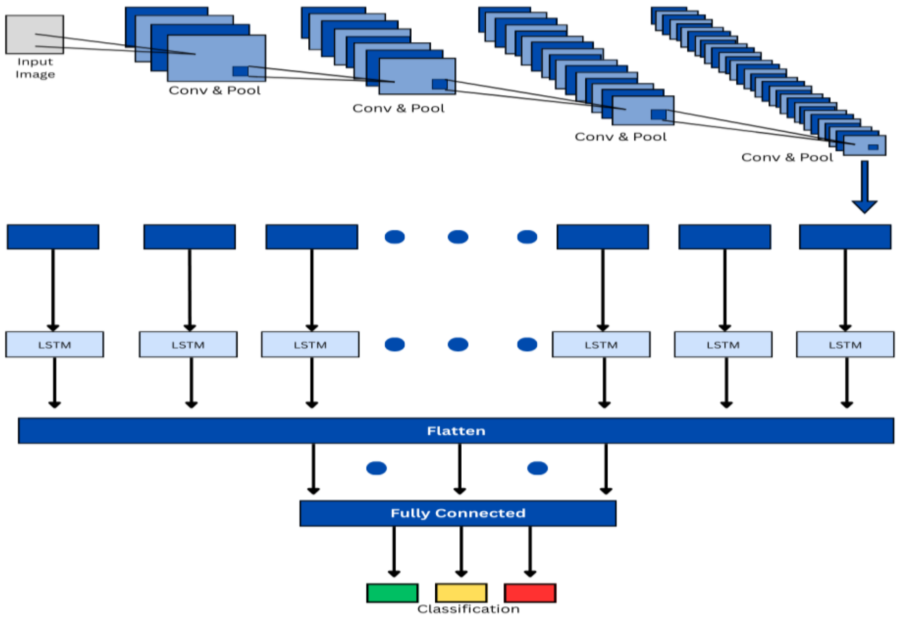


Fig. 5. Basic CNN-LSTM Hybrid Model Architecture

VGG16. In this study, the VGG16 architecture is utilized as a deep convolutional neural network to classify brain cancer based on MRI images, employing transfer learning techniques. The VGG16 design, originally trained on the ImageNet dataset, is employed without its upper fully connected layers to improve its robust feature extraction abilities while minimizing the risk of over-fitting. All convolutional layers are kept frozen to maintain the previously learned low-level and mid-level features of the images, and a custom classification head is incorporated that includes a Flatten layer, a dense layer featuring 256 neurons activated by ReLU, a Dropout layer with a regularization rate of 0.5, and a final softmax layer for predicting class probabilities. MRI images are scaled down to 224×224 pixels and adjusted to have pixel values within the range of 0 to 1 before being fed into the model. The model utilizes the Adam optimizer with a reduced learning rate of 0.0075 with batch size of 32 and epoch is set as 10.

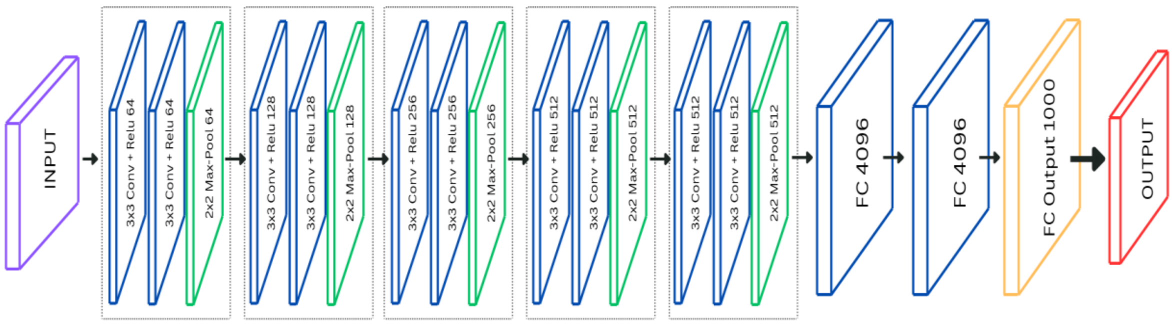


Fig. 6. Basic VGG16 Architecture

3.5 Evaluation Metrics

In order to assess how well the deep learning models, perform in classifying brain tumors, a range of established evaluation metrics were employed. These metrics provide detailed information on the capability of each model to distinguish between gliomas, meningiomas, and pituitary tumors. The metrics applied are:

Accuracy. Accuracy measures the overall correctness of the model by assessing the ratio of instances it accurately predicted.

$$\text{Accuracy} = \frac{\text{True Positives} + \text{True Negatives}}{\text{True Positives} + \text{True Negatives} + \text{False Positives} + \text{False Negatives}}$$

Precision. Precision indicates the proportion of true positive predictions to the total number of predicted positives, reflecting the model's capability to reduce false positives.

$$\text{Precision} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Positives}}$$

Recall. Recall assesses how well the model can accurately identify all actual positive instances, showing its effectiveness in reducing false negatives.

$$\text{Recall} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Negatives}}$$

F1-Score. F1-Score represents the harmonic mean of precision and recall, offering a balance between both measures, particularly in scenarios with imbalanced class distributions.

$$\text{F1 Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

4 System Architecture

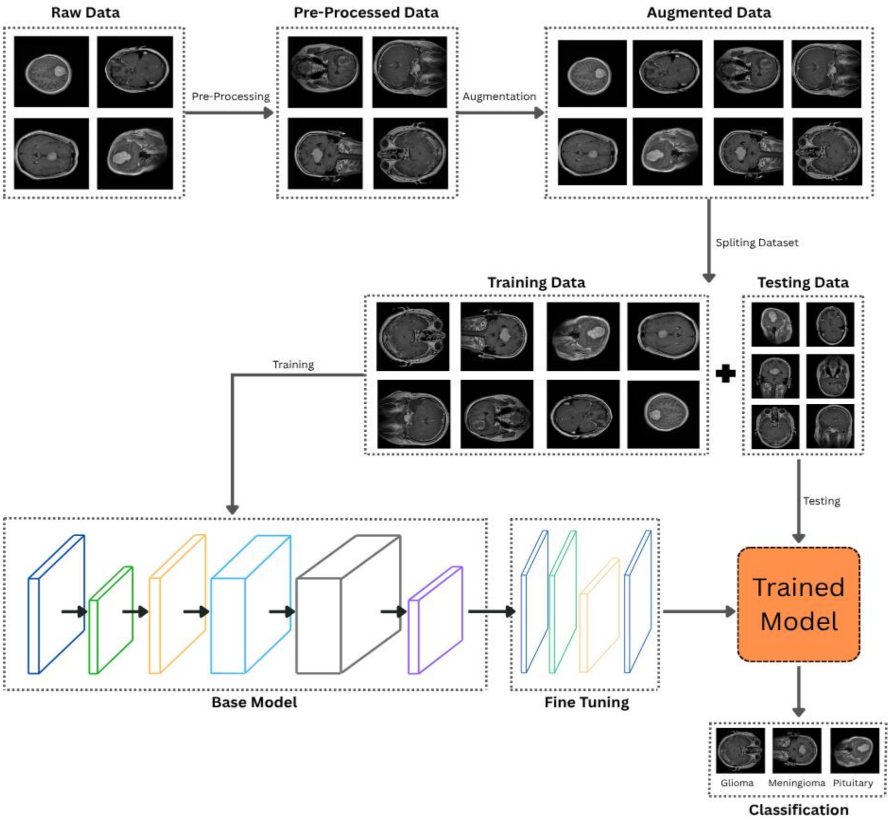


Fig. 7. Architectural overview of proposed ResNet18 and VGG16 models

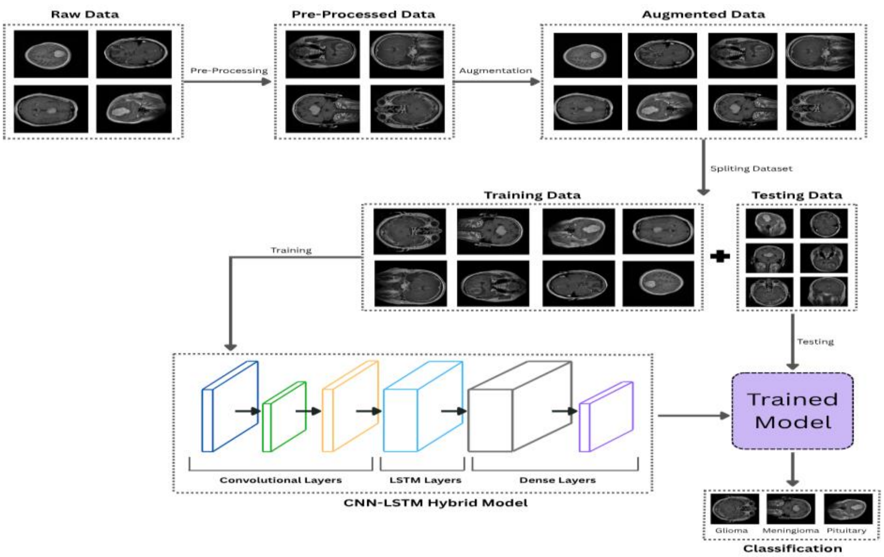


Fig. 8. Architectural overview of proposed CNN-LSTM hybrid model

5 Result and Discussion

5.1 System Performance

Table 2. Results obtained from ResNet18 model

Training	Accuracy	Precision (%)	Recall (%)	F1-Score (%)

Testing Ratio	(%)	Glioma	Menin	Pituitary	Glioma	Menin	Pituitary	Glioma	Menin	Pituitary
85:15	93.94	99	91	92	94	91	96	97	91	94
80:20	94.22	98	93	92	96	90	96	97	91	94
75:25	94.32	98	92	93	96	91	95	97	92	94
70:30	93.67	98	90	93	95	92	94	96	91	94
65:35	91.36	94	89	92	95	86	93	94	87	92
Average	93.50	97.4	91.0	92.4	95.2	90.0	94.8	96.2	90.4	93.6

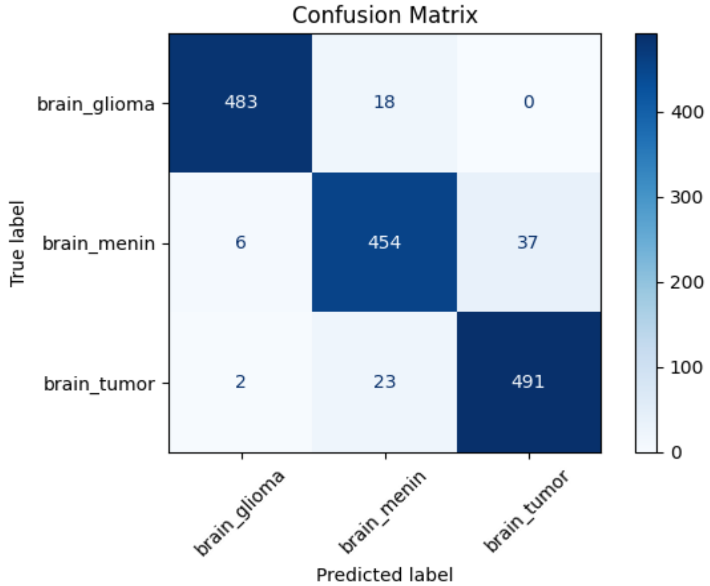


Fig. 9. Performance Visualization of ResNet18 when train and validated on 75:25 split ratio

Table 3. Results obtained from CNN-LSTM hybrid model

Training Testing Ratio	Accuracy (%)	Precision (%)			Recall (%)			F1-Score (%)		
		Glioma	Menin	Pituitary	Glioma	Menin	Pituitary	Glioma	Menin	Pituitary
85:15	93.31	98	86	94	90	94	94	94	90	94
80:20	93.46	94	90	96	95	93	92	95	91	94
75:25	93.01	97	86	95	92	93	93	94	89	94
70:30	90.76	87	95	90	96	76	97	91	85	93
65:35	90.65	99	87	87	84	88	98	91	87	92
Average	92.24	95.0	88.8	92.4	91.4	88.8	94.8	93.0	88.4	93.4

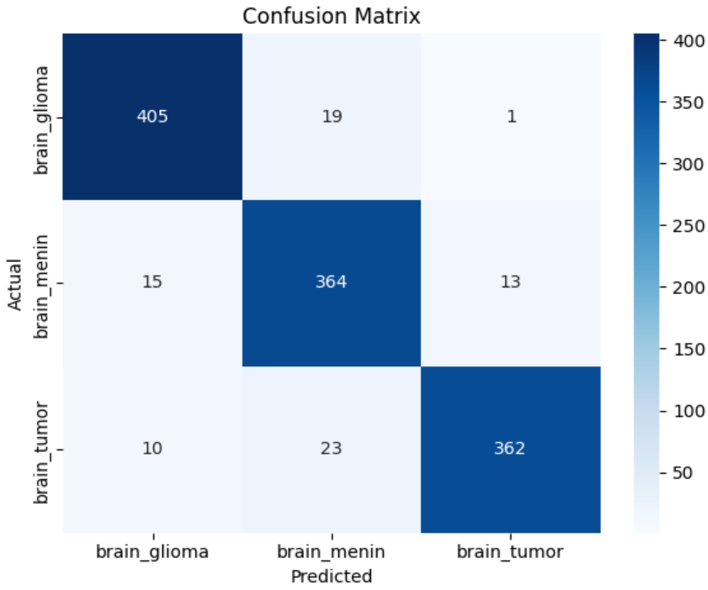


Fig. 10. Performance Visualization of CNN-LSTM hybrid-model when train and validated on 80:20 split ratio

Table 4. Results obtained from VGG16 model

Training Testing Ratio	Accuracy (%)	Precision (%)			Recall (%)			F1-Score (%)		
		Glioma	Menin	Pituitary	Glioma	Menin	Pituitary	Glioma	Menin	Pituitary
85:15	90.12	99	80	95	89	95	87	94	87	90
80:20	92.32	97	86	94	90	93	94	93	89	94
75:25	92.23	95	89	93	93	90	93	94	89	93
70:30	92.87	95	91	90	94	87	95	95	89	93
65:35	91.56	98	89	87	90	87	97	94	88	92
Average	91.82	96.8	87.0	91.8	91.2	90.4	93.2	94.0	88.4	92.4

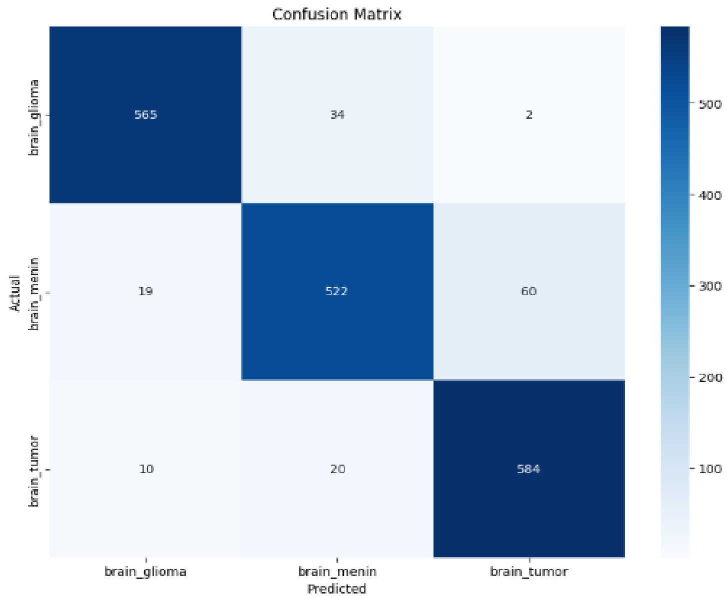


Fig. 11. Performance Visualization of VGG-16 when train and validated on 70:30 split ratio

5.2 Limitations

Although the proposed brain tumor classification models have shown promising outcomes, several shortcomings should be recognized, especially regarding their implementation in clinical environments. One major limitation is the small size and lack of diversity in the dataset, which may not adequately represent the variability found in actual patient populations. The lack of representation, especially for rarer tumor types, can hinder the model's capacity to generalize across various healthcare environments and populations, potentially affecting its diagnostic precision in clinical contexts.

Additionally, the reliance on 2D MRI slices, although efficient from a computational standpoint, may oversimplify the complex spatial characteristics of brain tumors, limiting the model's ability to accurately represent the volumetric shapes of tumors and possibly resulting in errors in classifications of unusual cases. The utilization of transfer learning with ImageNet pre-trained models, like VGG16 and ResNet18, presents another issue: the pre-training relies on natural images, which can introduce irrelevant or misleading feature priors when utilized for medical imaging tasks, thus impacting the interpretability and generalizability of the model.

Furthermore, while the combination of CNN and LSTM architectures aims to capture both sequential and spatial characteristics, it increases the computational demands of the model and heightens the risk of over-fitting, particularly when dealing with limited datasets. These constraints underscore the importance of thoroughly interpreting the results and illustrate the essential requirement for validating the model on varied data from clinical sources prior to contemplating its use in real-world scenarios.

6 Future Scope

The upcoming goals of this study aim to enhance the diagnostic efficiency, generalization skills, and practical application of brain cancer classification models. Advancements in deep learning architectures, particularly utilizing EfficientNet, Vision Transformers (ViTs), and hybrid CNN–Transformer models, offer prospects for improved feature extraction and superior classification performance. Initial experiments are currently being structured to assess transformer-based models, with intentions to create baseline comparisons utilizing 3D CNNs. The exploration of integrating multimodal data, which merges imaging with clinical details such as patient history or symptoms, is underway through preliminary pilot studies that could yield more thorough diagnostic insights. To address the critical issue of model interpretability, methods in explainable AI (XAI), such as Grad-CAM and LIME, will be incorporated into future models, enhancing transparency and building trust in clinical environments.

Additionally, shifting from 2D image slices to 3D MRI volumes may offer a more thorough spatial perspective, marking a key area for research. Expanding the dataset to include diverse MRI images from various medical centers will strengthen the model's reliability, and implementing synthetic data augmentation via GANs can address challenges associated with class imbalance. In the end, deploying these trained models in real-time clinical environments, either through edge computing devices or cloud-based platforms, could facilitate early diagnosis or enhance access to advanced diagnostic tools in both urban hospitals and under-resourced rural areas.

7 Conclusion

In this research, three deep learning models were compared: CNN-LSTM, VGG16, and ResNet18, for the task of classifying multi-class brain tumors using MRI scans. Among the models assessed, ResNet18 achieved the highest performance, reaching a classification accuracy of 93.50%. CNN-LSTM followed at 92.24%, and VGG16 at 91.82%, highlighting its superiority in both effectiveness and its capacity to generalize across various types of tumors. Overall during the course of experimentations it is observed that the training and validation accuracy for each model gradually increases and then stabilizes, while the training and validation loss gradually decreases and then stabilizes.

A key aspect of this research is the development and evaluation of a hybrid CNN-LSTM model that integrates spatial and sequential feature learning. This field has yet to be extensively investigated for the classification of brain tumor MRI scans. Additionally, all models were assessed utilizing a publicly accessible multi-class MRI dataset, promoting transparency and enabling reproducibility.

Based on the findings, ResNet18 is recommended as the most suitable model for use in clinical environments, thanks to its superior accuracy, reliability, and computational efficiency when compared to the more complex

CNN-LSTM model. These outcomes highlight the potential of deep learning technologies in aiding radiologists with non-invasive tumor identification and pave the way for future research that involves larger, more diverse datasets; features that enhance explainability; and integration with hospital imaging systems.

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