EFFECTIVE MRI-BASED BRAIN TUMOR CLASSIFICATION USING ADVANCED DEEP LEARNING TECHNIQUES

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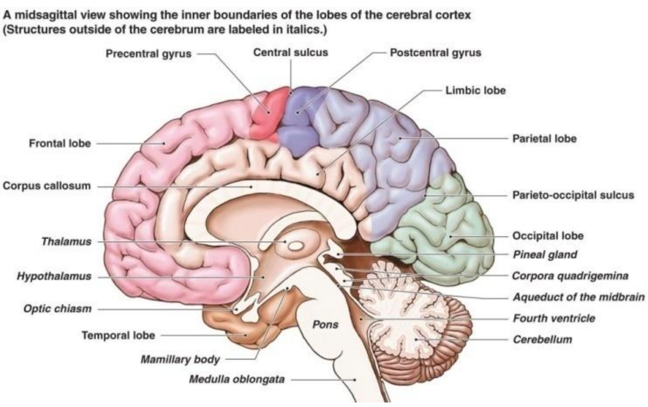
ABSTRACT:

The brain is crucial to the functioning of the nervous system, and classifying brain tumors in medical image analysis is an important and difficult effort due to the variety and complexity of tumor forms. Prompt and accurate analysis is essential for both patient outcomes and efficient treatment planning. Leveraging recent advances in artificial intelligence, especially deep learning, can greatly improve diagnostic precision and effectiveness. This study aims to develop an efficient, automated method for brain tumor classification that aids radiologists and reduces the time required for accurate diagnosis. We utilized the 'Brain MRI Scans for Brain Tumor Classification' dataset from Kaggle, consisting of 1,311 MRI scans classified into Pituitary, Meningioma, Glioma, and No tumor classes. This dataset was uniquely refined through an extensive data cleaning process,–and resizing of images Additionally, a range of data augmentation techniques–were applied to improve model robustness and generalization. Unlike existing approaches, our method introduces a carefully tuned ensemble of CNN architectures like GoogleNet, AlexNet, and SqueezeNet, with modified preprocessing and hyperparameter optimization to enhance classification accuracy significantly. GoogleNet achieved the highest accuracy of 97.74%, followed by AlexNet with 97.40%, and SqueezeNet with 95.83%, outperforming conventional models on similar tasks. The models demonstrated consistently high precision, recall, and F1 scores, underscoring their reliability. This study highlights how CNN-based techniques can assist radiologists in diagnosing brain tumors more precisely and quickly, opening the door for further innovations in medical imaging and deep learning.

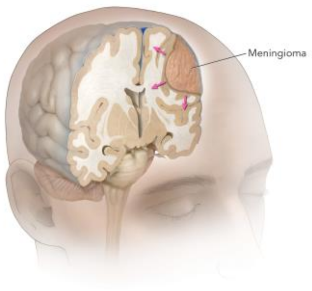
Keywords: Medical image, Brain tumor, Magnetic resonance imaging, Deep learning, Convolutional Neural Networks

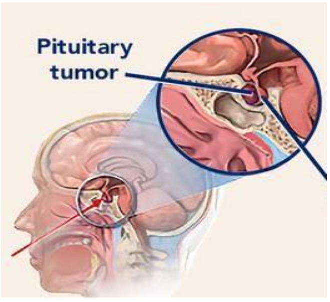
[1] INTRODUCTION

Brain tumors are the among deadliest malignancies, a precise diagnosis is crucial to a successful course of therapy. Automated procedures are necessary since traditional methods rely on radiologists manually examining cases, which is time-consuming and error-prone. Convolutional neural networks, in particular, are a promising development in deep learning (DL) that hold promise for medical picture analysis since they can learn intricate patterns from massive datasets. CNNs provide a non-invasive diagnostic tool by classifying various kinds of brain cancers using MRI pictures. This work suggests a deep learning method for classifying cancers, including pituitary, meningioma, and glioma, using CNNs. We use a publically available MRI dataset for data preprocessing, model training, and evaluation in our approach [1].Brain tumors, either benign or malignant; require precise classification for effective treatment, with MRI playing a crucial role in diagnosis. Deep learning, especially convolutional neural networks, extensively enhances diagnostic accuracy by automatically extracting information from MRI scans. This research investigates deep learning techniques for classifying brain tumors, highlighting their transformative potential in medical imaging [2]. Brain tumor involves uncontrolled increase of abnormal brain cells, necessitating prompt identification for effective management. Recent developments in deep learning, particularly using MRI, are extensively enhanced the accuracy of classifying brain tumors into four categories like Gliomas, Meningiomas, Pituitary tumors, and No-tumor[3].Artificial intelligence and medical imaging advancements have significantly enhanced brain tumor diagnosis and therapy, particularly for complex tumors like gliomas, meningiomas, and pituitary tumors. While traditional machine learning requires extensive feature extraction, deep learning systems, especially CNNs, excel in automatic feature withdrawal and classification. This work presents a fusion deep learning model using transfer learning and CNNs, acquiring high accuracy and effectively in MRI-based brain tumor classification and offering a scalable framework for future advancements. [4].As shown in Figure 1, The anatomical structure of the human brain along with examples of common images of brain tumors, including gliomas, meningiomas, and pituitary tumors. Are depicted to provide context for the types of tumors classified in this study.



(a)





(b) **(c)** **(d)**

Figure: 1. Anatomical Structure of the Human Brain and Examples of Common Brain Tumors
(a) Brain anatomy (b) Glioma (c) Meningioma (d) Pituitary [Google].

The complexity of the brain tumors makes diagnosis difficult, and the time-consuming and prone to error nature of traditional approaches using radiologists increases the problem. In order to improve diagnostic efficiency and accuracy, this study creates a strong CNN model for categorizing brain cancers from MRI scans [5].Brain tumors require precise diagnosis, and traditional methods like MRI and CT scans depend heavily on radiologists, leading to potential errors. This study develops a robust CNN model by categorizing different brain tumors from MRI images, enhancing diagnostic accuracy and efficiency by automating image analysis [6].

As compared to traditional diagnostic methods, which rely heavily on manual analysis by radiologists and are often prone to error and time-consuming, this study introduces a novel approach by employing an optimized of three CNN architectures GoogleNet, AlexNet, and SqueezeNet specifically fine-tuned for brain tumor classification. Proposed method leverages comprehensive data cleaning and augmentation, enhancing classification accuracy and diagnostic efficiency. The integration of advanced preprocessing and custom hyperparameter tuning significantly boosts model robustness, achieving up to 97.74% accuracy with GoogleNet, thereby outperforming state-of-the-art models on similar tasks and providing a scalable solution for real-world clinical applications.

[2] STATE OF THE ART

The two primary methods for classifying brain cancers are deep learning (DL) and machine learning (ML).Numerous studies areuse machine learning, including those that use Decision Tree (DT), Genetic Algorithms (GA), K-Nearest Neighbor (KNN), and Support Vector Machines (SVM).In several domains, deep learning has gained popularity as a method that uses complex models such as Long Short-Term Memory Networks (LSTM), Generative Adversarial Networks (GAN),Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN)The literature review offers a thorough overview of existing research and developments in brain tumor classification using MRI imaging and deep learning. This comprehensive analysis covers a range of current applications and methodologies, including convolutional neural networks, data augmentation techniques, and preprocessing methods. By examining these approaches, this section establishes a solid foundation and demonstrates the author's in-depth understanding of the field, highlighting the strengths and limitations of prior work and identifying gaps that this study aims to address[7,8].

Zhang, et al [7].This work demonstrate the fusion method combining deep learning (DL) and conventional machine learning (ML) for tumor of brain categorization, using CNNs for features extraction from MRI images and an SVM classifier for final classification. The hybrid model, which fuses deep learning features with handmade features, outperforms individual strategies.

Shaimaa E. Nassar et al [8]. suggested a reliable fusion deep learning strategy for classifying brain tumors based on MRIs, which begins with tumor identification preprocessing and segmentation. Using five-fold cross-validation and EfficientNet for feature extraction and optimization to fine-tune tumor sites, the model achieved 98.04% accuracy on the MRI dataset

T1W-CE. However, because several networks must be trained, the method has higher computing costs.

Sandeep Kumar et al [9]. Introduced a classification of brain tumor method using Transfer Learning and Deep Neural Networks, leveraging pre-trained Convolutional Neural Network models like ResNet or VGG for feature extraction. This approach achieves competitive accuracy in differentiating tumor classes, demonstrating the efficacy of transfer learning and deep learning in medical image analysis.

Hossein Mehnatkesh et al. [10] resents a deep residual learning structure of categorization for brain tumors using Magnetic Resonance Images, extracting discriminative features to improve accuracy. This intelligent-driven approach demonstrates competitive performance, advancing diagnosis and treatment planning in MRI imaging analysis.

Wadhah Ayadi et al [11]. Proposed brain tumors, among the deadliest cancers worldwide, vary in type and location, impacting survival rates significantly. Accurate MRI-based classification is crucial for treatment planning, facilitated by a proposed novel multilayer CNN model showing promising performance compared to current methodologies.

Bhusnurmath and Betageri [20]. Appears to focus on improving the visualization and analysis of CT images by converting raw pixel values to Hounsfield Units. A Hounsfield Units are a standardized scale used in computed tomography (CT) imaging to signify tissue density, which is essential for accurate diagnosis and interpretation.

[3] PROBLEM PP

The proposed research workflow is effectively demonstrated in the Figure 2This work presents a method specifically developed for classifying brain tumors using Magnetic Resonance Imaging (MRI) scans. This approach is based in a comprehensive dataset and leverages advanced data augmentation and deep learning models for optimal accuracy and efficiency. Our study utilizes the "Brain MRI Scans for Brain Tumor Classification" dataset, freely accessible via Kaggle [19].This study utilizes a unique dataset, 'Brain MRI Scans for Brain Tumor Classification' from Kaggle, which differs from those used in previous studies. The dataset contains 1,311 images categorized into four classes: 300 images of Pituitary tumors, 306 images of Meningiomas, 300 images of Gliomas, and 405 images depicting the absence of a tumor. The data augmentation to enhance the training process; later extensive data augmentation techniques exclusively only on training images not the testing images was applied, Therefore, the trained models were tested using only the original images from the dataset. The preprocessing steps included removal of duplicate samples, correction of mislabeled images, and image resizing to 224x224 pixels. In the next stage, three Convolutional Neural Network (CNN) models GoogleNet, AlexNet, and SqueezeNet were employed, both with and without preprocessing [8]. Next, three different optimized pre-trained models SqueezeNet, GoogleNet, and AlexNet were used to evaluate how well they perform in categorizing various types of brain tumors. The final four layers of the proposed CNN techniques were swapped out to contain the new image classifications (glioma, meningioma, pituitary, and notumor). The remaining layers were taken from the pre-trained networks. The specifics of these three architectures are discussed in the sections that follow.

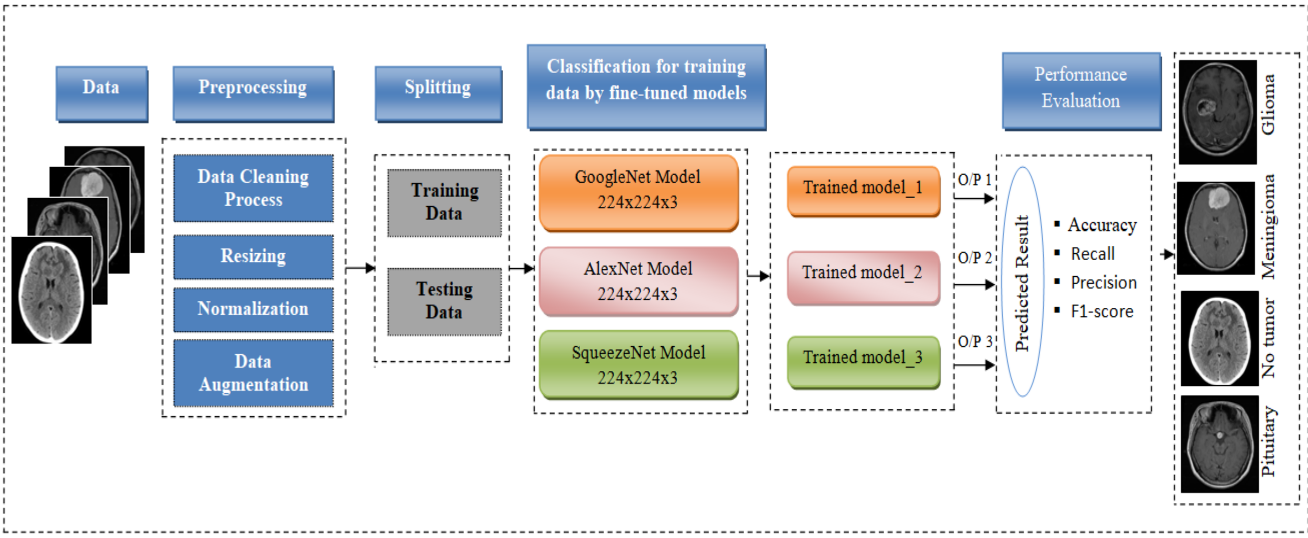
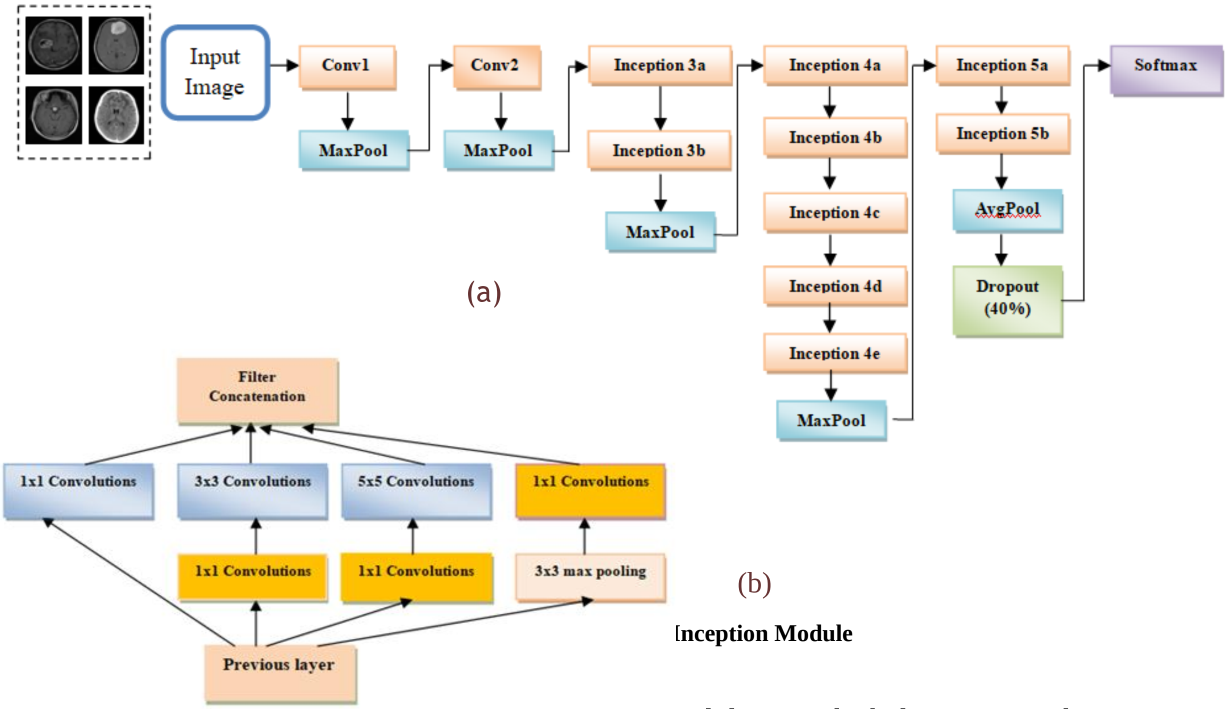


Figure 2: Brain tumor classification workflow using the proposed technique

[3.1] GoogleNet

GoogleNet, or Inception V1, is a groundbreaking CNN architecture by Google the champion of the 2014 ImageNet Large Scale Visual Recognition Challenge was that. It's defining Inception modules allow for concurrent convolutions with various filter sizes (1x1, 3x3, 5x5), capturing diverse details while reducing dimensionality and computational costs. Comprising 22 layers, it includes auxiliary classifiers to enhance gradient flow and mitigate the vanishing gradient issue. GoogleNet efficiently reduces parameters compared to earlier architectures and classifies images according to categories like "Meningiomas," "Gliomas," "Pituitary's," and "No tumors."

Post-training, the model's performance was validated, achieving high accuracy and producing a confusion matrix to illustrate classification effectiveness.



The Figure 3 shows: (a) Block diagram of GoogleNet structural design, which demonstrates the data flow through convolutional layers, max-pooling, Inception modules, and softmax for classification. (b) Inception Module, detailing the structure of an Inception module, combining multiple convolutional filters and pooling operations to capture multi-scale features.

[3.2] AlexNet

AlexNet, innovative convolutional neural network (CNN) architecture, achieved significant success by being the first model trained on 1.2 million images across 1,000 distinct classes for the 2012 ImageNet Large Scale Visual Recognition Challenge (ILSVRC)[8].The architecture, as shown in Figure 4, includes 5 convolutional layers followed by 3 fully connected layers. The first 2 convolutional layers are augmented with overlap max-pooling to enhance feature extraction. The outcome from both the fully connected layers and convolutional are then processed using ReLU (rectified linear unit) activation [12, 13]. Finally, an activation function softmax layer is applied to the last fully connected layer to predict the probabilities across 1,000 classes. AlexNet operates on input images sized at 227 × 227 × 3 pixels. In our specific application for classifying brain tumors (meningiomas, gliomas, pituitary tumors, and notumor). The last four layers of AlexNet were carefully tuned and fine-tuned to fulfill the unique demands of this categorization task. The below figure 4 illustrates the AlexNet model configured for brain tumor classification, starting with

227x227x3 input images. The architecture include 3 max-pooling layers, 5 convolutional layers, and 3 fully connected layers, culminating in a softmax layer for classifying images into four categories. Key layer configurations such as filter sizes, strides, and padding are detailed within the diagram.

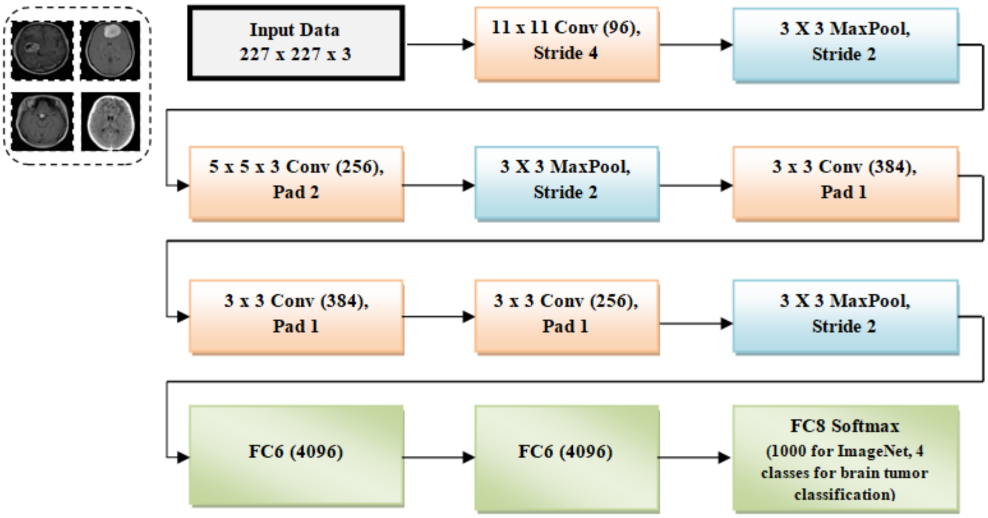


Figure 4: AlexNet Architecture

[3.3] SqueezeNet

SqueezeNet is convolutional neural network (CNN) that uses intend techniques, particularly the use of Fire modules, to significantly reduce the amount of parameters. primarily using Fire modules, Fig 5a show to facilitate it contain 15 layers with five different layers: SqueezeNet is a CNN that uses fire modules and other design techniques to minimize the amount of parameters. Fig 4a demonstrates that it has 15 layers total, five of which are distinct layers: 3 max pooling layers,2 convolutional layers, 1 global average pooling layer, 9 fire layers, and 1 outcome softmax layer[8].layers of "squeeze" and "expand" in a convolution layer makes up a fire module. The first step involves passing an input image through "conv1," a stand-alone convolutional layer. One filter is present in a squeeze convolutional layer. The below Figure 5: (a) SqueezeNet Architecture and (b) Fire Model - This figure illustrates the SqueezeNet model for brain tumor classification, highlighting its use of 'Fire' modules. These modules consist of squeeze layers with 1x1 convolutions and increase layers with both 1x1 and 3x3 convolutions, optimizing parameter effectiveness. The architecture leverages convolutional and max-pooling layers to classify input images effectively.

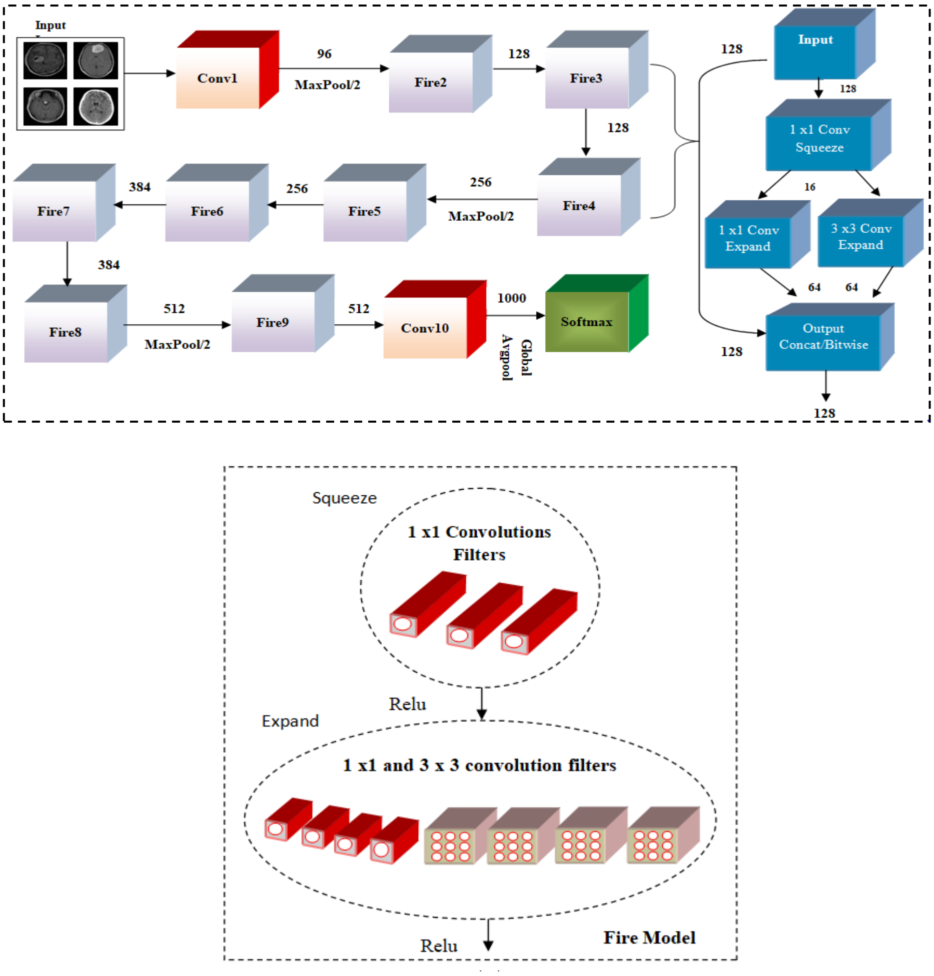


Figure 5: (a) SqueezeNet Architecture and (b) Fire Module

These are input into an enlarged layer, as shown in Figure 5bThe network begins with a layer composed of a mix of 1x1 and 3x3 convolution filters, which are designed to extract spatial features at varying scales. After that, there are eight "fire modules," with the labels "fire2" through "fire9." Following the conv1, fire4, fire8, and conv10 layers is max-pooling with a stride of 2.The fire module's layers are expanded and all of the squeezes are connected by the ReLU activation. To lessen over fitting, dropout layers are introduced after the Fire9 module[14].Let FM stand for Feature Maps, C for Channels, and f{y} be the result of using kernel w in the squeeze operation, as given in Equation (1)[15]:

$$f\{y\} = \sum_{fm1=1}^{FM} \sum_{c=1}^{C} w_f^c x_c^{fm1} \quad (1)$$

The four forms of brain tumors that need to be classified by this CNN model are meningioma, glioma, no tumor, and pituitary, as explained below:

- The final classification layer and the final learnable layer classify the input image based on the features that the convolutional layers of the network extracted;

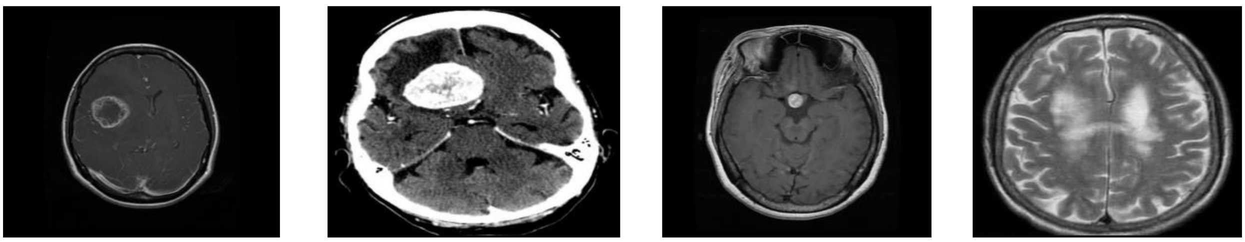
The filter size of new convolutional2d layer is [1, 1]. The number of filters set to 4, which correspond to the number of classes, should be used in place of the "conv10" layer.

[4] HARDWARE AND SOFTWARE DETAILS

The experiments are conducted on a system with an Intel Core i5-7200U CPU and 8 GB of RAM, operating on a 64-bit Windows 10 Pro environment. The implementation is done in Python, utilizing Anaconda 3 with Jupyter Notebook as the development environment. Key libraries such as TensorFlow and Keras are used for model building, with additional support from NumPy and OpenCV for data preprocessing. This configuration demonstrates the feasibility of running deep learning tasks on widely accessible hardware, ensuring reproducibility for similar research.

[4.1] Dataset And Preprocessing

This dataset contain a group of 1,311 high-resolution Brain MRI images [19], exclusively accurate for brain tumor classification and detection. Each MRI image is labeled with one of four classes: "Pituitary," "Meningioma," "Glioma," or "No tumor." This dataset contains 306 images of meningiomas, 300 images of gliomas, 300 images of pituitary tumors, and 405 images with no tumors. Images in the dataset are in 2D volumes with a resolution of 512x512 in jpg format. The Figure 6 illustrated four different types of brain tumor images of type: Glioma, Meningioma, Pituitary, and No tumor.



(a) (b) (c) (d)

Figure 6: Shows examples of images from the brain tumor dataset including: (a) glioma; (b) meningioma; (c) pituitary tumor; and (d) No tumor.

The preprocessing step for the Brain MRI Scans for Brain Tumor Classification involves several important stages to prepare the dataset for effective model training. The dataset, obtained from Kaggle [19], included 1,311 images categorize into four classes: Glioma, Meningioma, Pituitary and No Tumor. The dataset is divided randomly, with 70% allocated for training and 30% for testing. The data cleaning process included the removal of duplicate samples to ensure no redundant images were present, and the correction of mislabeled images to maintain the integrity of the dataset. To comply with the neural network's input specifications, every image is scaled to a uniform 224x224 pixel dimension. Following data cleaning, data enhancement techniques are functional to the training images. These techniques include: rotation with an angle range of 20 degrees, width and height scaling with a range of 0.1, Histogram equalization, and zooming with a range of 0.1. The augmented images significantly increased the range of the preparation dataset by **10%**, enhancing the ability of the model to improve its robustness and generalize. These augmentations helped in creating a more diverse and extensive training dataset, which is critical for training deep learning models effectively. Additionally, the MR images were resized to 224 x 224 x 3 to match the input dimensions required by CNN models GoogleNet, SqueezeNet, and AlexNet.

[4.2] Evaluation metrics

A confusion matrix and metrics including overall accuracy, recall (sensitivity), F1-score and precision, were used to estimate the performance of the suggested model, as outlined in references [8, 16]. The corresponding mathematical expressions are provided in Eqs. (2) to (5) below.

$$ACC = \frac{TP + TN}{TP + TN + FP + FN} \qquad (2)$$

$$\text{Recall (Sensitivity)} = \frac{TP}{TP+FN} \quad (3)$$

$$\text{Precision} = \frac{TP}{TP+FP} \quad (4)$$

$$\text{F1- Score} = \frac{2*\text{Presision}*\text{Sensitivity}}{\text{Precision}+\text{Sensitivity}} \quad (5)$$

These metrics emphasize the performance and reliability of each model in classifying brain tumors using MRI scans.

[4.3] Hyperparameter Tuning

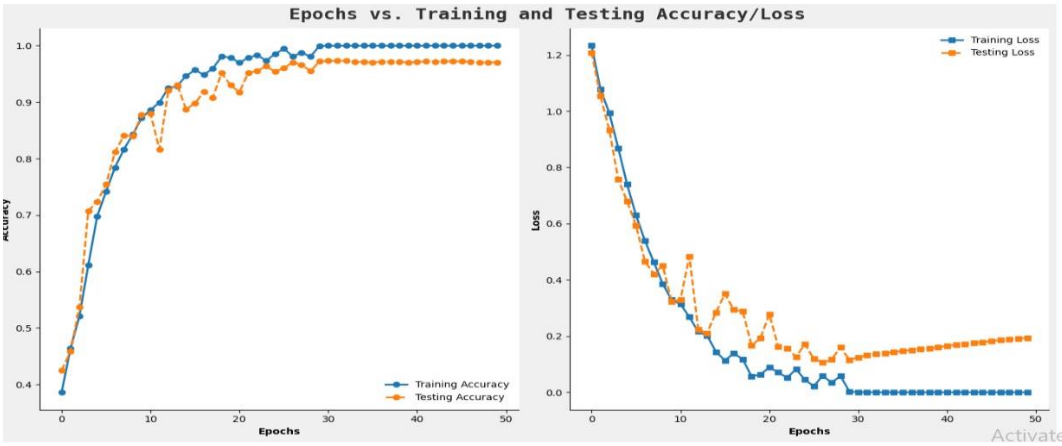
The aim of hyperparameter optimization is to improve the performance of a deep learning model by determining the most effective combination of hyperparameters. Table 1 outlines the training parameters for three deep learning models: GoogleNet, AlexNet, and SqueezeNet. All three models utilize the optimizer function Adam, a extensively utilized method well recognized for its adaptive learning rate and overall effective performance. The models are trained for 50 epochs. The choice of 50 epochs was based on an empirical evaluation where the model achieved a stable training and validation accuracy of around 97%, with a consistent decrease in loss. Extending training to 70 epochs did not yield any further improvements, suggesting that optimal performance was already reached at 50 epochs. At 100 epochs, while accuracy remained constant, a slight increase in validation loss indicated the onset of overfitting. Therefore, 50 epochs were chosen as the optimal point to balance accuracy and prevent overfitting.Meaning the entire training dataset is processed 50 times. The learning rate consistently set at 0.0001 across all models, determining the step size during each iteration towards minimizing the loss function. A verbose setting of 1 is applied, indicating that the training progress will be displayed. Additionally, the data is shuffled at the beginning of each epoch to reduce over fitting by mixing the training samples. Finally, each model uses a batch size of 10, which means the dataset is split into smaller groups of 10 samples for every update of the model's parameters. This uniformity in training parameters ensures a fair comparison of the performance of GoogleNet, AlexNet, and SqueezeNet under the same conditions.

[4.4] Analysis of Experimental results and discussion

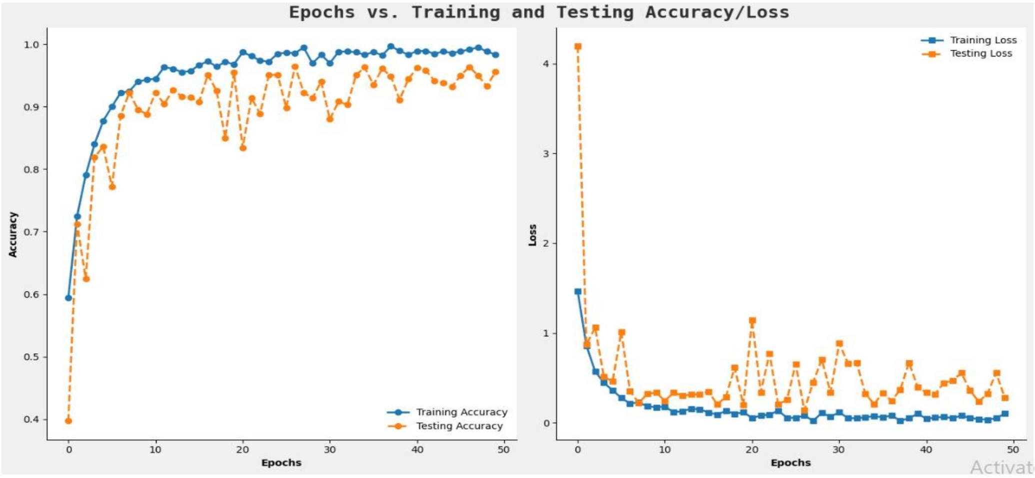
The assessment of three pre-trained deep learning (DL) techniques is covered in this part, along with a Deep learning GoogleNet, AlexNet, and SqueezeNet techniques that are suggested for categorizing different brain tumors using the "Brain MRI Scans for Brain Tumor Classification" dataset into four categories: gliomas, meningiomas, pituitary tumors, and no tumor. Table 1 shows the different parameter values.

Table 1 Parameter values employed in training networks

Parameter/Model	GoogleNet / AlexNet/ SqueezeNet
Optimizer	Adam
No. of epochs	50
Learning Rate	0.0001
Verbose	1
Shuffle	Epoch
Batch size	10



(a)



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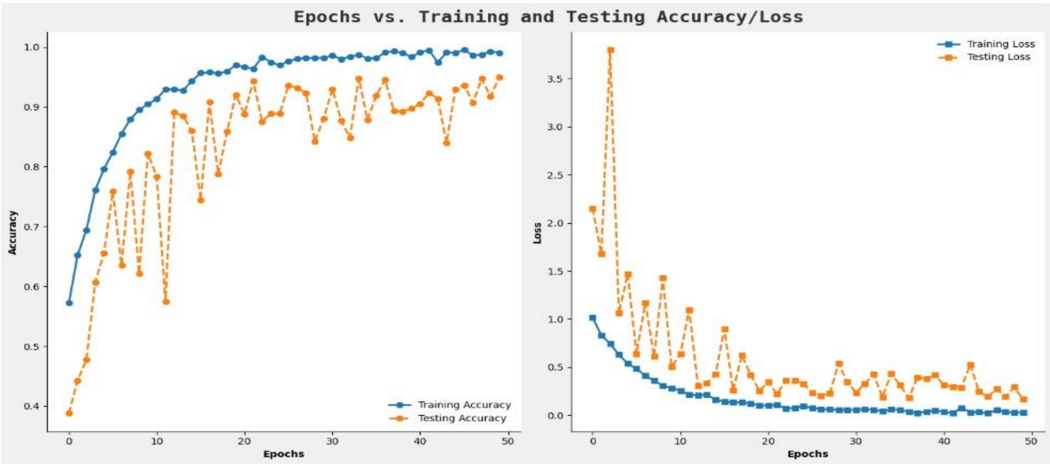
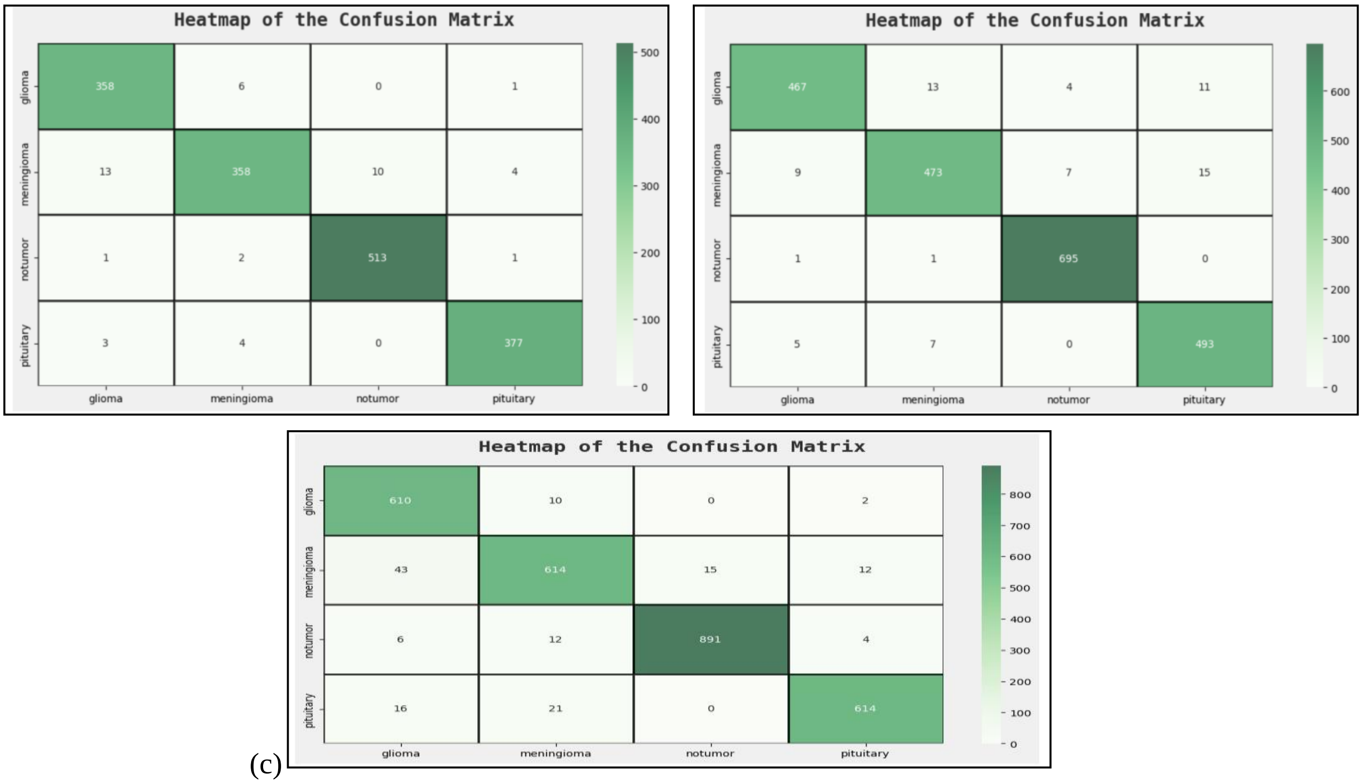


(c)

Figure 7: The loss and accuracy during the training and testing phases for (a) GoogleNet, (b) AlexNet, and (c) SqueezeNet 50 epochs

Figure 7 shows that for GoogleNet, AlexNet, and SqueezeNet, training accuracy increases steadily over the 50 epochs, stabilizing at high values. Testing accuracy also improves but with more fluctuations, particularly in AlexNet and SqueezeNet. Training loss consistently decreases for all models, indicating effective learning, while testing loss also shows a decreasing trend, albeit with some variability. These observations suggest that while the models are learning well during training, there are fluctuations in their performance on the test data, highlighting the need for careful monitoring to avoid overfitting.

Using the positive and false predictions of the model, a confusion matrix is constructed in organize to estimate the efficacy of the planned method. There are various groups denoted by the terms "glioma," "meningioma," "notumor," and "pituitary" in Figure 8, which shows the confusion matrices obtained during the tests. The highest classification ratio is observed for the "notumor" class. Table 2 offers a comparative analysis of the three refined pre-trained models that were chosen for picture classification based on how well they performed in classification tasks.



(c)

Figure 8: A Confusion matrix (a) GoogleNet; (b) AlexNet; and (c) SqueezeNet

The Table 2 highlights the significant boost in classification accuracy across different epochs for GoogleNet, AlexNet, and SqueezeNet due to preprocessing.

Table 2: This table summarizes the performance of GoogleNet, AlexNet, and SqueezeNet models with or without Preprocessing across various epochs, focusing on accuracy.

Models	Epoch	Accuracy of models before preprocessing	Accuracy of models After preprocessing
GoogleNet	10	72.74	87.46 87.46
	20	82.64	90.18
	30	84.26	96.89

	50	86.83	**97.74**
AlexNet	10	81	93
	20	81.64	94
	30	80	95
	50	82	**97.40**
SqueezeNet	10	50	70
	20	58	82
	30	69	85
	50	80	**95.83**

GoogleNet achieves the highest accuracy at 97.74% after preprocessing, followed by AlexNet at 97.40%. SqueezeNet also benefits, though it lags slightly behind with a maximum accuracy of 95.83%. These results emphasize the crucial role of preprocessing in enhancing model performance, particularly for more sophisticated architectures like GoogleNet and AlexNet.

The Table 3 represents the performance comparison of three convolutional neural networks GoogleNet, AlexNet, and SqueezeNet across various metrics. The table shows that GoogleNet achieve the highest accuracy at 97.74%, followed closely by AlexNet with an accuracy of 97.40%, while SqueezeNet has an accuracy of 95.83%. Additionally, the table includes metrics such as precision, recall, F1 score, test time, and training time for each model.

Table 3: Classification Accuracy and evaluation metrics for Brain MRI Scans for brain tumor classification dataset

Metrics	GoogleNet	AlexNet	SqueezeNet
Accuracy (%)	**97.74**	**97.40**	**95.83**
Precision(%)	**97**	**97**	**95**
Recall(%)	**97**	**97**	**95**
F1 Score(%)	**97**	**97**	**95**
Test-Time(Sec)	**2.73**	**0.83**	**2.24**
Train-Time (Sec)	**229.06**	**447.42**	**197**

The performance of the models was evaluated using several key metrics: accuracy, precision, recall, F1 score, test time, and train time. These metrics provide a comprehensive understanding of the model's effectiveness in classifying brain MRI scans for tumor classifications. It is observed from the Table 2 and Table 3 that For **GoogleNet**, without data augmentation, the model achieved accuracies of 72.74%, 82.64%, 84.26%, and 86.83% over 10, 20, 30, and 50 epochs, respectively. After applying data augmentation, the model's accuracy improved significantly to 87.46%, 90.18%, 96.89%, and 97.74% over the same epochs. The highest accuracy achieved by GoogleNet with data augmentation was 97.74%, with a precision, recall, and F1 score of 97%, and the test and train times were 2.73 seconds and 229.06 seconds, respectively. For **AlexNet**, the accuracies without data augmentation were 81%, 81.64%, 80%, and 82% over 10, 20, 30, and 50 epochs, respectively. With data augmentation, the accuracies increased to 93%, 94%, 95%, and 97% over the same epochs. The highest accuracy achieved by AlexNet with data augmentation was 97%, with corresponding precision, recall, and F1 score of 97%. The test and train times were 0.83 seconds and 447.42 seconds, respectively. For **SqueezeNet**, the model's accuracy without data augmentation was 50%, 58%, 69%, and 80% over 10, 20, 30, and 50 epochs, respectively. After applying data augmentation, the accuracies improved to 70%, 82%, 89%, and 95% over the same epochs. The highest accuracy achieved by SqueezeNet with data augmentation was 95%, with precision, recall, and F1 score of 95%. The test and train times were 2.24 seconds and 197 seconds, respectively. Data augmentation significantly improved the performance of all three models. Among them, **GoogleNet** achieved the highest accuracy of 97.74% after data augmentation, making it the better-performing model for brain tumor classification in this study.

[5] CONCLUSION AND FUTURE DIRECTIONS

This study presents a robust and efficient method for brain tumor classification using MRI scans, leveraging three CNN architectures: GoogleNet, AlexNet, and SqueezeNet. Our approach demonstrates the significance of data cleaning and augmentation techniques in enhancing classification performance**,** achieving accuracies of 97.74% with GoogleNet, 97.40% with AlexNet, and 95.83% with SqueezeNet**.** These results highlight the potential of deep learning models in medical imaging and underscore the importance of data preprocessing steps in achieving high accuracy and robustness. For future research, there are several promising directions to explore. Fine-tuning hyperparameters and applying advanced data augmentation methods could further improve model performance**.** Additionally**,** using transfer learning with pre-trained models on diverse datasets may enhance generalization capabilities. Implementing ensemble methods and improving model explain ability will also add value, particularly in clinical settings. Validation on real-world clinical data and integrating models into clinical decision support systems will provide practical utility and validation, making the approach more applicable to healthcare environments. Lastly, applying cross-validation techniques will ensure the robustness and reliability of the models. By addressing these areas, future research can build upon the findings of this study, contributing to advancements in medical image analysis and supporting the development of more precise, dependable brain tumor detection systems. Ultimately, such improvements will aid in early diagnosis and treatment, enhancing patient outcomes and advancing healthcare technology.

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