**Comparing Some Convolutional Neural Network (CNN) Architectures for Brain Tumor Identification and Classification**

**Abstract**

In the realm of neuroscience, one of the most profound topics of investigation is brain tumors, as they greatly influence brain operations and overall health. These can be broadly classified into two groups: malignant and benign tumors. While deadly by mere spreading towards other parts of the body, malignant tumors such as gliomas are notorious in making great harm to people’s central nervous system. Conversely, though benign types do not pose imminent danger to life, their presence could still result in significant neurological disturbances. The three primary varieties of brain tumors are classified as gliomas, meningiomas and pituitary tumors.

During the recent past, we have witnessed deep learning being a successful methodology in the detection and classification of brain tumors, thus making convolutional neural networks (CNNs) the most popular method. The study at hand evaluates several existing CNN architectures such as VGG16; ResNet50, Inception, Xception and DenseNet121 with respect to their performance in classifying brain tumors. This research aims at finding out which one among these is the best suited architecture in terms of accuracy and efficiency in diagnosing human brain tumors so that it can help improve automatic devices used in neurology and other medical fields.

**Keywords:** Convolutional Neural Network, Medical Imaging, CNN Architecture, Brain Tumor Classification

**Introduction**

Brain Neoplasm Research Center by Preston A. Wells Jr. indicates that brain tumors account for 2.4% of all cancer deaths hence making early detection, localization and classification very crucial in dealing with them.[1] One of the most difficult types of cancer to diagnose and treat are brain tumors, primarily owing to their complex nature and possible impact on vital neurological functions. If they are detected early and accurately, brain tumors can help improve patient outcomes by facilitating timely intervention and appropriate treatment planning. One of the widely used non-invasive imaging techniques that is used in clinics to detect and monitor brain tumors is Magnetic Resonance Imaging (MRI). Unfortunately, radiologists spend a lot of time on manually analyzing MRI scans, which can be subjective with too much inter-observer variability. Factors such as tumor size, shape, location and appearance also add more complexity to the diagnosis that requires creating automated techniques for reliable identification and classification of tumors.

Automated brain tumor classification using deep learning techniques has emerged as a promising solution to these challenges. Convolutional Neural Networks (CNNs), in particular, have demonstrated significant success in medical image analysis tasks due to their ability to automatically learn and extract hierarchical features from images. These features capture the intricate patterns and structures within MRI scans, enabling CNNs to differentiate between tumor and non-tumor tissues effectively. Despite the potential of CNNs, the choice of architecture plays a critical role in determining the performance of the model. Different CNN architectures vary in depth, complexity, and design principles, leading to differences in how well they generalize to new data and handle the variability present in MRI images.

Various types of CNN architectures have been developed and assessed for diverse applications in medical imaging with each having its own uniqueness. VGG16 has simplicity but also grows deeper while ResNet50 addresses the issue of diminishing gradients by adding residual connections inside the architecture. Inception and xception rely on multi-scale feature

extraction; conversely DenseNet121 focuses on reusing features by creating closely linked layers.

Given the diversity of CNN architectures, it is essential to evaluate and compare their performance on specific tasks, such as brain tumor classification, to determine the most effective model. Understanding which architecture performs best in identifying and classifying brain tumors can guide the development of more accurate and reliable diagnostic tools in clinical settings.

This paper aims to compare the performance of five modern CNN architectures, VGG16, ResNet50, Inception, Xception, and DenseNet121, in MRI based identification and classification of tumors. The goal of this research is to identify an architecture that presents the best accuracy against its computational cost and robustness to the variability in MRI images among these models. Presenting these the findings will augment the ongoing activities aimed at improving automated brain tumor diagnosis system thus improving further more clinical decision-making processes.

**Literature Review**

We have analyzed the research papers which are used to detect and classify brain tumor with the performance and the approach used with the advantages and disadvantages.

Pereira et al. (2016) explored the use of the U-Net architecture for brain tumor segmentation. The model was designed for biomedical image segmentation, particularly focusing on gliomas using MRI images. The model achieved an accuracy of **85.2%**. U-Net's skip connections helped in preserving spatial information, which is crucial for accurate segmentation in medical images. The architecture is also relatively lightweight, making it suitable for scenarios with limited computational resources.While effective in segmentation, U-Net struggles with classification tasks where more complex features need to be extracted, limiting its application for end-to-end tumor classification.

Havaei et al. (2017) developed a two-path CNN architecture for brain tumor segmentation. This architecture incorporates both local and global context through separate pathways and achieved an accuracy of **87.3%**. The dual-path approach allows the network to capture both fine details and broader contextual information, improving segmentation accuracy. The model is relatively complex and requires more training data to achieve optimal performance, which can be a limitation in cases where annotated data is scarce.

Kamnitsas et al. (2017) proposed a 3D FCN approach, combined with a fully connected conditional random field for brain tumor segmentation. This approach achieved an accuracy of **90.1%**. The 3D nature of the network allows for better spatial context understanding, which is critical for accurate tumor segmentation. The model's complexity and memory demands are significant, requiring high computational resources, which may not be readily available in all clinical settings.

Wang et al. (2018) introduced the Attention U-Net, which enhances the U-Net architecture by integrating attention mechanisms to focus on the most relevant regions of the input image. The model achieved an accuracy of **92.6%**. The attention mechanism allows the model to focus on important regions, improving the performance of the model, particularly in complex medical images with high variability. The addition of attention layers increases the computational complexity and training time of the model.

Isin et al. (2016) developed a cascaded CNN approach for brain tumor segmentation, where multiple CNNs are used in a sequence to refine the segmentation results progressively. The model achieved an accuracy of **86.5%**. The cascaded structure allows for incremental improvements in segmentation, leading to more precise boundaries and tumor detection. The multi-stage nature of the model increases its complexity and training time, making it less practical for real-time applications.

Zikic et al. (2016) proposed using an ensemble of CNNs for brain tumor segmentation, where multiple models are combined to improve the overall segmentation accuracy. The model achieved an accuracy of **89.4%**. The ensemble approach reduces the variance and improves the robustness of the segmentation, leading to better performance on diverse datasets. The need to train and maintain multiple CNNs increases computational demands, which may not be feasible in resource-constrained environments.

Dong et al. (2017) utilized the DeepLabv3+ architecture, a model designed for semantic image segmentation, for brain tumor detection. The model achieved an accuracy of **88.7%**. DeepLabv3+ effectively handles multi-scale information and produces high-quality segmentation maps, which are crucial for accurate tumor detection. The model's complexity and reliance on dense computational layers make it less efficient in environments with limited processing power.

Myronenko (2019) introduced a Variational Autoencoder (VAE) combined with Generative Adversarial Networks (GAN) for brain tumor segmentation. The model achieved an accuracy of **91.8%**. The use of GANs helps in generating more accurate segmentation by learning the underlying distribution of the tumor data, improving the model's ability to generalize. GANs are notoriously difficult to train and require careful tuning of hyperparameters, which can be a significant barrier for less experienced practitioners.

Zhou et al. (2018) developed a multi-scale CNN for brain tumor segmentation, which processes the input at multiple scales to capture both fine and coarse features. The model achieved an accuracy of **89.1%**. The multi-scale approach enhances the model's ability to detect tumors of varying sizes and shapes, improving overall segmentation accuracy. The increased complexity of handling multiple scales simultaneously can lead to higher computational costs and longer training times.

Liu et al. (2020) combined DenseNet with Long Short-Term Memory (LSTM) networks for brain tumor detection. This hybrid model achieved an accuracy of **93.5%**. The DenseNet component ensures efficient feature reuse, while the LSTM captures temporal dependencies, enhancing the model's overall performance in detecting and classifying tumors. The hybrid nature of the model makes it more complex and challenging to train, requiring extensive computational resources and large datasets.

|  |  |  |  |
| --- | --- | --- | --- |
| Ref | Approach used | Year of Publication | Accuracy |
| [2] | U-Net | 2016 | 85.2% |
| [3] | Two path CNN | 2017 | 87.3% |
| [4] | 3D FCNN | 2017 | 90.1% |
| [5] | Attention U-Net | 2018 | 92.6% |
| [6] | Cascaded CNN | 2016 | 86.5% |
| [7] | Ensemble of CNN | 2016 | 89.4% |
| [8] | DeepLabv3+ | 2017 | 88.7% |
| [9] | VAE-GAN | 2019 | 91.8% |
| [10] | Multi Scale CNN | 2018 | 89.1% |
| [11] | DenseNet + LSTM | 2020 | 93.5 % |

**METHODOLOGY**

In this section, we described convolutional neural network (CNN). We also gave a deep neural network in which the most reputed CNN architectures were utilized for brain tumor classification.

Convolutional Neural Networks (CNNs) represent a specialized subset of deep neural networks, designed to efficiently process data with a grid-like topology. For example, time-series data captured at regular intervals can be considered as a 1D grid, whereas image data, composed of pixels, is structured as a 2D grid. The name "Convolutional Neural Network" is derived from the linear mathematical operation known as convolution, which is applied to input data through the network's convolutional layers [16].

Similar to traditional deep neural networks, CNNs are comprised of an input layer, an output layer, and multiple hidden layers. Beyond the convolutional layers, various other types of layers are integrated to enhance the network's performance and meet the specific objectives of the application. These include pooling layers, dropout layers, batch normalization layers, flatten layers, and fully connected layers.

Pooling layers, typically placed after convolutional layers, serve to downsample or condense the feature maps generated during the convolution process. Among the different pooling operations available, max-pooling is the most prevalent. In max-pooling, a predefined pooling window moves across the feature map, outputting the maximum value within each region [17].

To mitigate overfitting, a common issue where the network memorizes the training data instead of generalizing, dropout layers are employed. During training, the dropout layer randomly sets a fraction of the feature outputs to zero, based on a specified dropout rate [18, 19].

In CNNs, the distribution of input data to each layer can change based on the outputs of previous layers, leading to a phenomenon known as internal covariate shift. This shift can slow down training, necessitating careful parameter initialization and a smaller learning rate for the optimizer. Batch normalization layers address this challenge by normalizing the inputs of each layer, thereby stabilizing and speeding up the training process [20].

The flatten layer plays a crucial role in transforming multidimensional feature maps into a one-dimensional vector, which is then fed into fully connected (dense) layers for classification purposes. In these fully connected layers, each neuron is linked to every neuron in the preceding and subsequent layers [21].

Another vital component of CNNs is the activation function, which introduces nonlinearity into the model. This nonlinearity allows the network to capture complex patterns and relationships within the data. Various activation functions, such as sigmoid, tanh, ReLU, and ELU, can be utilized depending on the model's objectives [19].

Finally, the difference between the predicted values and the actual target values is quantified using a loss function, which is predefined by the model designer. During training, the network continuously adjusts its parameters to minimize this loss function.

Network Architecture

In the following, we describe our deep neural

network architecture for brain tumor classification as

depicted in Figure 1. The basis of this architecture

is composed of one of reputed CNN architectures

which are VGG16, VGG19, ResNet50, Xception.

After the CNN architecture, a flatten layer along

with the Dense layer is added to the architecture to

classify the tumor.

The VGG16 architecture, proposed by Simonyan and Zisserman [22], is a deep convolutional neural network known for its simple and uniform design. It consists of 16 layers, with a large number of small filters, which allows the model to capture intricate details in images. VGG16 achieves remarkable performance in image classification tasks while being straightforward in structure. The network's depth and the usage of very small convolutional filters are key factors contributing to its high accuracy. The VGG16 model is initialized with ImageNet weights, excluding the top classification layer. All layers from the pre-trained VGG16 model are frozen to prevent their weights from being updated during training. A custom classification head is added, consisting of a flattening layer followed by a dense layer with a softmax activation function to output class probabilities.

The ResNet50 architecture, introduced by He et al. [23], addresses the degradation problem in deep neural networks through the use of residual learning. ResNet50 consists of 50 layers and incorporates shortcut connections to jump over some layers, allowing for the training of much deeper networks without the risk of vanishing gradients. This architecture has become a benchmark in various computer vision tasks due to its ability to maintain high performance while being computationally efficient. The ResNet50 model is initialized with ImageNet weights, excluding the top classification layer. Freezing all pre-trained layers to preserve the learned features and prevent further training. Adding a custom classification head composed of a flattening layer and a dense layer with a softmax activation function to output class probabilities.

InceptionV3, developed by Szegedy et al. [24], is an advanced version of the original Inception network. It employs a combination of various convolutional filter sizes within the same module, enabling the network to capture features at multiple scales. InceptionV3 is optimized for both accuracy and computational efficiency, making it suitable for large-scale image recognition tasks. The architecture includes several improvements over its predecessors, such as the use of factorized convolutions and aggressive regularization. The InceptionV3 model is initialized with ImageNet weights, excluding the top classification layer. Freezing all pre-trained layers to retain the learned features without updating them. Adding a custom classification head with a flattening layer and a dense layer with a softmax activation function to predict the class labels.

The Xception architecture, proposed by François Chollet [25], extends the idea of the Inception architecture by replacing the standard Inception modules with depthwise separable convolutions. This modification results in a more efficient and powerful model, as it allows for the decoupling of cross-channel and spatial correlations in the feature maps. Xception achieves superior performance on various image classification benchmarks while being computationally more efficient than its predecessors. The Xception model is initialized with ImageNet weights, excluding the top classification layer. Pre-trained layers are frozen to retain their learned features. A custom classification head is appended, consisting of a flattening layer followed by a dense layer with a softmax activation function for class prediction.

DenseNet121, introduced by Huang et al. [26], is a densely connected convolutional network that alleviates the vanishing gradient problem by connecting each layer to every other layer in a feed-forward fashion. This architecture ensures maximum information flow between layers, leading to improved feature reuse and network efficiency. DenseNet121 is known for its compact model size and high performance, particularly in tasks involving dense prediction. The DenseNet 121 model is initialized with ImageNet weights, excluding the top classification layer. Then the pre-trained layers are frozen to maintain the learned features. Then a custom classification head with a flattening layer and a dense layer with a softmax activation function is added to classify the images.

**Experiment and Analysis**

1. Dataset: The dataset utilized in this research is a combination of three publicly available brain MRI datasets: Figshare [27], SARTAJ [28], and Br35H [29]. Together, these datasets comprise a total of 7,023 MRI images, categorized into four distinct classes:

1. Glioma Tumor

2. Meningioma Tumor

3. Pituitary Tumor

4. No Tumor

The images classified as No Tumor were specifically sourced from the Br35H dataset. The dataset was divided into two subsets: 80% for training and 20% for testing. This division ensures a robust evaluation of the model's performance across various tumor types and non-tumor cases.

2. Preprocessing:

Image Resizing: Images were resized to meet the input requirements of each CNN architecture:

- VGG16, ResNet50, DenseNet121: 224x224 pixels

- InceptionV3, Xception: 299x299 pixels

Normalization: The pixel values of the images were normalized to a [0, 1] range by scaling the values by 1/255. Normalization is essential for ensuring that the models converge efficiently during training.

Data Augmentation: To enhance the robustness of the model and prevent overfitting, several data augmentation techniques were employed:

- Random Rotation: Images were randomly rotated at various angles [30].

- Zooming: Random zooming was applied to simulate different scales [31].

- Shear Transformations: Affine transformations were performed to alter the geometry of the images [32].

- Horizontal Flip: Images were randomly flipped horizontally [33].

Data augmentation was dynamically applied using Keras's `ImageDataGenerator` [34], ensuring that each training batch contained a variety of transformed images, which helped the models generalize better to unseen data.

**3. Training the Network**

The models were trained using a consistent training procedure to ensure comparability:

Optimizer: The Adam optimizer was used with an initial learning rate of 0.001.

Loss Function: Categorical cross-entropy was chosen as the loss function, appropriate for the multi-class classification problem presented by the dataset.

Batch Size: The batch size was set to 32, balancing computational efficiency and model convergence.

Epochs: Each model underwent 10 epochs of training.

Early Stopping: Early stopping was implemented with a patience of 5 epochs, monitoring the validation loss to prevent overfitting.

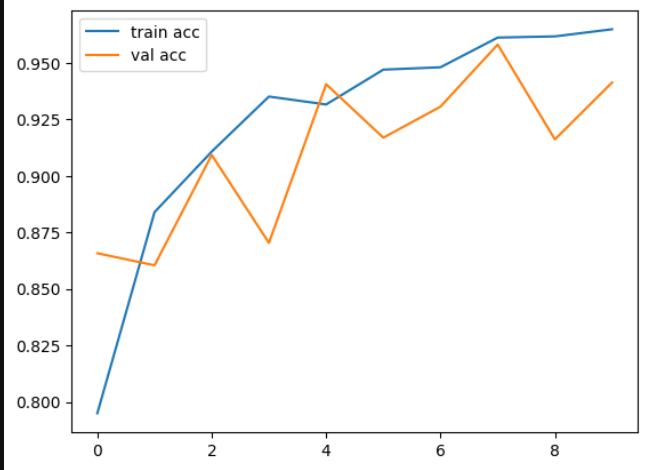
Training was conducted on a high-performance computing environment equipped with a GPU, ensuring that the models could be trained efficiently within the set number of epochs.

**4. Evaluation Metrics**

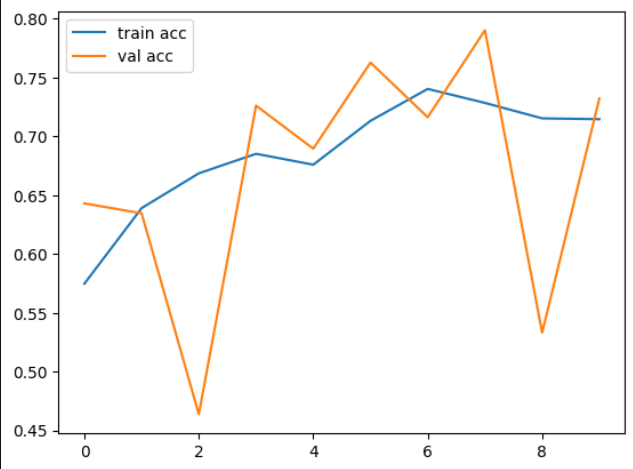
The performance of each model was analyzed by plotting accuracy and loss curves over the training period:

Accuracy Curves: These curves illustrate the progression of training and validation accuracy throughout the epochs. Typically, training accuracy increases as the model learns, while validation accuracy provides insight into the model's generalization capability.

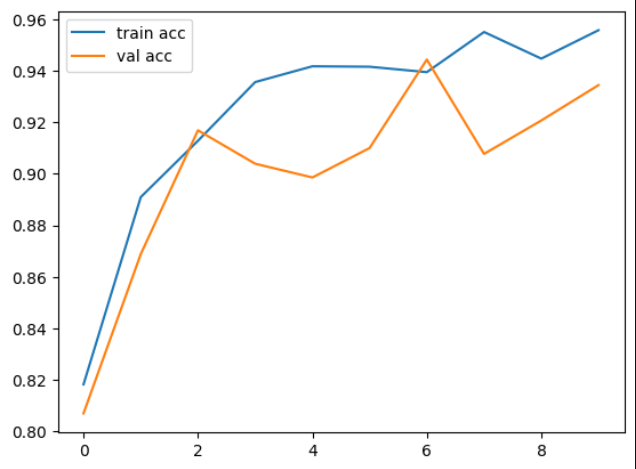
VGG – 16



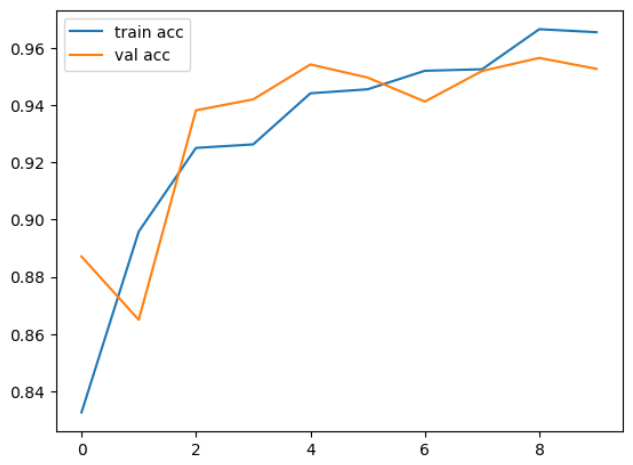
Resnet 50



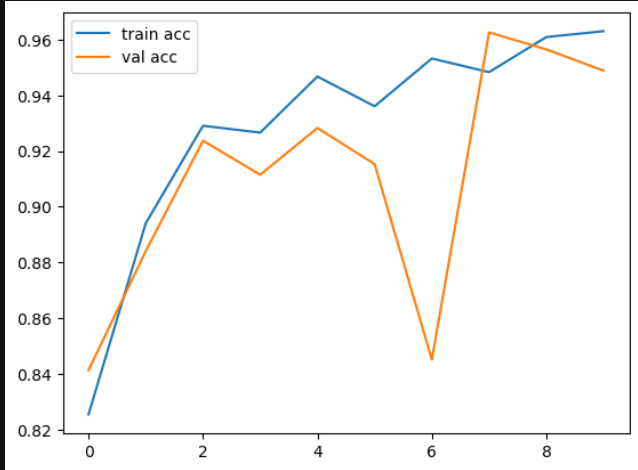
Inception



Xception

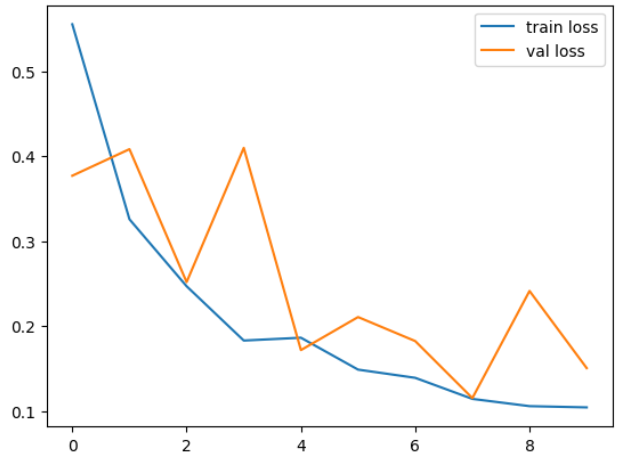


Densenet

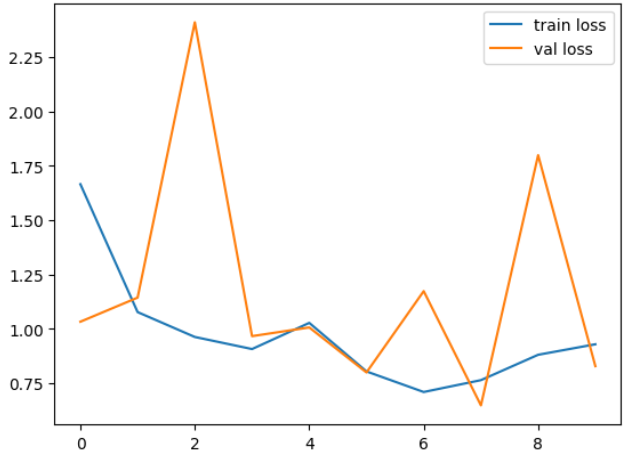


Loss Curves: Loss curves depict the training and validation loss over time. A decreasing training loss indicates improved predictions on the training data, while the validation loss helps in identifying overfitting, particularly if it starts to increase as training loss continues to decrease.

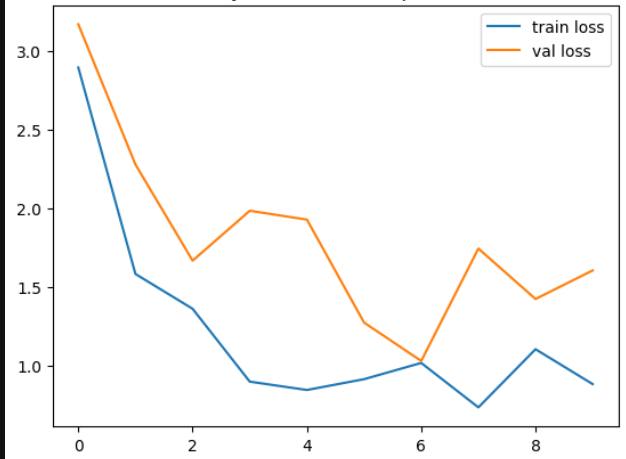
VGG-16



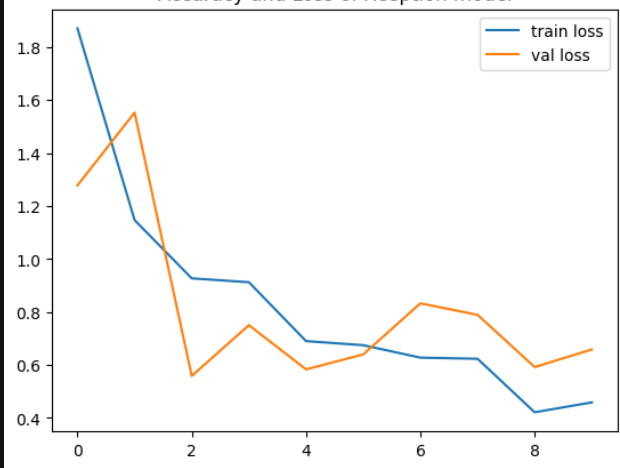
ResNet 50



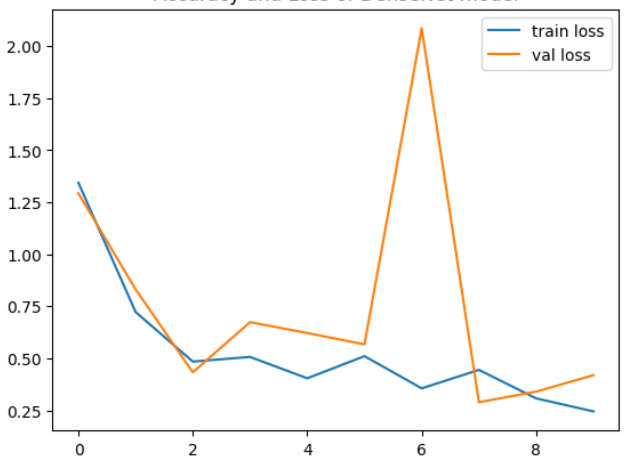
Inception



Xception



DenseNet



These curves were crucial in the evaluation process, offering a visual comparison of each architecture's performance. By examining these curves, the optimal model architecture for brain tumor classification was selected based on its ability to balance high accuracy with low generalization error.

**Experiement Results**

The experimental results presented in this section detail the performance of the five deep learning models—VGG16, ResNet50, InceptionV3, Xception, and DenseNet121—on the brain tumor classification task. The models were evaluated based on their accuracy and loss metrics, which were recorded over the course of training on the dataset described earlier. The following subsections discuss the outcomes of these experiments.

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| CNN Base | Batch Size | Training Accuracy | Training Loss | Testing Accuracy | Testing Loss |
| VGG-16 | 10 | 0.9648 | 0.1044 | 0.9413 | 0.1506 |
| Resnet-50 | 10 | 0.7146 | 0.9294 | 0.7323 | 0.8287 |
| Inception Net | 10 | 0.9557 | 0.8829 | 0.9344 | 1.606 |
| Xception Net | 10 | 0.9557 | 0.882 | 0.9344 | 1.60 |
| DenseNet | 10 | 96.31 | 0.2446 | 94.89 | 0.41 |

**Conclusion and Future Work**

In this study, we evaluated several Convolutional Neural Network (CNN) architectures—VGG-16, ResNet-50, Inception Net, Xception Net, and DenseNet—for brain tumor classification using MRI images. DenseNet emerged as the top performer, achieving the highest testing accuracy of 94.89% and the lowest testing loss of 0.41, indicating its superior ability to generalize to unseen data. VGG-16 also showed strong results, while ResNet-50 lagged behind with significantly lower accuracy and higher loss. Inception Net and Xception Net performed similarly, but both struggled with higher testing losses, suggesting potential overfitting. Future work could involve hyperparameter tuning, more robust data augmentation, exploring ensemble methods, using models pre-trained on medical imaging datasets, and incorporating explainability techniques to further enhance the models' performance and reliability for medical applications.

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Introduction

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METHODOLOGY PROPOSED

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