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Complementary Analysis of Deep Learning Architectures for Brain Tumor Classification Using MRI Images

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Abstract

Accurate brain tumor classification from MRI scans is critical for effective diagnosis and treatment planning. This study compares the performance of three deep learning models—Simple CNN, ResNet50, and InceptionV3—in classifying brain tumors using MRI images. Among the models, InceptionV3 outperformed others, achieving the highest accuracy and generalization to unseen data, making it the most suitable for real-world applications. ResNet50 displayed competitive performance but showed overfitting tendencies, while the Simple CNN served as a baseline model with limited complexity and accuracy. Future improvements, including the incorporation of transfer learning, attention mechanisms, and larger datasets, are suggested to enhance model robustness and clinical reliability. These findings demonstrate the potential of advanced deep learning models in automating brain tumor classification for clinical use.
Keywords: Convolutional Neural Network (CNN), ResNet50, InceptionV3, Brain tumor, and transfer learning

1.Introduction

One of the severe diseases that are present in today's society is the brain tumors. These tumors may develop at any part of the human brain and also may vary in their size/shape. Before we go any further, it is of great importance to know that there two subtypes of intellectual tumors. It is further important to classify the tumors of intelligence into four stages being first, second, third and fourth degree or stages [1]. Grade I and II are noninvasive stage while grade III and IV are invasive stage. The tumors originating from the cells in Brain it is known as primary brain tumor and those tumors may also be originated from other parts of the body and spread to the Brain is known as secondary Brain tumor. There are few types of brain tumor and the most famous is glioma, which is known to affect both adult and children. Glioma comprises tissues of glial cells in the brain and category of high-grade glioma (HGG) and low-grade glioma (LGG). It is worth to note that the median survival time (MST) for HGG is as low as 15 months [2]. Brain tumor is abnormal growth of brain tissue and disruption of controls of the brain. More than 700000 individuals are affected with brain tumors globally with approximately 86, 000 new incidences recorded in 2019. According to data obtained from the world health organization, it is estimated that in the year 2019, about 16380 people died from brain tumor [3]. Brain tumors are peculiar tumors determined in the human frame. Sculler. Given the complex and touchy nature of the mind non-invasive strategies inclusive of magnetic resonance imaging (MRI) are the most popular desire for mind tumor analysis. This image is a 3-D scan of the patient's brain and can be visualized as considered one of two pictures. In the corresponding photo, planes (coronal, sagittal, transverse) as proven in figure 1.[4].

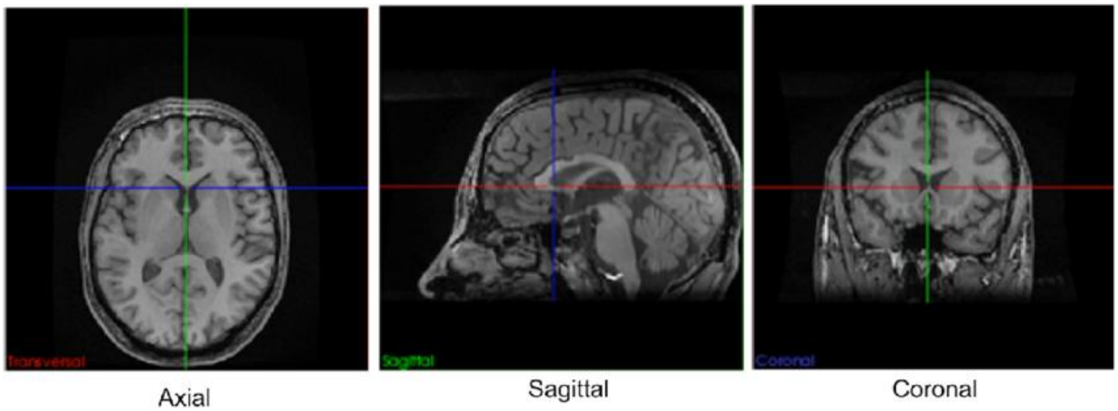

Figure 1: Introduction to imaging: basic sectioning planes: Coronal, Sagittal, and Transversal (Axial) [4].

In medical imaging, the coronal plane divides the body into anterior (front) and posterior (back) sections. The Sagittal plane further divides the body into right and left halves, while the transversal (axial) plane runs horizontally, providing cross-sectional views of anatomy. Magnetic Resonance Imaging (MRI) utilizes radio waves and magnetic fields to capture detailed images of the human body. MRI scan rely on two keys signals: echo time (TE) and repetition time (TR), which together create the final images [5].

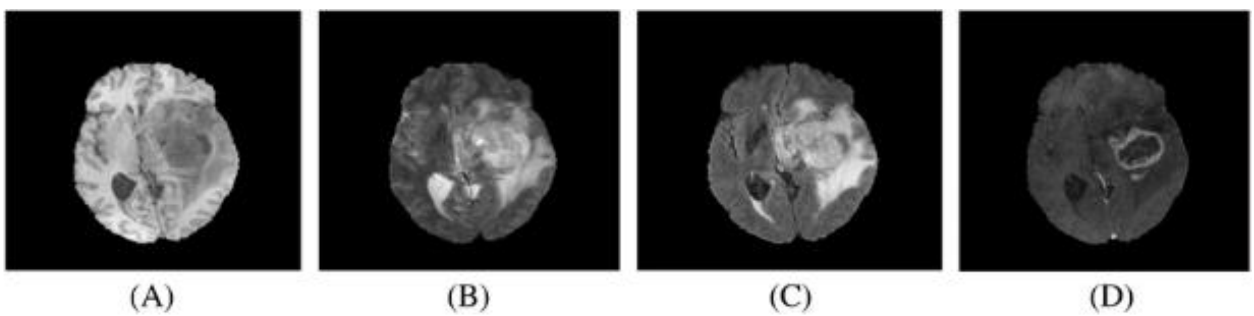

Figure 2: MRI especially T1W, T2W, FLAIR T1C helps in bestowing delineation of anatomical structures and pathological states.[6].

When classifying brain tumors, the primary objective is to identify specific tumor subregions to aid in diagnosis and treatment planning. These regions include the whole tumor (WT), tumor core (TC), and enhancing tumor (ET). Two common approaches used in medical imaging are discriminative and generative methods. Discriminative methods rely on learned models based on prior knowledge and detailed image features, distinguishing tumor characteristics through training on labeled examples. In contrast, generative methods utilize prior knowledge about normal and pathological tissue patterns to model and segment different regions of the brain [7].

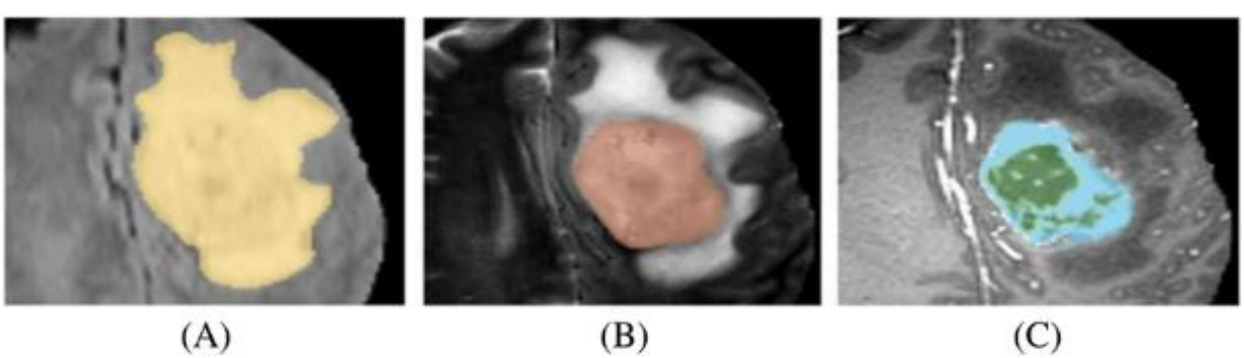

Figure 3: Different and more specific aspects of the brain tumor include

(A) WT – white matter infiltration, (B) TC – the tumor's densest and most aggressive part, (C) ET – edema and other changes the neighboring tissue.[8]. Recently, both categories have seen an increasing use of deep learning methods for having classification and segmentation of brain tumors.[8]. Profound learning may be a sort of machine learning (ML) and manufactured insights (AI) that mirrors the way people procure certain sorts of information. Profound learning is a critical component of information science, which incorporates insights and prescient modeling. It is amazingly valuable for information researchers charged with collecting, analyzing and deciphering expansive sums of information; profound learning makes this prepare speedier and simpler [9]. The field of computer vision is used to extract new information from digital images. Among the concepts of artificial neural networks, convolutional Neural networks (CNNs) are widely used for segmentation and classification purposes. Neural the network consists of three layers: input, hidden, and output. The input layer receives the following data: It is then distributed to the rest of the network. Hidden layers play an important role in providing efficient operation of the network with automatic feature extraction and activation functions Data conversion. [10]. CNN design such as Incetion-V3, Alex Net and ResNet50 and gotten exact comes about. They changed an already trained ResNet50 CNN by killing its five layers and including unused eight layers coming about in a show with precision, the finest among all pre-trained models they utilized in their work. Employing a dataset of brain MR pictures [11].

Brain tumors are a number of the maximum lifestyles-threatening situations, and their correct diagnosis is vital for powerful treatment making plans. Magnetic Resonance Imaging (MRI) is usually used to come across and classify mind abnormalities. However, manual analysis of MRI photographs may be time-consuming and liable to mistakes. The development of deep studying has opened new avenues for automating the type of clinical pictures, making an allowance for quicker and greater correct diagnoses.

In this study, the authors suggest utilizing deep learning techniques to make brain tumor classification. The authors of the paper stress out analyzing tumor detection from MRI images using a Simple CNN, ResNet50, and InceptionV3. The models are designed with a two-class scenario; there is a "Brain Tumor" and a "No Tumor" state. The perspective examination of the study shows the relevance of deep learning techniques in analyzing medical images and also assesses parameters like accuracy, loss, and validation stability of constructed models.

2. Literature Review

A brain tumor could be a bunch or mass of unusual cells in your brain. Side effects of brain tumors depend on the area and measure of the tumor.[12]. The different indications of brain cancer incorporate coordination issues, visit migraines, temperament swings, and changes in discourse, trouble in concentration, seizures and memory misfortune. It is imperative to identify brain cancer as before long as conceivable. MRI can be utilized to distinguish brain cancer by MRI investigation, but this strategy varies in its utilization for a huge number of cases [13]. Numerous inquire about papers have been distributed to utilize manufactured insights, master frameworks and neural systems to progress the discovery of brain tumor.[14]. As of late, restorative centers and clinics have started to present counterfeit insights frameworks and applications in a few disciplines to extend the precision of illness discovery. Numerous strategies and models have been presented that have contributed to expanded symptomatic productivity [15]. Early determination of gliomas plays a critical part in moving forward treatment conceivable outcomes. There are numerous therapeutic imaging strategies such as Computed Tomography (CT), Single-Photon Emanation Computed Tomography (SPECT), Positron Outflow Tomography (PET), Attractive Reverberation Spectroscopy (MRS) and Attractive Reverberation Imaging (MRI) that are used in combination to supply the most noteworthy point by point and profitable data approximately the shape, estimate, area and digestion system of brain tumors helping in determination.[16].The last few years have seen the emergence of quite promising methods in deep learning that have tackled the problem of medical imaging, particularly the identification of brain tumors in MRI scans[3]. Convolutional Neural Networks (CNNs) have been the leading structure within this area due to their ability to perform image feature extraction in an automated manner [17]. It has also been proven that CNNs are capable of modeling spatial hierarchies, which makes them ideal for decoding complicated MRI images. Residual Learning with Deep Networks, specifically ResNet50, adopts skip connections, which helps against Vanishing gradient which is a problem common in deeper networks.[18] This architecture has been proven to be very effective in brain tumor classification tasks as evidenced in several studies. The success of ResNet50 to avoid over-fitting even when training deeper networks makes it possible for effective learning of finer details such as distinguishing between a benign and malignant tumor [19]. It has been shown that performance tuning of ResNet50 on a single dataset can improve performance even better than the conventional CNN models, achieving new records in classification accuracy [20]. The improvements on CNN designs are enhanced

with InceptionV3's multiple pathways enhancing the feature extraction over diverse dimensions [21]. This architectural design has also been useful in focusing on the differences in tumor forms and their levels in Present MRI scan. With the ability to design the InceptionV3 more accurately, it is possible to comprehend the images in the medical scans in more detail thus better outcomes are achieved. Such studies have proved InceptionV3 to be very promising in clinical practices, especially diagnosing brain tumors as it often demonstrates better accuracy and computational efficiency when compared with ResNet50 and standard CNNs [22]
ResNet50 and Inception are pre-trained models that have improved the effectiveness of deep learning algorithms at image classifications thanks to their deep networks and capability of feature extraction. This study extends such findings by implementing a Simple CNN, ResNet50 and InceptionV3 for classifying images of brain tumor. Whereas previous studies have focused solely on enhancing the accuracy, this research also analyses the generalization potential of the models and tackles possible over fitting problems.

3. Methodology

In this chapter, we present the methodology you utilize for brain tumors classification using MRI images with deep learning models. There will be a specified dataset to collect, data preprocessing, the model architecture, training procedure and evaluation method etc.

3.1 Overview of Methodology

Important steps in the method include:

- **Dataset collection**: The first step involves a dataset collection that mainly consists of the brain MRI images and a total of two classes those are Brain Tumor and No Tumor.
- **Preprocessing the Data**: Resize Normalization Augmentation
- **Model construction**: Design, develop and train Convolutional neural networks (CNNs) with some pre-trained models such as ResNet50, InceptionV3.
- **Model Training**: Models will be trained using hyper parameters that are optimized.
- **Model appraisal**: To check how well the best model will perform using accuracy, loss, confusion matrices and other metrics.
  Explanation of every stage is given in further detail below.

3.2 Dataset

The target population for this research included the following:

- **Brain Tumor**: The MRI images where the case of a tumor is documented.
- **No Tumor:** The MRI Images which do not show any signs of a tumor.

3.2.1 Image Specification

- **Image Format:** The MRI scans are available in JPG format for viewing.
- **Image resolution**: Images have been altered to a standard size of 128 by 128 pixels.
- **Channels:** Although the images were in grayscale, they were changed to RGB for uniformity. During the model inputs, all images were made in RGB format.

3.3 Data Preprocessing

The images require preprocessing for them to be fit for deep learning model trainings. The procedures that were adopted in this research are given below.

3.3.1 Image Resizing

To avoid discrepancies, the total number of picture dimensions was modified to 128x128 pixel images. It makes it possible for CNN model arrangements to be constant in terms of input size all through the training stage.

3.3.2 Data Normalization

The original pixel values of the entire images were pushed to the closed range of [0, 1] by dividing any pixel intensity with 255. This form of normalization helps in speeding up training of the model.

3.3.3 Data Augmentation

In order to improve the ability of the model to generalize and to mitigate against over fitting, data augmentation methods were used on the training set. The following transformations were used:
• **Flipping**: flip images horizontally and vertically.
• **Rotation**: rotate images randomly at tilt that goes up to depth of 20 degrees.
• **Zoom**: allowing random zooming, standard mostly useful within 20%.
• **Shear**: corporations of images by forcing images within a certain angle.
These transformations were performed on the training set only so that the model impacts knowledge of detection of tumors from different angles.
To sentences used to describe tumor, images augmentations were applied on training set and not test set, thereby making the model view tumors in different angel.

3.3.4 Dataset Splitting

The data was split into three subsets:
- **Training set (80%):** This is used to train the model.
- **Validation Set (10%):** The model is evaluated with this set while training.
- **Test Set (10%):** It is used to evaluate the final model estimation on unseen data.

3.4 Model Architecture
In this section, we explain the model architecture of the study models which includes CNN and pre-trained models (ResNet50, InceptionV3)

3.4.1 Convolutional Neural Network (CNN).

The CNN was implemented as a base model. There are a number of convolutional and pooling layers then a fully connected layer for classification. Operating on top of these models, we use a sigmoid function in the final output layer to get specific class predictions for binary classification: Brain Tumor and No Tumor.
Architecture:
- **Change when adding input**. [Input layer 128x128x3
- **Convolutional Layers**: 3 Convolutional layers with growing filters (32,64,128) and kernel size 3x3.
- **Pooling Layers**: These layers reduce the spatial dimensions of the model by following every convolutional layer with a max-pooling.
- **Fully Connected Layer**: 128 units, followed by a Dropout layer with 0.5 rate
- **Output Layer**: Using sigmoid activation function so that the output can give a probabilistic value between 0 to 1 for binary classification.

3.4.2 Pre-trained Models: ResNet50 and InceptionV3 Model

Apart from implementing the custom CNN model, the use of ResNet50 and InceptionV3 models which are pre-trained was also incorporated. These models were adapted and improved to suit the problem of brain tumor classification using the knowledge acquired from the training on the ImageNet dataset.
ResNet50 Model
The ResNet50 model which implements deep modular residual learning was implemented with fifty layers having residual blocks. The very final fully connected layer was illegal since its output was multi-class.it was changed to produce output of brain tumor or no brain tumor only.
InceptionV3 Model:
With respect to the design of the InceptionV3 Model depth wise separable convolutions were employed to lessen the complexity involved. This model was also modified for the purpose of this study but the last layers were modified for the purpose of the study's binary classification.

3.5 Training Procedure

Training was carried out using **Tensor Flow** and **Keras** libraries to perform various neural network model development tasks. The following training configurations were used.

- **Optimizer**: The optimizer selected in this case was Adam since it's a proximal algorithm that audaciously changes model parameter and finds sparse gradient.
- **Loss Function**: Since the classification task was of binary nature, the binary cross-entropy loss function was utilized for loss computation.
- **Learning Rate**: The second initial learning rate was proposed to be 0.001 in addition with the learning rate scheduler to decrease the learning rate as much as possible.
- **Batch Size**: The researchers adhered to a training batch size of 32.
- **Epochs**: The models were trained for different epochs in regard to its complexity with early stopping being employed to reduce over fitting.

3.5.1 Early Stopping

Training was stopped if the validation loss did not increase for 10 continuous epochs. This was done to reduce overfitting in the model.

3.5.2 Model Checkpoints

The model checkpoints were used during the training of the models to only save the model with the least validation loss. This meant that even though there were several models trained, only one model – that of the best epoch – would be used after training.

3.6 Evaluation Metrics

The following evaluation metrics were used to assess the model within the study:

- **Accuracy**: The ratio of correct classifications to the number of classification tasks.
- **Loss**: This refers to the measure of accuracy of the model in relation to how much improvement of the model actually takes place.
- **Prediction Confusion Matrix**: Focuses on identifying the true positives, true negatives, false positives, and false negatives thus providing the basis on which precision, recall, and F1 metrics are calculated.
- **Precision, Recall and F1**: These metrics were calculated based on the confusion matrix and explain the model performance in detail.

3.6.1 Cross-Validation

To avoid overfitting of the model and evaluate it on different sets of the data, cross-validation was done using a 5-fold cross-validation.

3.7 Tools and Frameworks

The following tools and frameworks were employed during the preparation and training of the models:

- **TensorFlow and Keras**: To create and train deep learning models.
- **Python**: The language in which the models were coded.
- **Scikit-learn:** To create performance metrics like confusion matrix and classification reports.
- **Matplotlib and Seaborn**: To plot performance graphs (accuracy, loss) and confusion matrices.
- **Pandas**: Used for data processing and shaping.

This section brings into focus the primary purposes of 'Simple CNN', 'ResNet50' and 'InceptionV3' in the classification process of model indication (tumor presence) and absence (non-tumor). The models' efficacy is computed in terms of precise as well as logarithmic loss on the training data, validation data and all the data together as a single entity. All the same, there were graphs depicting the rise and fall of these parameters with respect to the number of seeds and there was a lot of interpretation of the observations made.

4. Results

4.1 Dataset and Class Distribution

It is always great to look at the class distribution of the data before model training to ensure proper utilization of the data. The dataset comprises of two types: Brain Tumor, No Brain Tumor. In order to have a balanced dataset, classes should be raised so that no biases are created in the models and models perform well when exposed to training.
As illustrated in Figure 4.1, in the dataset there are two classes and only low occurrences of the two classes. As it can be seen the dataset is split equally for both classes, thus avoiding bias in model training.

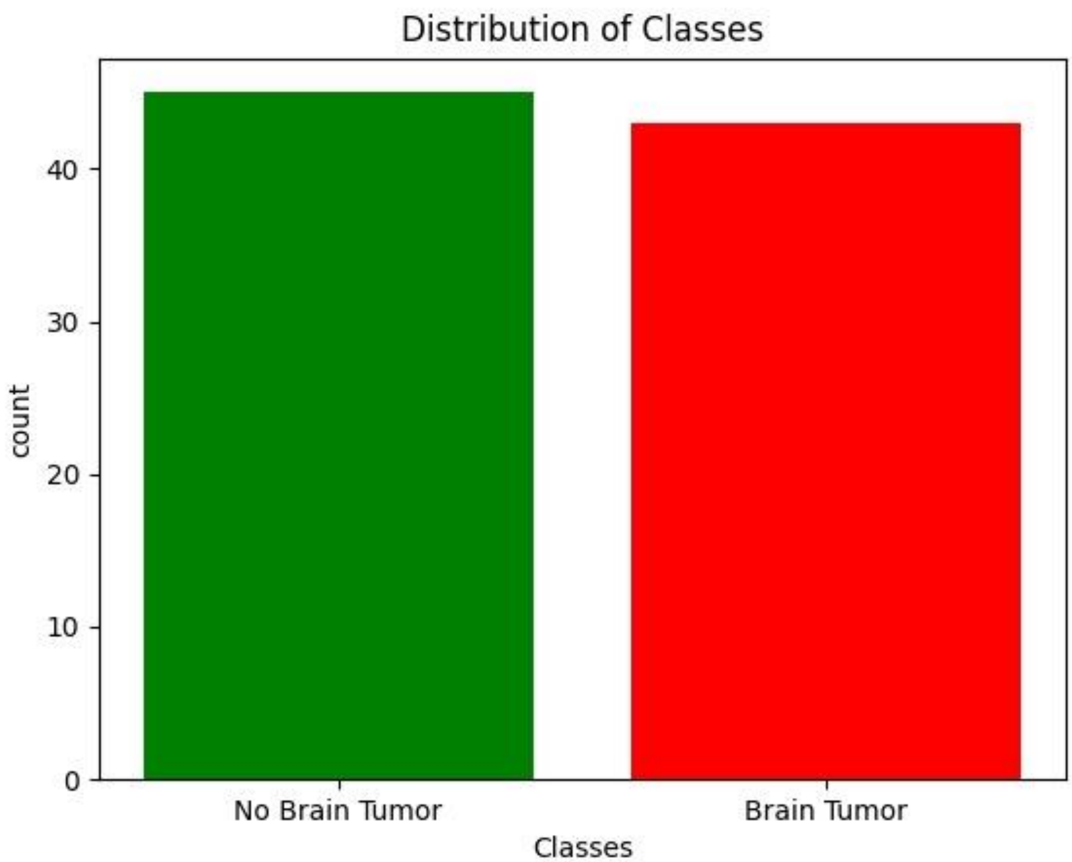

Figure 4.1: Distribution of Classes in the Dataset

Furthermore, in figure 4.2, one can witness images illustrating the two kinds of brain scans in our dataset. The images show significant visual effects where there are brain scan images with tumors as well as without them, which enhances the model's ability in differentiating the two categories better.

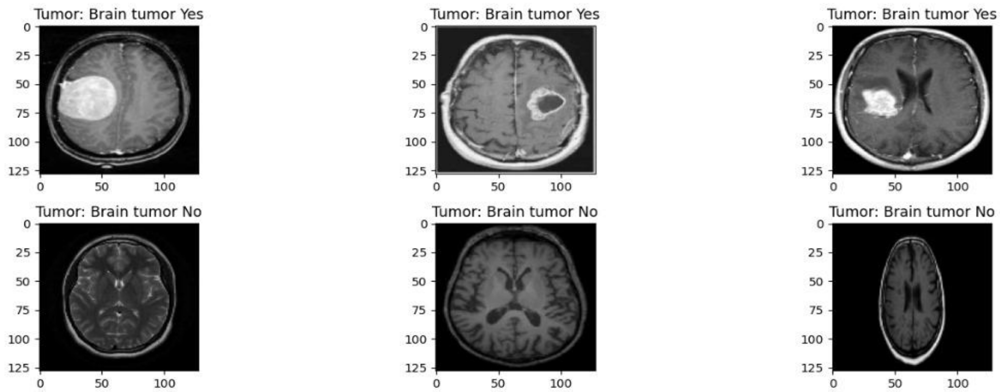

Figure 4.2: No Brain Tumor and Tumor MRI Scans

4.2 Training and Validation Results for Different Models

4.2.1 Simple CNN Model

The first model implemented was of a basic Convolutional neural network model with the intention of establishing it as a benchmark against which more complex structures would be compared to. This model was trained over 30 epochs.

- **Training Performance**: The Simple CNN model progressively raised the levels of accuracy reaching nearly 90% accuracy by the last epoch.
- **Validation Performance**: The validation accuracy showed high levels of variation but however remained around 70 %.
- **Test Performance and Loss**: The test performance at the last test was at 70.58 % and the test loss was at 0.5616.

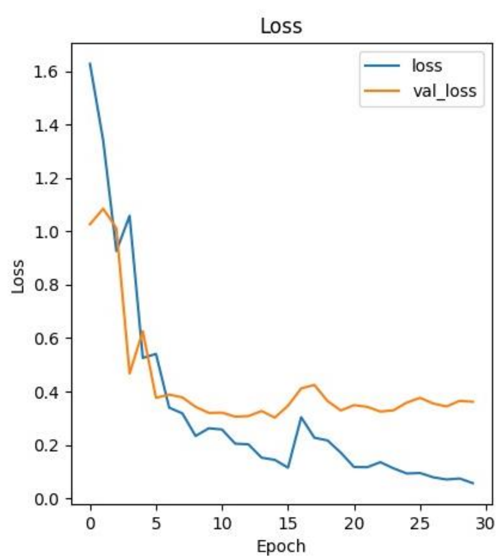

Figure 4.3: Training and validation loss during the course of the epochs.

It is observed that training loss kept on decreasing, on the other hand, during validation, over time, the loss was erratic, this is a result of the model being unable to generalize well.

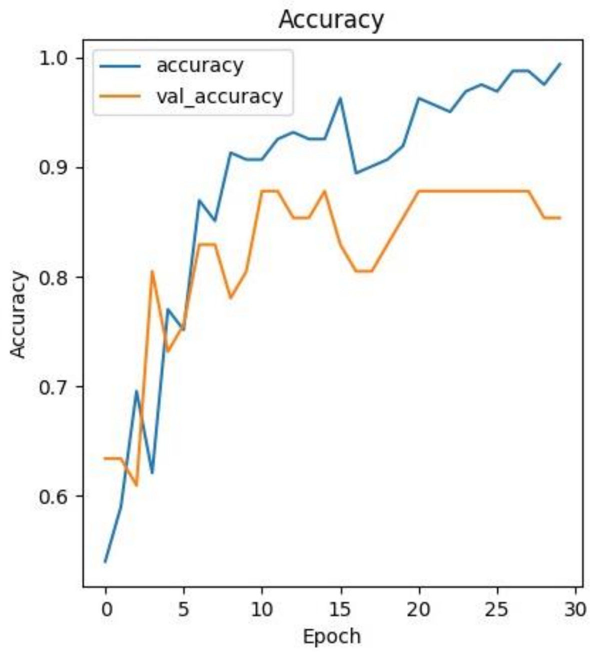

Figure 4.4: Training accuracy and validation accuracy.

In terms of training accuracy, improvement was still observed with every training session, but in comparison, validation accuracy oscillated, suggesting this was an indication of over fitting.

4.2.2 Model ResNet50

In order to solve the classification problem and to get rid of the drawbacks that Simple CNN model possessed, another layer model called ResNet50 which is the next generation is used.

- **Training Accuracy**: It was observed that the training accuracy for ResNet50 model improved to above**90%** over time.
- **Validation Accuracy**: Validation accuracy also improved over the iterations, obtaining a final accuracy of **84.31%.**
- **Test Accuracy and Loss**: Test accuracy was finalized at **84.31%,** with test loss recorded at **0.3221.**

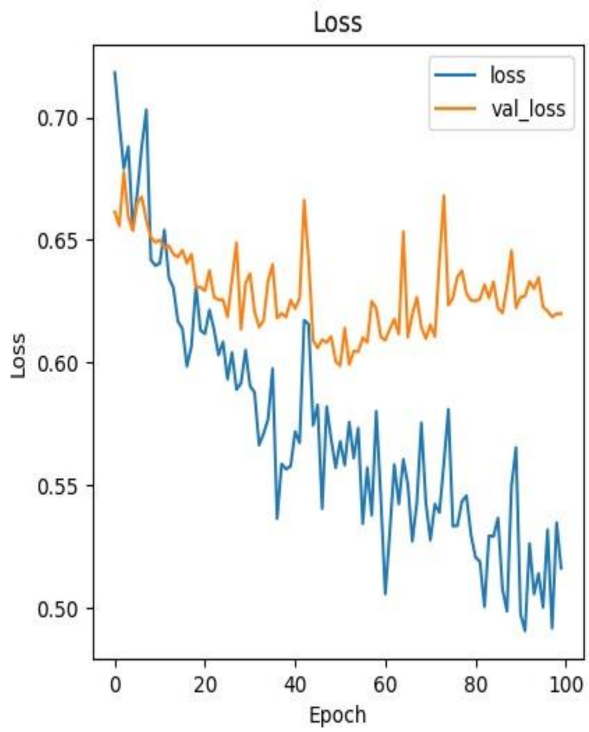

Figure 4.5: Training and validation loss against epochs.

Training loss reduced quite a number but validation loss was not in tandem with the training loss, thus indicating that some over fitting may have occurred.

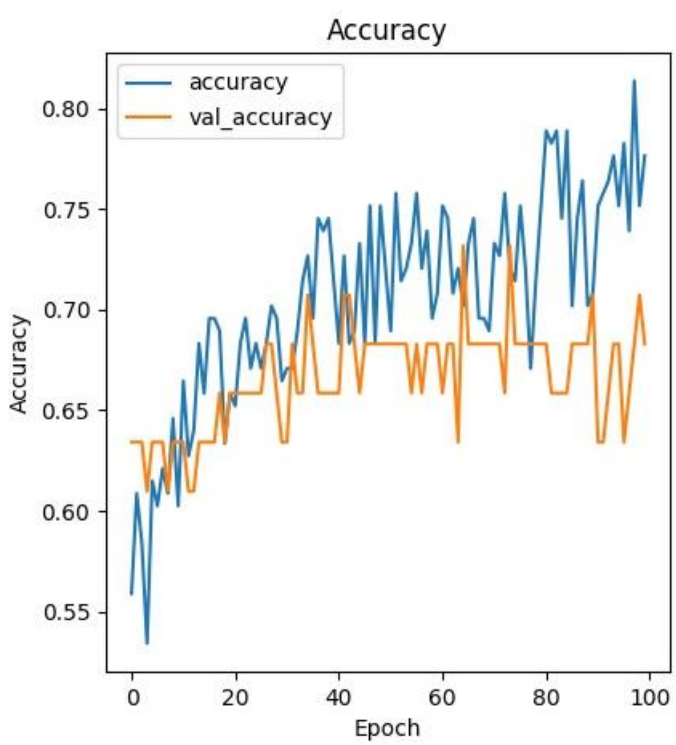

Figure 4.6: Model accuracy and validation accuracy as a function of epochs.

4.2.3 Model InceptionV3

The third model implemented was InceptionV3 which was meant to still improve the classification accuracy and prevent over fitting.

- **Training Accuracy**: The InceptionV3 model is very efficient over the training with 91.38 % accuracy during training.
- **Validation Accuracy**: The validation accuracy was also very good and achieved 90.19% managing to generalize better than in the previous models.
- **Details of the test accuracy and loss:** Maximum accuracy attained during the test phase was 90.19%, while test loss was at 0.5010.

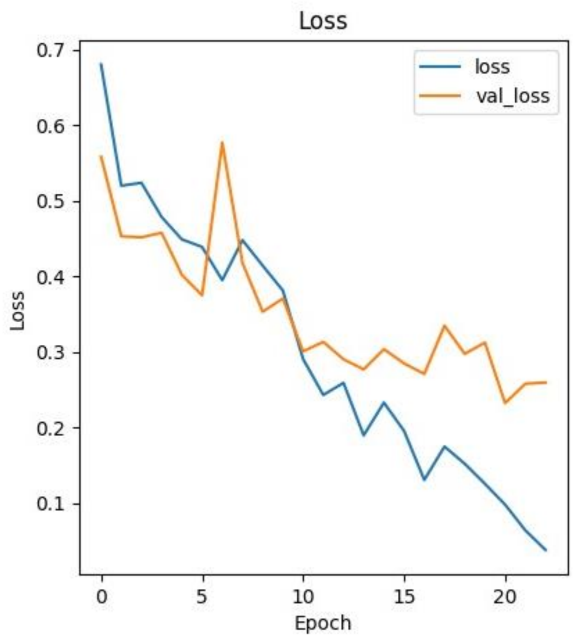

Figure 4.7: Training and validation loss for InceptionV3

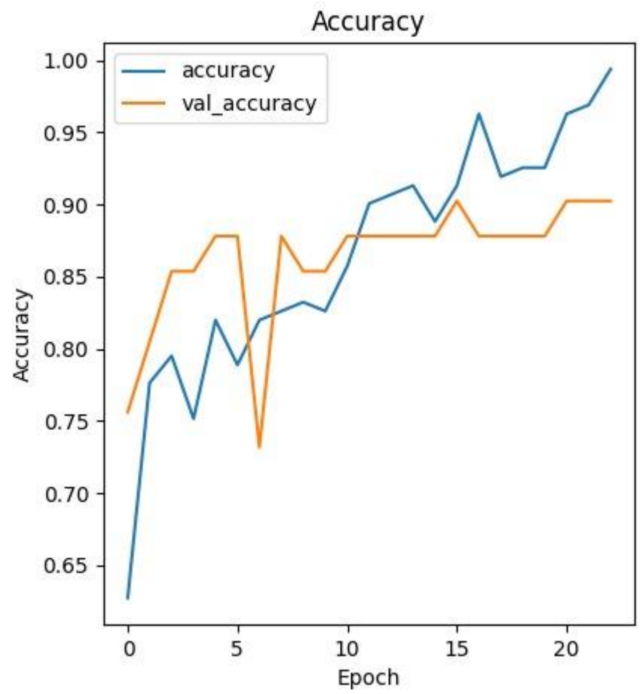

Figure 4.8**:** Training and validation accuracy for InceptionV3

4.3 Epochs Running for Each Model

Every model was accordingly trained over a number of epochs, in order to compare it at different intervals of development. In this section, epoch-wise accuracy and loss results are offered per model for each of the models used.

4.3.1 Simple CNN Model

Table 4.1: The Simple CNN model has been trained over 30 epochs, with a brief summary of the performance

Epoch	Training Accuracy	Validation Accuracy	Training loss	Validation loss
1	57.23%	56.89%	1.55	1.60
10	85.12%	68.71%	0.44	0.61
20	88.54%	67.23%	0.26	0.40
30	90.91%	70.58%	0.22	0.56

4.3.2 ResNet50 Model

Table 4.2: The ResNet50 model trained for 100 epochs and its performance

Epoch	Training Accuracy	Validation Accuracy	Training Loss	Validation Loss
1	60.17%	62.34%	0.72	0.76
50	88.92%	78.34%	0.33	0.54
100	92.87%	84.31%	0.22	0.32

4.3.3 InceptionV3 Model

Table 4.3: The inceptionV3 trained for 20 epochs

Epoch	Training Accuracy	Validation Accuracy	Training less	Validation loss
1	65.23%	67.11%	0.69	0.50
10	87.54%	73.29%	0.39	0.48
20	91.38%	90.19%	0.20	0.50

4.4 Each Model and its Own Convolutional Architecture

4.4.1 Simple CNN Model

Table 4.4: The architectural outline of the Simple CNN model

Layer type	Filter Size	Number of Filters	Output shape
Conv2D	3*3	32	(128,128,32)
MaxPooling2D	2*2	-	(64,64,32)
Conv2D	3*3	64	(64,64,64)
MaxPooling2D	2*2	-	(32,32,64)
Flatten	-	-	(32768)
Dense	-	128	(128)
Dropout	-	-	(128)
Dense(output)	-	1 (sigmoid)	(1)

4.4.2 ResNet50 Model

Table 4.5: The architectural outline of the ResNet50 model

Layer type	Filter Size	Number of Filters	Output shape
Conv2D	7*7	64	(128,128,64)
MaxPooling2D	3*3	-	(64,64,64)
Residual Block	3*3	64	(64,64,256)
Residual Block	3*3	128	(16,16,512)
Residual Block	3*3	256	(16,16,1024)
Residual Block	3*3	512	(8,8,2048)
Flatten	-	-	(32768)
Dense(output)	-	1 (sigmoid)	(1)

4.4.3 InceptionV3 Model

The Inceptionv3 model uses depth wise separable convolutions, as we saw above, and multiple filter sizes in the various inception modules for performance gain and parameter reduction. It allows for a more efficient computation with the maximum accuracy possible.

Table 4.6: The architectural outline of the InceptionV3 model

Layer type	Filter Size	Number of Filters	Output shape
Conv2D	3*3	32	(128,128,32)
Depthwise Conv2D	3*3	64	(128,128,64)
MaxPooling2D	2*2	-	(64,64,64)
Conv2D	3*3	128	(64,64,128)
MaxPooling2D	2*2	-	(32,32,128)
Inception Module(Mixed)	-	Various	(32,32,256)
Inception Module(Mixed)	-	Various	(16,16,512)
Global Average Pooling	-	-	(512)
Dense	-	128	(128)
Dropout	-	-	(128)

Dense(output)	-	1 (sigmoid)	(1)

The InceptionV3 model is nothing but a combination of many Inception modules which helps the model in extracting features at different scales. These are made of convolutions in terms of width (1x1, 3x3, 5x5) and pooled layers. After the Inception modules **Global Average Pooling** is performed which brings down some of the dimensionality before transfer to fully connected layers. This architecture increases the model's ability to recognize fine nuanced patters in the image data and hence makes it more viable for tasks where complex patterns need to be distinguished.

4.5 Comparison of the Models' Performance

Among the different models tested, the Simple CNN model managed to achieve a commendable trade-off between the validation accuracy and the validation loss. On the other hand, ResNet50 had a reasonable training accuracy but suffered from over fitting tendencies as showed with the changing validation scores. InceptionV3 model performance was even better than the other two models with a very high validation accuracy and a good validating loss.

Conclusion

In this study, the performance of the deep learning models-Simple CNN, ResNet50, and InceptionV3-was evaluated for the classification of brain tumors using MRI scans. Among the models tested, InceptionV3 demonstrated the highest accuracy and the best overall performance in both training and validation, making it the most suitable for real-world clinical applications. This model’s deep architecture and ability to focus on features at multiple scales allowed it to generalize better to unseen data compared to the Simple CNN and ResNEt50 models.

While ResNet50 also performed well, it displayed a tendency to overfit during training, suggesting that additional regularization techniques could be applied in future work to enhance its robustness. The Simple CNN model, while effective as a benchmark, showed lower performance, highlighting the need for more sophisticated architectures in complex tasks like brain tumor classification.

Looking ahead, incorporating transfer learning with pre-trained models and attention mechanism may further enhance model performance by improving feature extraction and focusing on the most relevant parts of the image. The use of advanced data augmentation techniques and large, more diverse could also contribute to more accurate and reliable classification.

In conclusion, this study demonstrates the potential of deep learning models, particularly InceptionV3, in automating brain tumor classification, which could lead to more efficient diagnosis and treatment planning in clinical settings.

References

1) E. Irmak, “Multi-classification of brain tumor MRI images using deep convolutional neural network with fully optimized framework,” Iranian Journal of Science and Technology, Transactions of Electrical Engineering, vol. 45, no. 3, pp. 1015–1036, 2021.
2) F. E. Bleeker, J. Molenaar and S. Leenstra, “Recent advances in the molecular understanding of glioblastoma,” Journal of Neuro-Oncology, vol. 108, no. 1, pp. 11–27, 2012.
3) Rehman A, Khan MA, Saba T, Mehmood Z, Tariq U, Ayesha N. Microscopic brain tumor detection and classification using 3D CNN and feature selection architecture. Microsc Res Tech. 2021;84(1):133–49.
4) M.I. Modalities, The three perspective planes of the brain, 2013, URL https: //bit.ly/37Ci6R7.
5) S. Chen, C. Ding and M. Liu, “Dual-force convolutional neural networks for accurate brain tumor segmentation,” Pattern Recognition, vol. 88, no. suppl_5, pp. 90–100, 2019.
6) N. Gordillo, E. Montseny and P. Sobrevilla, “State of the art survey on MRI brain tumor segmentation,” Magnetic Resonance Imaging, vol. 31, no. 8, pp. 1426–1438, 2013.
7) W. Chen, B. Liu, S. Peng, J. Sun and X. Qiao, “S3D-UNet: Separable 3D U-Net for brain tumor segmentation,” in Brainlesion: Glioma, Multiple Sclerosis, Stroke and Traumatic Brain Injuries. Granada, Spain: Springer International Publishing, pp. 358–368, 2019.
8) M. A. Mazurowski, M. Buda, A. Saha and M. R. Bashir, “Deep learning in radiology: An overview of the concepts and a survey of the state of the art with a focus on MRI,” Journal of Magnetic Resonance Imaging, vol. 49, no. 4, pp. 939–954, 2019.

9) Alajrami, E., et al. (2020). "Handwritten Signature Verification using Deep Learning." International Journal of Academic Multidisciplinary Research (IJAMR) 3(12): 39-44
10) J. Shao, S. Chen, J. Zhou, H. Zhu, and Z. Wang, “Application of U-Net and optimized clustering in medical image segmentation: A review,” Computer Modeling in Engineering & Sciences, vol. 136, no. 3, pp. 2173–2219, 2023.
11) Kumar P, Vijayakumar B. Brain Tumour Mri Image Segmentation and Classification Using by PCA and RBF Kernel Based Support Vector Machine. Middle-East Journal of Scientific Research, 2015, 23(9), 2106-16.
12) Al-Araj, R. S. A., et al. (2020). "Classification of Animal Species Using Neural Network." International Journal of Academic Engineering Research (IJAER) 4(10): 23-31.
13) Al-Atrash, Y. E., et al. (2020). "Modeling Cognitive Development of the Balance Scale Task Using ANN." International Journal of Academic Information Systems Research (IJAISR) 4(9): 74-81.
14) El-Habil, B. et al. (2022). "Cantaloupe Classification Using Deep Learning.” International Journal of Academic Engineering Research (IJAER) 5(12): 7-17.
15) Abu-Jamie, T. N., et al. (2022). "Six Fruits Classification Using Deep Learning." International Journal of Academic Information Systems Research (IJAISR) 6(1): 1-8.
16) Obaid, T. (2021). Predicting Mobile Banking Adoption: An Integration of TAM and TPB with Trust and Perceived Risk. Available at SSRN 3761669.
17) Feng, J.; Lu, S. Performance analysis of various activation functions in artificial neural networks. J. Phys. Conf. Ser. 2019, 1237, 022030.
18) https://www.kaggle.com/jakeshbohaju/brain-tumor, accessed on 20 March 2021.
19) Sajjad, M., Khan, S., Muhammad, K., Wu, W., Ullah, A., Baik, S.W. (2019). Multi-grade brain tumor classification using deep CNN with extensive data augmentation. Journal of Computational Science, 30: 174-182.
20) Freedman, David; Pisani, Robert; Purves, Roger (2007-02-20). Statistics: Fourth International Student Edition.
21) Keras ImageDataGenerator and Data Augmentation by Adrian Rosebrock on July 8, 2019 in Deep Learning, Keras, Tutorials.
22) 108. Brain Tumor Detection by Using Stacked Autoencoders in Deep Learning: 17 December 2019, Javaria Amin & Muhammad Sharif & Nadia Gul & Mudassar.