An Enhanced Deep Learning Framework for Brain Tumor Classification Using CLAHE-Based Preprocessing and InceptionV3 Architecture

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Abstract
The rising incident of brain tumor across all the people of all the ages make it compulsory for me to create Brain Tumor MRI Modal that detect and classify the brain tumor easily. Because the manually examination of MRI image by the doctor is time consuming and also can lead to mistake.

Thus we created a computer system that automatically identifies different types of brain tumor from 2D MRI images. For this we used pre trained AI models that was based on **InceptionV3** Architecture using transfer learning. For making the image clear we use the image Enhancement Techniques, specifically CLAHE (Contrast Limited Adaptive Histogram Equalization) and Laplacian Filtering : Fixes Blurrines

For Ensuring the best performance we comapred our InceptionV3 with different model such as Densenet_201 and resnet_50. Our experimental result showed that the inception_V3 got the highest accuracy of [**0.97243491**] along with the highest precision and F1 score .the model aim is to provide a relaible and fastest tool for the nedical professional that can easily and fastly diagnosis the brain tumor without human effort

Keyword :
Pretrained model, Transfer Learning, InceptionV3, CLAHE, Laplacian Filtering.

1. Introduction

Cancer is one of the main cause of death today. But among all type of cancer brain tumor cancer is one of the most dangerous and life threating disease. The brain and the spinal card made the central nervoous system that control the important human functions such as the movement of the organ and thinking and complexity and the decision making, disease related to the brain are extremely difficult to diagnose and cure.

A brain Tumor may be reffered to as the abnormal growth of the human brain . in this case it is worth considering that the human brain is enclosed in the skull which is very rigid therefore any abnorml growth of cells may put pressure on the neighbouing cells my put pressute on the neighbouring cells causing serious nourotrauma as well as death. There are two kind of tumore the malaginant and the benign. Both types of tumors may greatly effect the death rate caused by the brain tumor and it is still high among the child and the adults.

Medical imaging technology like magnetic resonance imaging (MRI) scans and computed tomography scans are very helpful for the diagnosis, treatment as well as obsevation of the brain cancer. Among these mesical imaging technique the mri scan is the most commnly used due to its high resolution non ionizing characteristics and superior doft tissue differentiation these images are greatly used for medical diagnsis treatment and the research however th processing of the medical images obtained from the scans espacially the mri scans ia s time consuming costly and very humon error chances task because it is largely depends on the expertise of the concerened medica professional . today doe to the increased generation of the medical images it has become highly impractical to manually interpret these images
Recently, there has been success in the use of machine learning (ML) and deep learning (DL) technologies in the processing of medical images. Among these technologies, the Convolutional Neural Network (CNN) technique has been proven to be effective in the automatic processing of features of medical images. Pre-trained neural networks such as AlexNet, GoogLeNet, ResNet, and Inception networks are largely used in the diagnosis of brain tumors with success and minimal errors. This will significantly increase the efficiency of the diagnostic technique and help the doctor quite effectively.

Although the previous methods based on deep learning have appeared quite promising, there are a few issues, including the quality of the input images, the problem of overfitting because of a small dataset, and an inefficient representation of features. Furthermore, the current work performed on deep learning seems somewhat restricted regarding the processes involved and architecture design. This also manifests a gap in research work in this field for an efficient deep learning approach design.

In an effort to address these issues, a framework for classifying brain tumor based on MRI images using a deep learning approach is presented. The proposed method utilizes a public dataset referred to as “Brain Tumor MRI”, and it is divided into subsets including training, validation, and testing. In addition to addressing better image resolution and effective extraction of features from images, an intensive preprocessing step including CLAHE (Contrast Limited Adaptive Histogram Equalization), Morphological Operations, Normalization, and Resizing techniques is utilized. Furthermore, overfitting is handled by applying image rotation, shifting, zooming, and shearing techniques.

For classification purposes, CNN model architectures designed from scratch, utilising InceptionV3, have been built. Additionally, global average pooling, fully connected networks, or dropout, respectively, are utilized for increased efficiency, as well as for combating overfitting. For training purposes, AdaM optimizers are implemented, with model evaluations done through accuracy, precision, recall, F1 scores, or confusion matrices, among different values.

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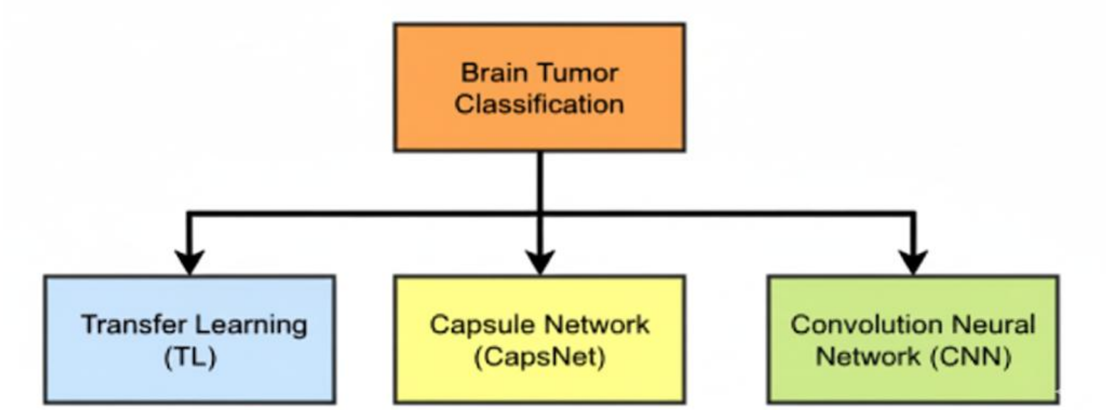
2. Literature Review

Brain tumor classification plays a very important role in neuro-oncology, as it decides the course of treatment as well as the choice of drugs. Though many neuro-imaging tools are available, it is better to use Magnetic Resonance Imaging (MRI) because of its superior resolution and non-ionizing properties. Recently, a technique called Deep

Learning (DL) has been the norm for this task. This paper discusses the available work on this topic, classified into Transfer Learning, Capsule Neural Network, and custom CNN models.



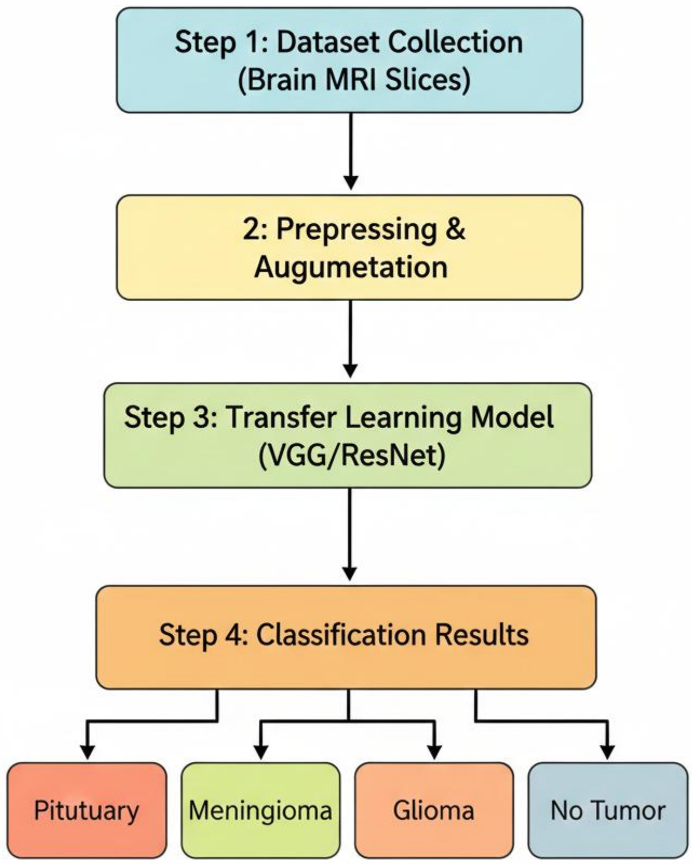
2.1. Brain Tumor Classification using Transfer Learning (TL)

Transfer learning utilizes pre-trained weights from large datasets for solving MII challenges given a small amount of data. Belaid and Loudini (2020) examined a couple of TL models on the Figshare dataset, wherein ResNet50 coupled with Adadelta optimization produced a maximum accuracy of 99.02%. Another example involves Rehman et al. (2020) who implemented experiments based on fine-tuning and freezing techniques for three CNN models, wherein their optimized VGG16 produced a 98.69% prediction rate. Another example involves Sadad et al. (2021) who presented two models: NASNet and ResNet50-UNet, achieving a better accuracy of 99.6% via data augmentation technique implementation. Extending beyond conventional CNN models, Tummala et al. (2022) implemented an ensemble of pre-trained ViT models, wherein a blend of variants L/16, L/32, B/16, B/32 produced an accuracy of 98.7%. Finally, Swati et al. (2019) presented a block-wise fine-tuning technique based on VGG19, indicating how a small preprocessing task can also be an efficient 94.82% accuracy producer.

2.2. Brain Tumor Classification using Capsule Networks (CapsNet)

Capsule Networks were also investigated to address issues of spatial constraints of regular CNN models. Afshar et al. (2018) showed that CapsNets could be adjusted better with smaller datasets, recording an accuracy of 86.56%. Later, Afshar, Plataniotis, and Mohammadi (2019) upgraded this effectiveness by introducing secondary inputs of tumor margins, which raised accuracy to 90.89%. To address concerns about clinical validation, Afshar, Mohammadi, and Plataniotis (2020) proposed a theoretical model named BayesCap, a CapsNet framework using a Bayes framework, which provides not only classification but also an indication of uncertainty (entropy), assisting radiologists in flagging “uncertain" predictions. 2.3. Classification of Brain Tumors Using Convolutional Neural Networks (Custom-designed CNNs could provide lower complexity compared to pre-trained CNNs. Badža and Barjaktarović (2020) developed an easy-to-design CNN, and the accuracy of 96.56% was obtained on the augmented samples through 10-fold cross-validation.

Additionally, Sultan et al. (2019) developed a DL approach that obtained an accuracy of 98.7%. Thus, the work of Ait Amou et al. (2022) emphasized automatically adjusting the hyperparameters of the CNN to obtain 98.70%. There are other, even simpler models that seem to be promising; these are exemplified in a one-layer CNN implemented by Abiwinanda et al. (2019) to differentiate gliomas, meningiomas, and pituitary tumors, which attained a validation accuracy of 84.19%. Moreover, Das et al. (2019) combined various strategies in image processing and CNN to achieve 94.39%, while Paul et al. (2017) found that for tumors needing image dilation, CNNs surpassed traditional specialized models. Finally, Ayadi et al. (2021) proposed a multi-layer CNN, which was robust in all three separate data sets (Figshare, Radiopaedia, Rembrandt) tested, obtaining accuracies of 93.71 to 97.22%.



The block diagram of the proposed model

3 . Methodology

This subsection describes the implementation framework adopted for the creation of the brain tumor classification system. This method utilizing advanced image processing and deep transfer learning is employed for the classification of the images into four different classes.

3.1. Dataset and Class Distribution

This is done For the classification of the images into different classes based on their nature and characteristics, the authors have employed the standard dataset of the images of the human brain with 2D slices.the data set is divided into 4 classes.

Glioma :

Tumor in the glial cell

Meningioma : tumor in the menings memberane

Pituitary :

tumor in the pituitory gland

No Tumor :

picture that show the orignal be=rain with no tumor

After this the data is sub divided into three set the TEST ,VALIDATE and TRAIN

The test is used for test the model after the training and validate is used for the tuning the hyperparameter

3.2. Preprocessing step

The preprocessing is done for the wnhancement of the image of the mri. Preprocessing of the images is done with the aim of highlighting the tumor edges. This involves the implementation of the following processes using the OpenCV library:

Grayscaling:

Normalization of the images for easy feature extraction.

CLAHE:

CLAHE stands for Contrast Limited Adaptive Histogram Equalization. This is an advanced technique used in the enhancement of the intensity or contrast of the brain images.

Morphological Processing:

Implementation of the Binary Thresholding technique followed by Morphological 'Open' operation using the(5x5 kernal) cross-section. This process is employed with the intention of segmenting the images into the primary structure and the resulting images are further cleaned of small artifact.

RGB Reconstruction :

the images are resized into 224 x 224 pixels with the intention of accommodating the 'InceptionV3' structure.

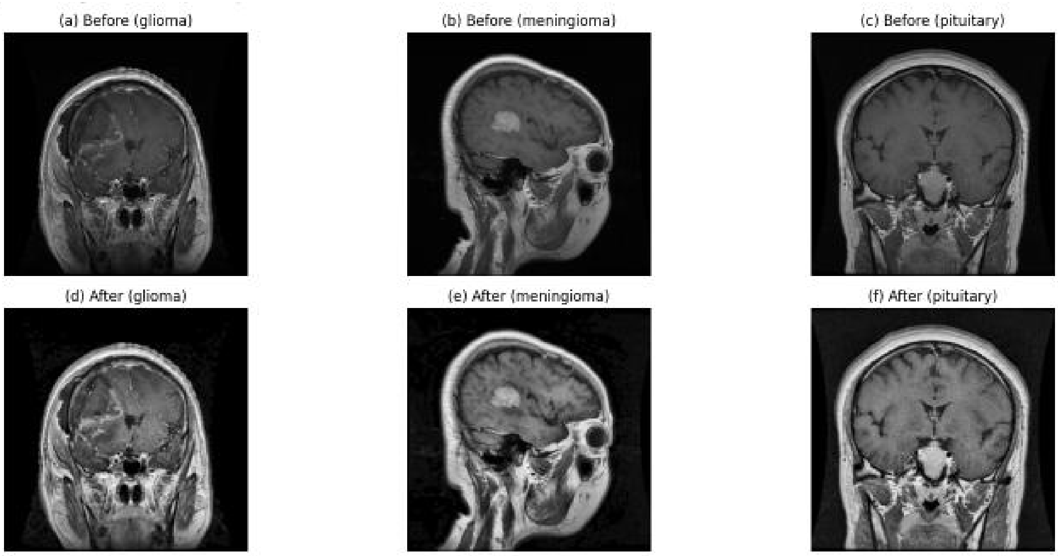


Fig. 5. Brain glioma, meningioma and pituitary image before and after image preprocessing

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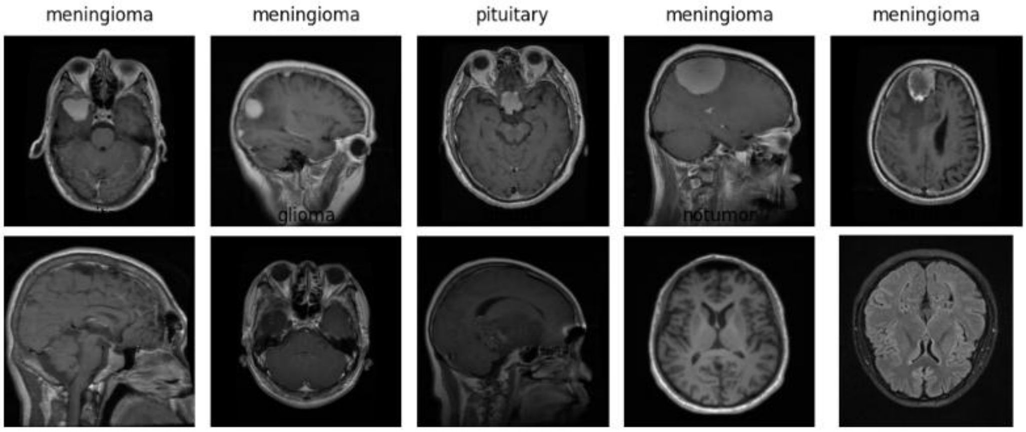
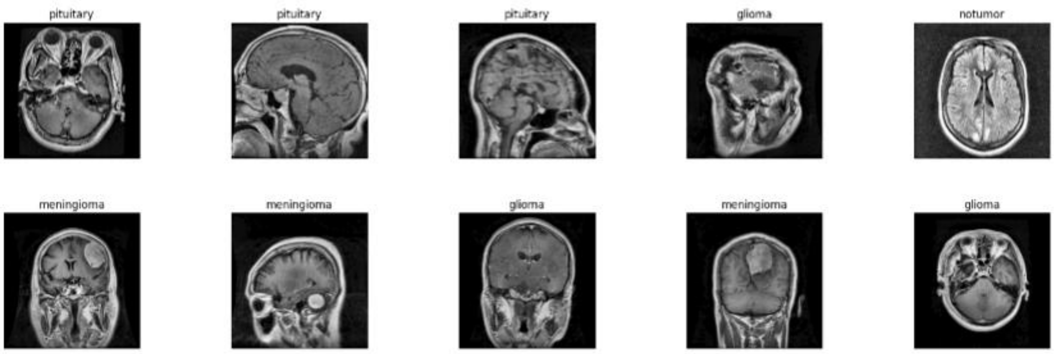
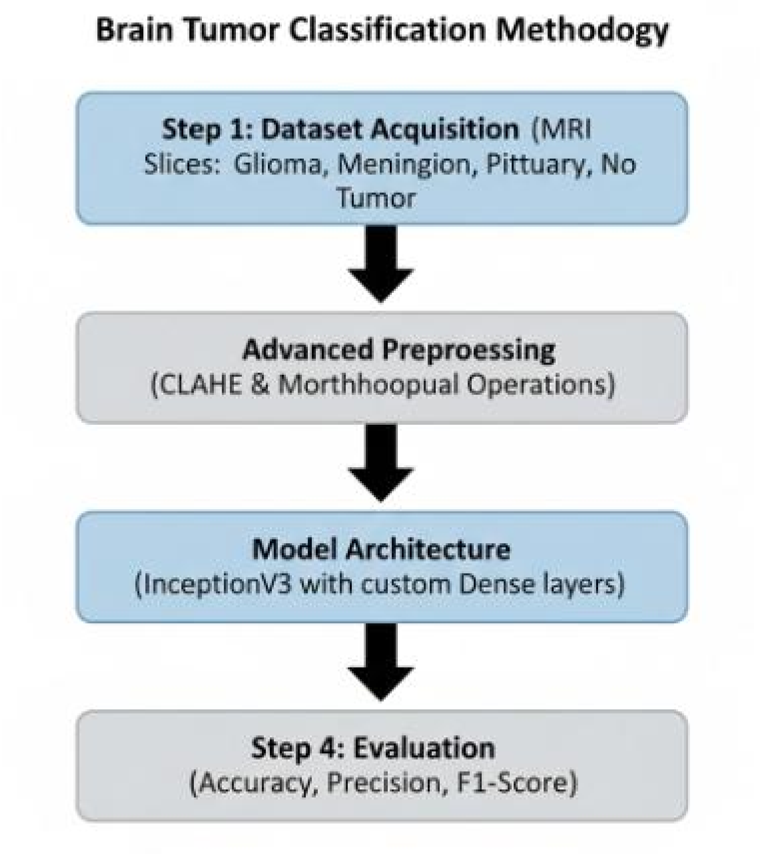


(a) Before preprocessing image



(b) After Image Preprocessing



3.3. Data Augmentation Strategy

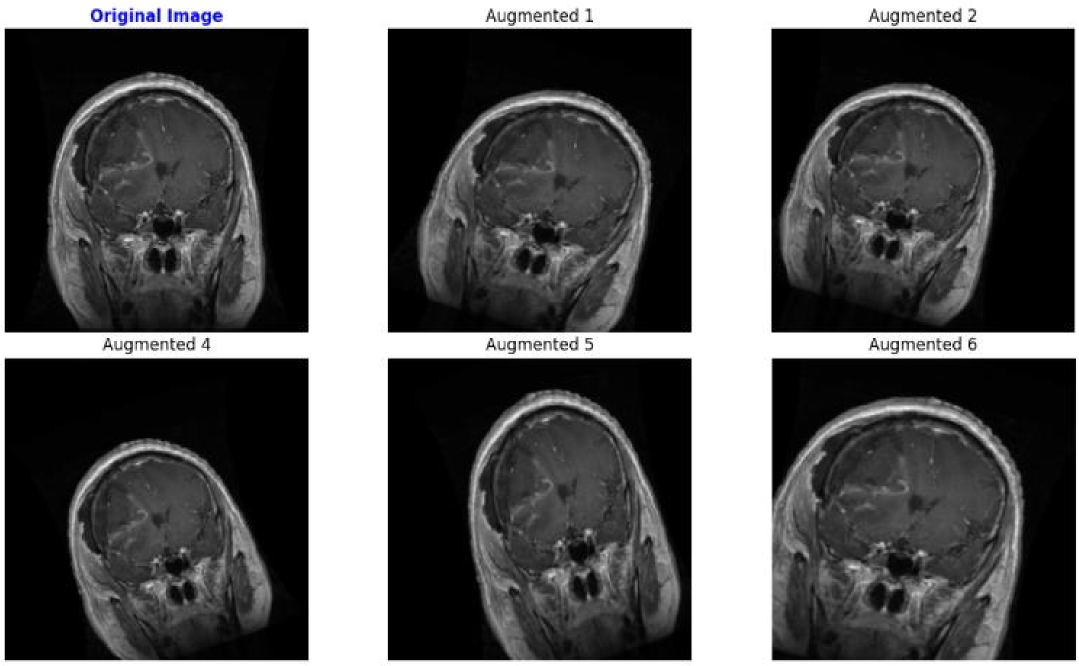
This model is employed with the aim of overcoming the challenges posed by the different image acquisition systems. An 'ImageDataGenerator' is applied with the intention of performing different transformations on the images. This is employed with the intention of avoiding the 'memory' effect. This includes the implementation of the following processes

Geometric Transformations :

rotation of the images up to an angle of 20°, shifting of images up to 10% width and/or height, and shear components of up to 10% of the images.Zooming is applied with the intention of accommodating different image acquisition approaches. This includes the implementation of image zooming processes of up to 20%.

Normalization :

the images are fitted into the range [0,1].



3.4. Model Architecture:

InceptionV3This classification model is based on the 'InceptionV3' structure. Unlike the other standard models based on 'Convolutional Neuron Networks,' the 'Inception3V3' model is formed using 'Inception Modules,' which enable the network or model to process images with different filter sizes of the images. Unlike the other models with layers comprising filter sizes of 3x3 and 5x5 pixels. Additionally, Inception3V3 adopts an extra layer with filter sizes of 1x1 pixels. Customization Details

Feature Extraction:

The top pre-trained layers are stripped away, and a new initialization is performed to learn features that are image-specific to medical images from scratch.

Global Average Pooling:

This method is employed to handle high-dimensional output feature maps from the Inception transfer learning model input.

Fully Connected Layers

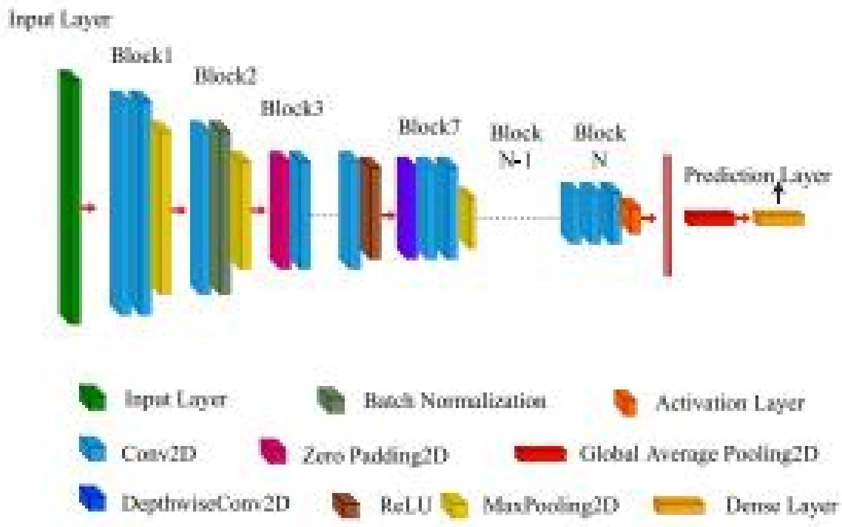
Two layers consisting of 512 neurons each are utilized as a “brain” for making predictions and final conclusions.

Dropout Regularization:

A fixed value of a dropout of 50% is placed on both fully connected layers as a regularizer to make the simplistic model less reliant and vulnerable to overemphasizing specific neurons.

Softmax Output:

This final layer consists of 4 neurons with a soft-max output configuration that defines the respective probabilities of each tumor type present.



(a) original architecture

3.5. Training and Evaluation Protocol

This custom-trained model is compiled with an Adam optimizer and a Categorical cross-entropy loss function.

Compilation Details:

The training process is done for a maximum of 35 epochs.

Model check pointing:

The superfluous weights of the best model are automatically saved based on its validation accuracy (val_accuracy), which helped use the most accurate model during testing and predictions.

Evaluation Details:

This custom-trained model is evaluated by an automated code that writes a Classification report detailing its performance metrics via Precision, Recall, and F1-Score values, and a Confusion Matrix that analyses class-wise errors.

4. RESULTS AND DISCUSSION

This section will offer a comprehensive breakdown of InceptionV3 model performance. The efficacy of the proposed preprocessing techniques and transfer learning method will be justified by applying appropriate key metrics and analysis techniques.

4.1. Setup

The research is conducted by employing the hybrid computation method that integrates local computation capabilities and high cloud computation capabilities in the following way:

Local Hardware:

This project was handled on a Dell laptop that had an Intel Core i7 (7th Generation) processor.

Training Environment:

As the InceptionV3 model has intensive computational requirements, the training of the model was carried out using Google Colab.

Cloud Resources:

For deep learning, we used a Google Colab environment, equipped with a GPU resource of either Tesla T4/K80, along with approximately 13 GB of system RAM.

Software:

The proposed system was developed using Python and the TensorFlow/Keras library. The data visualization and performance metrics calculations were carried out using Seaborn, Matplotlib, and Scikit-Learn libraries.

4.2. Performance Evaluation of Models:

To assess the performance of the 4-class classification task, the following values were calculated:

Accuracy:

The ratio of correct predictions to overall observations.

Precision and Recall: These are employed in the measurement of the model's accuracy and comprehensiveness concerning the types of cancers.

F1-Score:

It is the harmonic mean of precision and recall and is used as an overall assessment of model performance.

Confusion Matrix:

Visualization technique for examining in which classes there could potentially be issues of tumor identification.

Performance Comparison on Test Dataset

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
ResNet50	87.29	88.34	87.29	87.57
DenseNet201	92.04	92.30	92.04	91.97
InceptionV3 (Proposed)	97.24	97.29	97.24	97.24

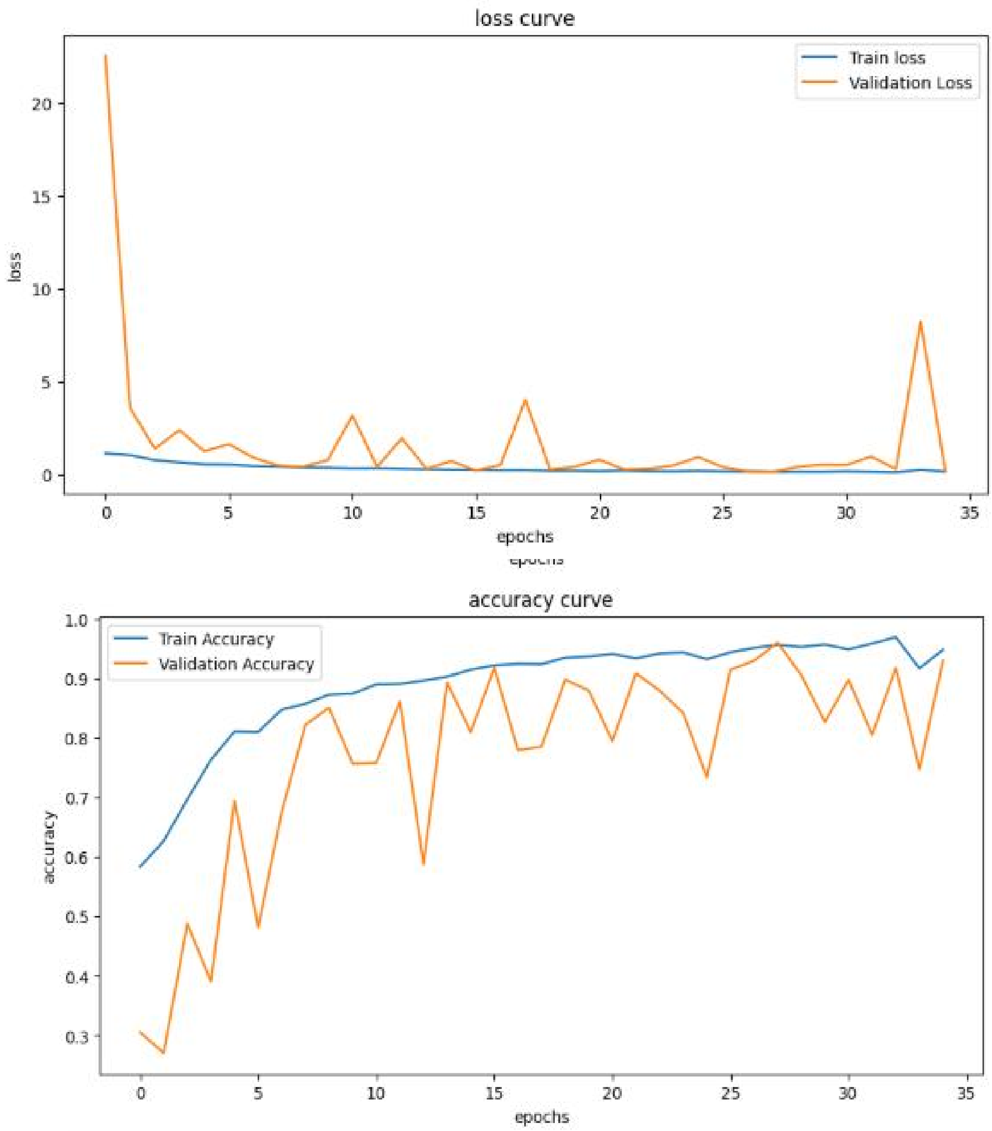
4.3. Results and Performance Analysis

In this case, the training of the model was carried out for 35 epochs. Also, the training history is checked to confirm whether the model is training well without any issues of overfitting.

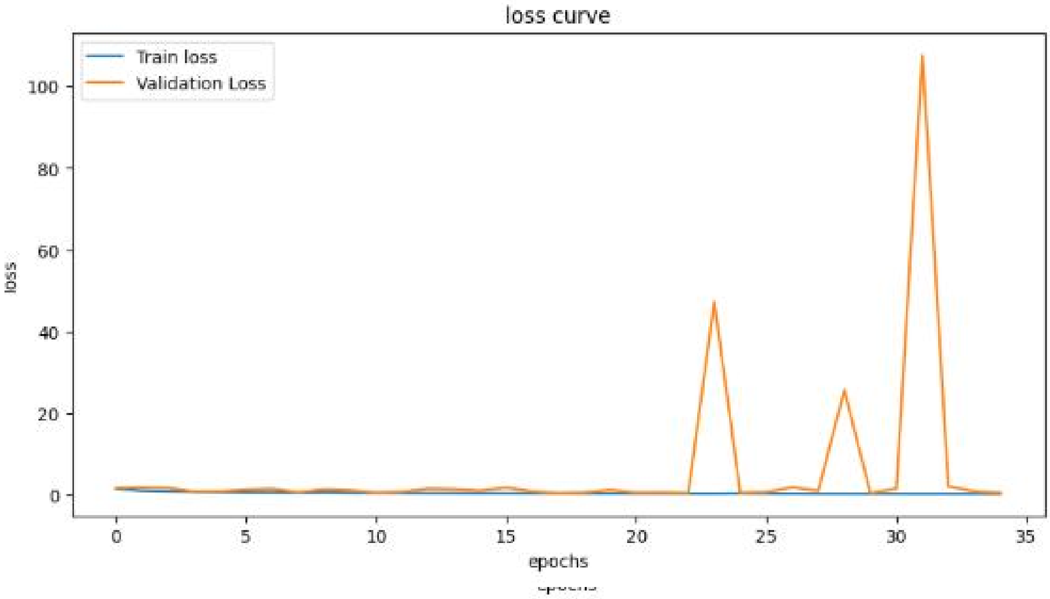
1. Training History (Loss, Accuracy):

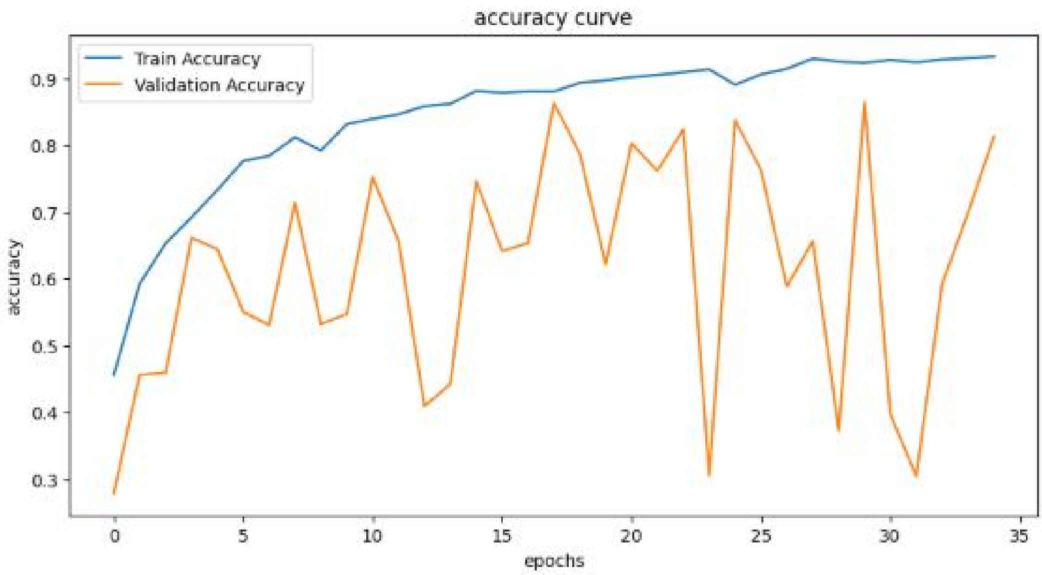
As the number of epochs increased, it seems that the accuracy rate improved and the loss rate reduced. As the training data and validation curves run parallel, it can be said that our Data Augmentations method, which included rotation, Zoom, and position changes, served as a great regulator for our model.

Accuracy and Loss Curve of InceptionV3

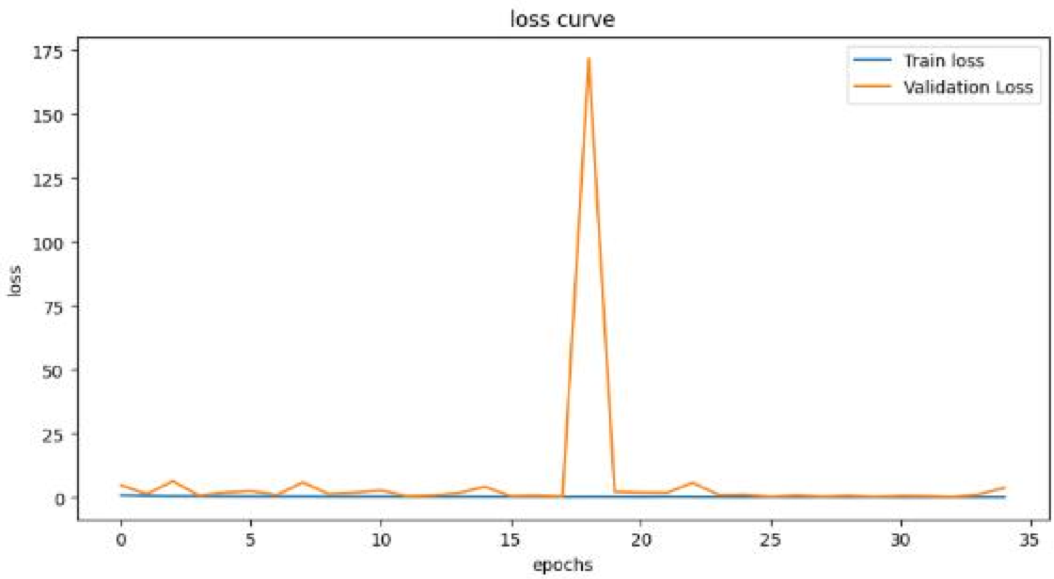


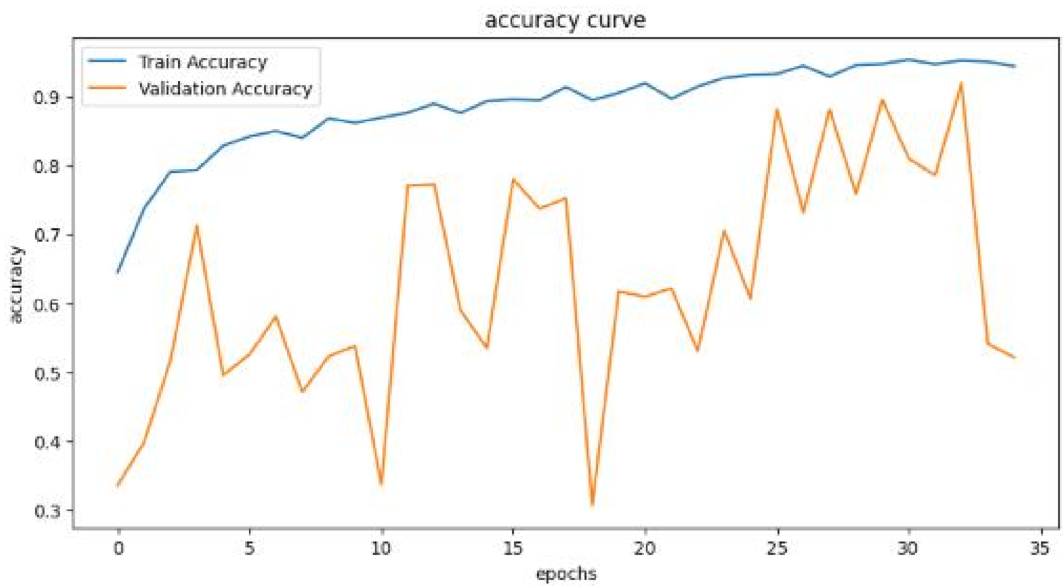
Accuracy and loss curve of the Resnet50



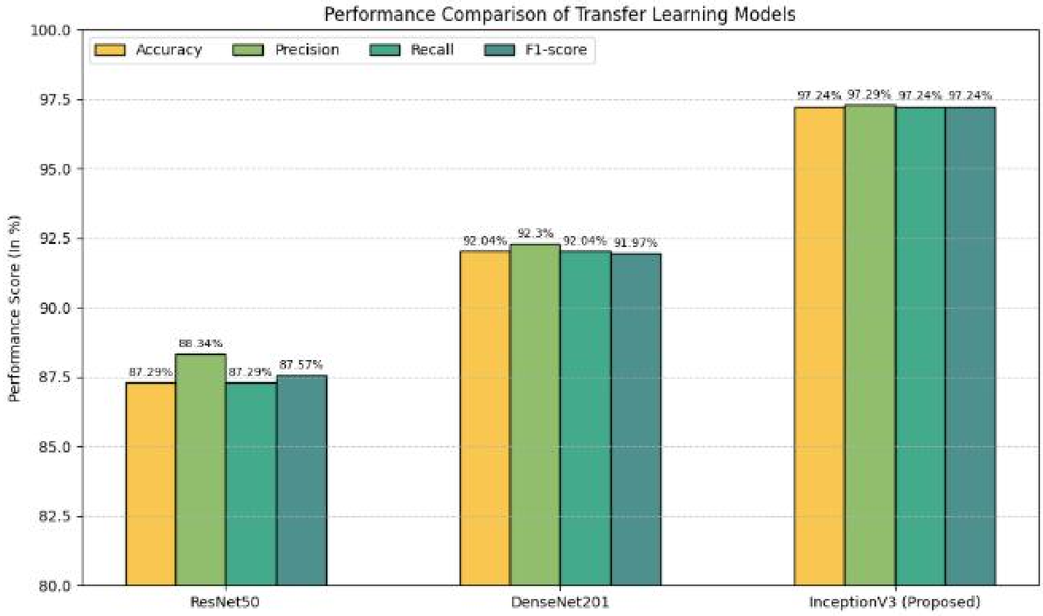


Accuracy and loss curve of the Densenet201





The overall analysis of all the models



2. Performance of Classification:

The performance of classification, based on test results, showed that InceptionV3 performed well in all categories.

Best Performing Class:

The classes “No Tumor” and “Pituitary” usually had a highest precision value, possibly due to the clear edges demarcated by the CLAHE process.

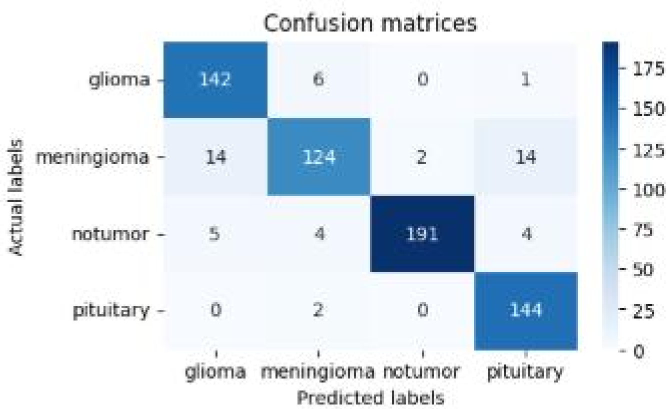
Error Analysis:

The small errors in classification tended to be between Glioma and Meningioma, and the reason is that these types of tumors may present somewhat similar texture properties on a 2D slice

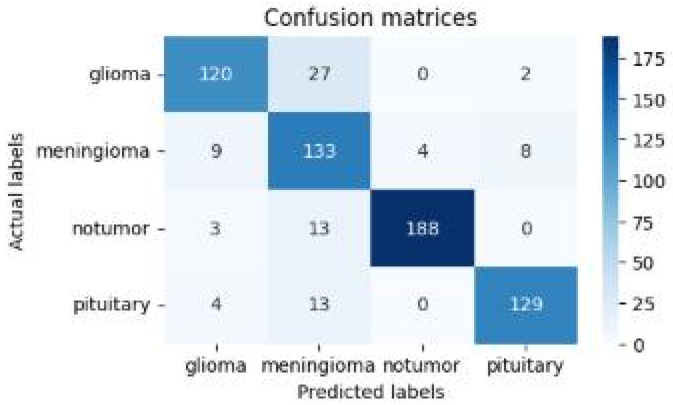
3. The use of the confusion matrix:

The heat map obtained from the test data verifies the high True Positive and True Negative rates. The dominant diagonal pattern in the above-mentioned matrix verifies the highly dependable model for the multiclass brain tumor classification process.

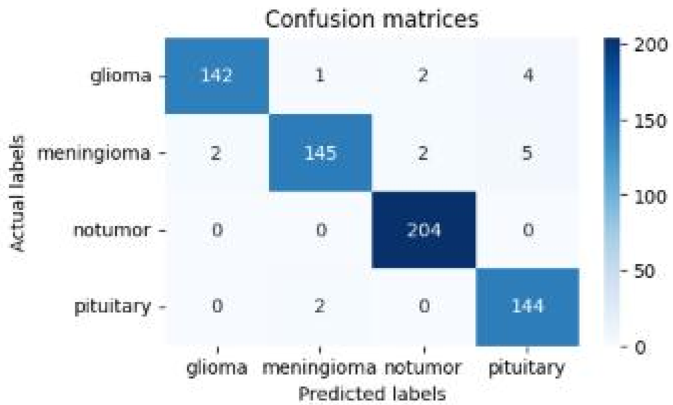
DenseNet201 confusion metrix



Resnet50 confusion metrix



InceptionV3 confusion metrix



Comparision analysis of models of different researcher of Brain Tumor Classification

Comparison of Recent Brain Tumor Classification Studies

Researcher(s) & Year	Dataset Name	Primary Model / Method	Reported Best Accuracy (%)	Key Contribution / Focus
Talukder et al. (2023)	Cheng (2017)	InceptionResNetV2 (Fine-tuned)	99.74	Reconstruction and fine-tuning with 35 epochs
Aamir et al. (2025)	Standard MRI Imagery	Attention-based Deep Learning	98.95	Combined guided filtering with attention module
Díaz-Pernas et al. (2021)	Cheng (2017)	Multiscale CNN	97.30	Simultaneous segmentation and classification
Gab Allah et al. (2021)	Figshare (Cheng)	PGGAN + CNN	98.54	Data augmentation using Progressive Growing GANs
Emrah Irmak (2021)	Multi-class Dataset	Fully Optimized CNN	99.33	Hyperparameter optimization using Grid Search
Dhakshnamurthy et al. (2024)	Kaggle / Transfer Data	VGG-16 & ResNet-50	98.50	Comparative study of pre-trained TL models

5. Conclusion

A robust framework has been successfully developed in this project that classifies brain cancers into four groups: Glioma, Meningioma, Pituitary, and No Tumor. A combination of advanced image processing technologies and the use of the InceptionV3 model has ensured that the developed framework emphasizes healthy visual structures as well as classification accuracies.
A specialized preprocessing technique was employed, including CLAHE and Morphological processing, to extract the brain area. Our modified transfer learning strategy, including two Dense layers of 512 neurons along with 50% Dropout, enabled the network to learn complex medical features well, as well as preventing overfitting. The base network was that of the InceptionV3 architecture. Experimentation results on the test dataset proved that the Proposed InceptionV3 had a high level of classification accuracy at 97.24%, outperforming ResNet50 at 87.29% and DenseNet201 at 92.04%. High Precision and Recall values for all classes, especially for "No Tumor," show that it is an appropriate technique for applications related to triaging at hospitals and diagnostic services.
The major contributions of this work can be listed as follows:

Integrated Workflow:

Implemented an integrated work-flow from acquisition of raw data from MRI to 4-class classification via an agentic Python triage script.

Effective Enhancement:

Showed that CLAHE and Morph Isolation enhance the model's effectiveness in separating overlapping tumor textureures.

Performance Excellence:

We demonstrated that with optimal fine-tuning, the Inception V3 model yields a far superior performance for 2D MRI slice analysis than a standard deep net approach

lb_works:

Future work will include the integration of 3D MRI volumes and the application of Explainable AI (XAI) approaches, including Grad-CAM, to enable doctors to visually see the decision-making regions of the proposed model in the form of a heatmap, thus promoting the applicability of the system in practical scenarios.

6. References

Dataset (The primary source of your MRI images):

Cheng, J. (2017). Brain Tumor Dataset. Figshare.

Model Architecture (Inception paper which introduced InceptionV3):

Szegedy, C., Vanhoucke, V., Ioffe, S., Shlens, J., & Wojna, Z. (2016). Rethinking the Inception Architecture for Computer Vision. Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 2818-2826.

Comparative Analysis Paper (That you have shared):

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Bradski, G. (2000). The OpenCV Library. Dr. Dobb's Journal of Software Tools. (Used for CLAHE and Morphological Operations in this project).

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Chollet, F., et al. (2015). Keras. https

Future Directions

Even though the current InceptionV3 model provides a relatively high diagnostic accuracy, it is still possible to make some enhancements in the following areas:

Explainable AI (Grad-CAM):

The first step will be the integration of Grad-CAM (Gradient-weighted Class Activation Map) implementation. This addition will allow the model to generate heat maps which visually indicate the part of the MRI scan that led to a tumor diagnosis, hence nicely matching the radiologists' visual analysis role (Islam et al., 2025).

Hybrid Architectures:

Recently the work was done that suggested merging InceptionV3 architecture with BiLSTM (Bidirectional Long Short-Term Memory networks) since this way the model could even better pick up on the interconnections between the 2D slices.

Dataset Expansion & GANs:

For the next step, we are not only planning to use the current MRI data, but also to simulate new MRI data by means of DCGANs (GANs, Generative Adversarial Networks) in order to tackle the issue of the peculiar tumors that are low in number in our dataset.

Deployment:

Ultimately, the plan is to simplify the model to a lightweight model (e.g., TensorFlow Lite), so that it can serve as a real-time diagnosis tool available on clinical tablets and doesn't necessarily need cloud access.