



BRAIN TUMOR CLASSIFICATION USING INCEPTION RESNET V2 CONVOLUTIONAL NEURAL NETWORKS

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Abstract: Brain tumors are one of the most lethal diseases due to the uncontrolled development of abnormal cells within the brain. Magnetic Resonance Imaging (MRI) is a medical device that provides digital images and helps radiologists and neurologists identify the kind and presence of brain tumors. To classify MRI images of brain tumors, an objective, automatic, and more dependable method is required because the human and subjective classification process is laborious and prone to errors. To get beyond the limitations of traditional testing methods, artificial intelligence is thought to be a suitable tool for identifying the type of brain tumor from magnetic resonance imaging. Convolutional neural networks are one tool for enhanced automatic classification (CNN). This paper shows how the Inception ResNet v2 architecture in CNN is used to categorize MRI brain cancers into four groups via transfer learning: glioma tumors, meningioma tumors, pituitary tumors, and no tumors.

KEYWORDS: Brain Tumor, Transfer learning, Data Augmentation, Pituitary.

1. INTRODUCTION

A Brain Tumour is an undesirable development of cells within the brain. It can lead to hazardous diseases. It can happen at various parts of the cranial nerves or the surrounding brain membranes. These tumors specifically begin at the skull. In the medical domain, image classification and computer vision techniques result in the progress of treatment. These procedures will help in the detection of pruning disorders like cancer. Many lives are in danger due to delays in the detection of health issues. Automated techniques provide better efficiency compared to traditional manual ones. It performs the early detection of diseases with precise accuracy. Many software platforms have built-in algorithms for tumor detection and classification. It helps in quick decision-making in critical conditions. These techniques provide tumor segmentation, which enables images for the identification of boundaries of the tumor. It is a crucial step for treatment planning and recognizing the development stage of the disease. The large datasets undergo a training process to acquire better performance and reliability. Computer-aided diagnosis (CAD) or brain tumor classification (BTC) overcome visual analysis. These methods play an efficient role in the detection of brain tumor types. It can reduce invasive surgery or biopsy. There are two methods for the classification of brain tumors [1-3].

Traditional brain tumor classification (BTC) methods [2] involve preprocessing steps for tumor detection, categorization, and segmentation. The workflow consists of numerous functions such as Image acquisition, Preprocessing, Region of interest, segmentation, Feature extraction, Dimensionality reduction, classification, and Performance evaluation. Deep learning-based methods require fewer preprocessing steps as they learn the relevant features from raw data. It depends on training data for learning illustration and detecting the process. Many deep learning methods use convolutional neural networks (CNNs). CNNs are essential to classify brain tumors as they acquire hierarchical features from input data. It contains Kernels at

each input image. Kernels called filter layers extract features from images. Output layers can be presented as activation maps.

2. LITERATURE SURVEY

2.1 Bayesian Deep Learning (BDL)

The technique of Bayesian Deep Learning (BDL) has risen to prominence as an effective method for classifying brain tumors, capable of dealing with uncertainties and incorporating preexisting knowledge. Early research projects utilized these BDL methods for jobs such as the segmentation of brain tumors from MRI scans. Specifically, a 2018 study by Khan et al. [2] employed Bayesian Convolutional Neural Networks (CNNs) to account for uncertainties in the tumor boundaries and dimensions during the segmentation process. A research study by Choi et al. in 2020 [3] found that tumor segmentation accuracy could be substantially boosted by incorporating Bayesian regularization in Graph-based Convolutional Neural Networks (GCNNs). This creative strategy successfully mitigates uncertainties within the model. This groundbreaking method effectively tackles the uncertainties present in the model. In the same vein, Zhu, and the team in 2019 zeroed in on brain tumor classification using multimodal MRI data, harnessing the power of Bayesian neural networks to deal with uncertainties and boost the model's adaptability to diverse imaging data. Havaei and company (2017) [5] emphasized the critical need to measure uncertainty in Convolutional Neural Networks (CNNs) for successful brain tumor segmentation. To accomplish this, they utilized a Bayesian Deep Learning (BDL) technique to estimate and illustrate the unpredictability of their predictions. The writers emphasized the value this method could bring in supporting medical professionals to better understand the model's assurance levels and facilitate more educated decisions regarding patient care.

2.2 Support Vector Machines (SVM)

Over the past few years, brain tumor detection and categorization underwent a flurry of methodological advancements. This led to the emergence of Support Vector Machines (SVM), gaining prominence as a key stage following Bayesian Deep Learning (BDL) [2] in this research area. At first, researchers delved into different approaches exploiting clinical databases, specifically MRI images of brain tumors. The research performed by Denys et al [1] depicts a functional study of MRI images of brains of human and non-human primates. The trailblazing work of Selvaraj et al. (2007) [6] marked the introduction of a binary classifier employing first and second-order statistics, integrated with a Least Square SVM classifier. This breakthrough provided the foundation for machine learning usage in this sphere. Using this foundation as a springboard, Sarkar et al. (2020) [7] introduced a technique aided by computers that employs a genetic algorithm as a tool for feature extraction, working together with SVM for the detection and classification of brain tumors. With this model, they accomplished an impressive classification accuracy of 98.3%. This research represented a meaningful advancement from conventional statistical practices, transitioning towards the amalgamation of SVM and demonstrating its effectiveness in precisely categorizing brain tumors using MRI data. This shift underscored a growing inclination towards machine learning implementations, particularly the resilience and triumph of SVM classifiers in undertaking brain tumor categorization tasks after the initial adoption of Bayesian Deep Learning methods.

2.3 Rise of CNN

Brain tumor classification research has seen significant developments, progressing from Support Vector Machines (SVM) to more advanced Convolutional Neural Networks (CNN). In the early stages, various strategies were investigated using clinical resources, such as MRI scans of brain tumors. Selvaraj and his team (2007) [6] laid the foundations for machine learning implementations by developing a binary classifier that relied on statistics and SVM. Following this, Sarkar and co. (2020) [7] put forth a computer-assisted method that harnessed genetic algorithms and SVM, resulting in commendable accuracy. Yet, SVM's inability to efficiently process intricate image data led to a pivot towards more refined techniques. The advent of CNNs sparked a transformative wave in the categorization of brain tumors. Designed for job-specific purposes, such as detecting brain tumors from MRI scans, CNNs work using numerous distinctive layers that handle and decipher visual information. These networks leverage convolutional layers to unearth complex features, use activation functions like ReLU to add in non-linear aspects and employ pooling layers to reduce the volume of learned features. In the Wang et al. study of 2018, [8] the dominant potential of CNN structures to draw out detailed patterns from MRI scans for accurate tumor identification was highlighted, marking a crucial progress milestone in the research field. Transitioning from SVM to CNN represented a critical step towards dynamic deep learning methods, emphasizing the unparalleled abilities of CNNs for processing complex image tasks, especially in the area of brain tumor classification. However, there remain hurdles to overcome, such as obtaining high-quality datasets and clarifying the reasoning

behind the decisions made by the CNNs. This led towards the development of our novel CNN architecture which is known as the InceptionResNetV2. The Figure. 1 represents the intricate architecture of the InceptionResNetV2 Network with extraction of features within the images in the dataset and classifying them into 4 final classes with excellent accuracy.

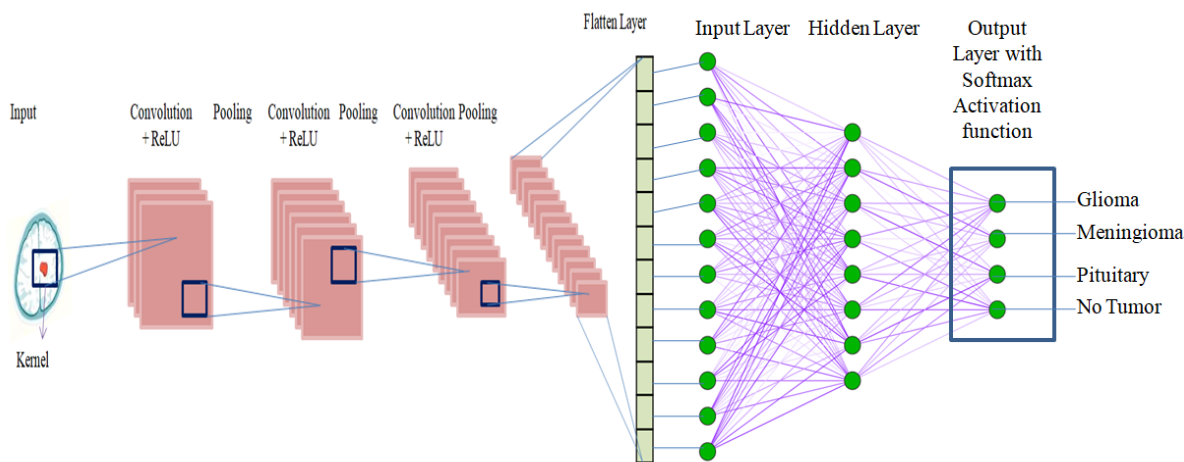


Figure 1. InceptionResNetV2 architecture

3. METHODOLOGY

Figure 2 represents the working procedure of our proposed model that aims to identify and classify brain tumors accurately using InceptionResNetV2 architecture. The architecture has several components, including the dataset with train and test data, image preprocessing, feature extraction, and the prediction model.

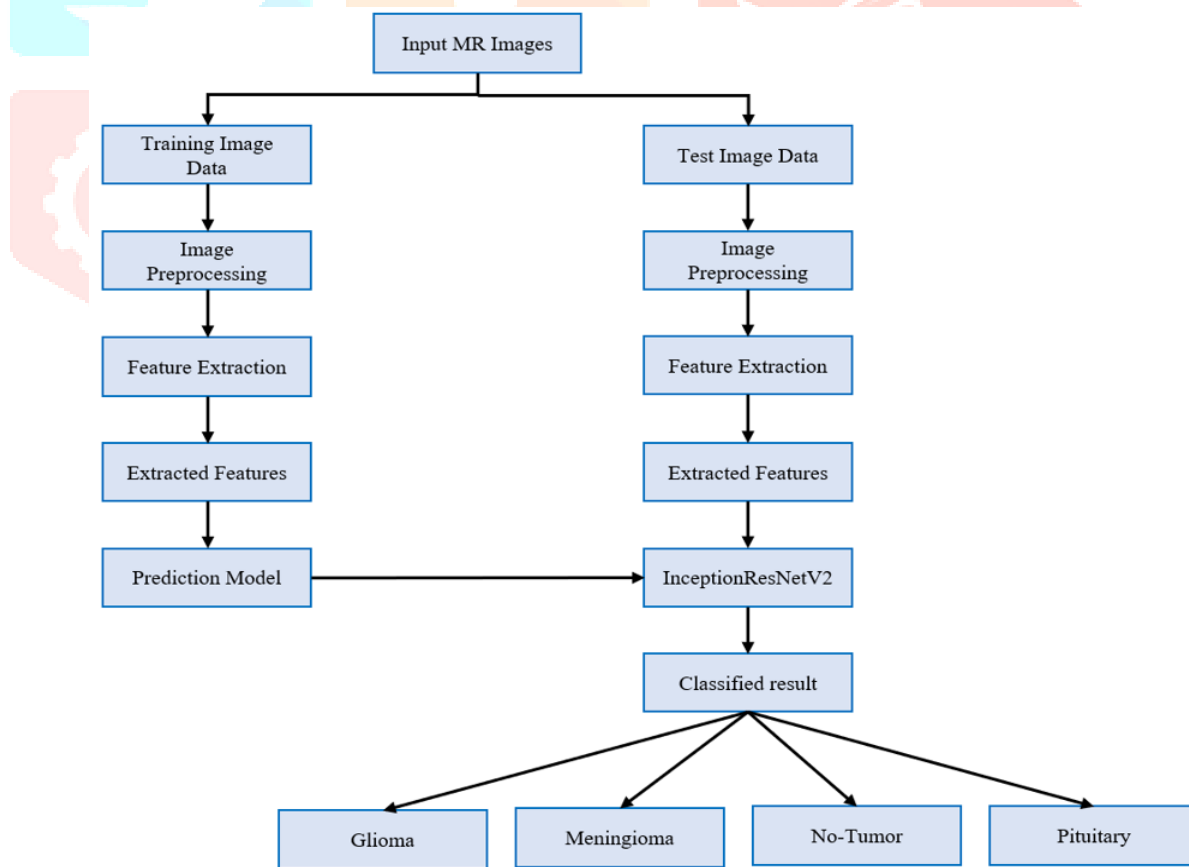


Figure 2. Block diagram of the proposed method for identifying and classifying the tumor

3.1 Dataset: Choosing a proper dataset is the primary involvement in classifying brain tumors from MRI images. We collected our dataset from the honest website, Kaggle database[9], which contains 7023 MRI images, including training and testing data.

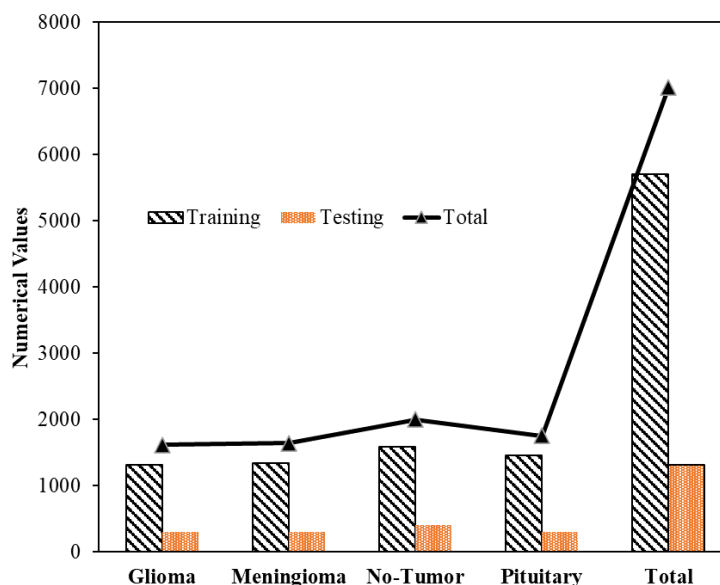


Figure 3. Numerical information of data

Figure3 describes the statistical information of the dataset, specifying 5712 training images from the dataset and 1311 testing images from the dataset. The dataset is divided into two sets, 70% assigned for training and the remaining 30% designated for testing.

3.2 Preprocessing: Preprocessing is a technique that helps to increase the quality of images and follow-up analysis. The High noise levels make it difficult to differentiate between normal and abnormal tissue. Removing the noise helps to improve the efficiency of classifying the tumor name. The benefits of preprocessing include visual enhancement that provides outstanding support to professionals. The MRI dataset images are in the kernel sizes (1x1, 3x3, 5x5). Image sizes represent the input layer of CNN to make the images preprocessed, standardized, and resized. Here, the input image is preprocessed in the process of cropping, and the image decreases the resolution to downgrade the pixel for further steps.

3.3 Feature Extraction: Feature extraction involves removing unnecessary information and deploying the feature as Tumor[16], which can extract as sent to test the image with the help of a trained model to classify the categorized tumor name from the following Figure 3.

3.4 Proposed System: The Inception-ResNetV2 is a deep learning architecture that amalgamates the strategies of Inception and ResNetV2. It merges the multi-level feature extraction of Inception with the residual links of ResNet, resulting in a network famed for its efficiency and accuracy. This structural arrangement enables quicker training times, superior classification precision, and reduced computational intricacy. It effectively seizes diverse characteristics at multiple scales through the use of factorized convolutions and simultaneous operations. Inception-ResNet-v2 deftly balances computational thriftiness and robust performance, deeming it a useful tool for a range of computer vision assignments, especially image classification and feature extraction.

The InceptionResNetV2 model is indeed a hybrid architecture that inherits characteristics from several prior Convolutional Neural Network (CNN) models. It combines elements from the Inception and ResNet architectures, each bringing unique features that contribute to its performance:

3.4.1 Understanding Inception Module:

- The inception module pays attention to enhance computing efficiency by utilizing a variety of filter dimensions within a single layer.
- It aims to grasp attributes at diverse spatial scales by conducting convolutions using dissimilar kernel sizes (1x1, 3x3, 5x5) concurrently and merging the results.
- This structure diminishes computational complexity and simultaneously captures both local and broad scale features effectively.

3.4.2 Explaining Residual Connections (from ResNet):

- Residual connections, also known as skip connections, as first seen in ResNet, provide a pathway that allows the skipping of some layers or blocks by merging the input and the output of a given layer.
- This technique helps tackle the issue of disappearing gradients, aiding in the efficient training of large-scale networks by promoting smooth gradient flow during backpropagation.
- The inclusion of these residual connections is beneficial in preserving the flow of information, which further assists in the training of extremely deep neural networks.

3.4.3 Characteristics Inherited:

- InceptionResNetV2 inherits the efficient multi-scale feature extraction capabilities of the Inception module.
- It also adopts the concept of residual connections from ResNet, aiding in the training of deeper networks by addressing gradient vanishing issues.
- The architecture combines these characteristics to achieve a balance between computational efficiency, feature representation, and training stability, resulting in a powerful and effective model for various computer vision tasks, including image classification, object detection, and segmentation.

3.5 Train the Model: To train the model we adopted some standard preprocessing techniques like image resizing, pixel normalization, and data augmentation. These steps play a vital role in ensuring the model's robustness and generalization to unseen data.

This paper examines the Glioma, Meningioma, No-tumor, and Pituitary brain tumor images which are shown in below Figure 4 to differentiate brain tumors in the process of the model that was trained.

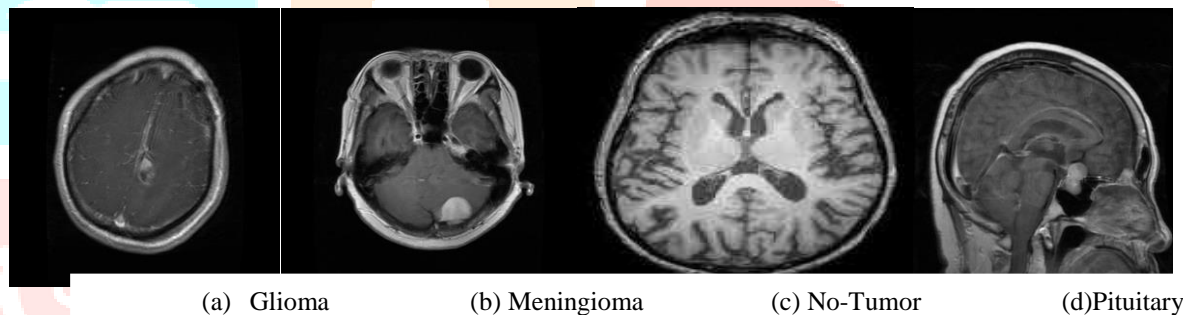


Figure 4. Training images of (a) Glioma (b) Meningioma (c) No-Tumor (d) Pituitary brain tumors

Micro-Average Receiver Operating Characteristic (ROC) has a False Positive Rate (FPR) on the x-axis while a True Positive Rate (TPR) on the y-axis. FPR includes a proportion of negative instances (no tumor) incorrectly classified as positive (having tumors). TPR includes a proportion of positive instances (tumors) correctly classified as positive. As shown in the Figure 5. below, the graph starts at the bottom-left corner and shows a threshold of all instances classified as negative, resulting in both FPR and TPR being zero. As the threshold increases, more instances are classified as negative, showing increases in both FPR and TPR. The ROC curve visualizes the performance of the model for different thresholds. It also acts as a tool for evaluating binary classification models such as brain tumor classification.

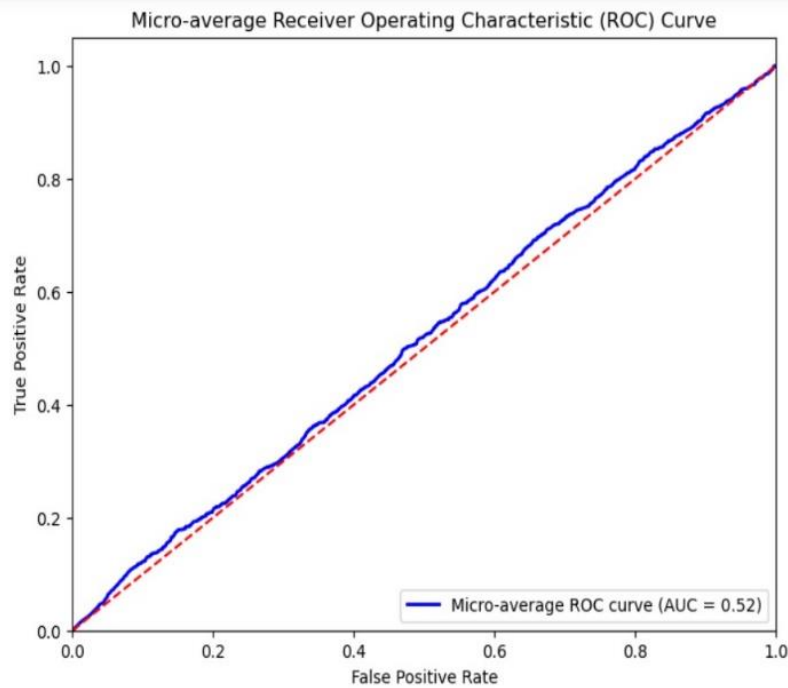


Figure 5. ROC Curve

3.6 Validation Accuracy versus Training Accuracy:

Figure 6 describes Epochs versus Accuracy. The X-axis specifies epochs while the Y-axis with accuracy. The x-axis value represents several training values. The y-axis represents values from 0 to 1, where 0 indicates no accuracy, and 1 indicates perfect accuracy. Training accuracy is the performance of trained data, while validation accuracy is the performance of unseen data. Training accuracy increases much faster than validation accuracy due to overfitting. Validation accuracy may plateau or decrease as training accuracy constantly increases. The separation of the line graph represents overfitting. The plot lays out the model progression and improves the performance of unseen data.

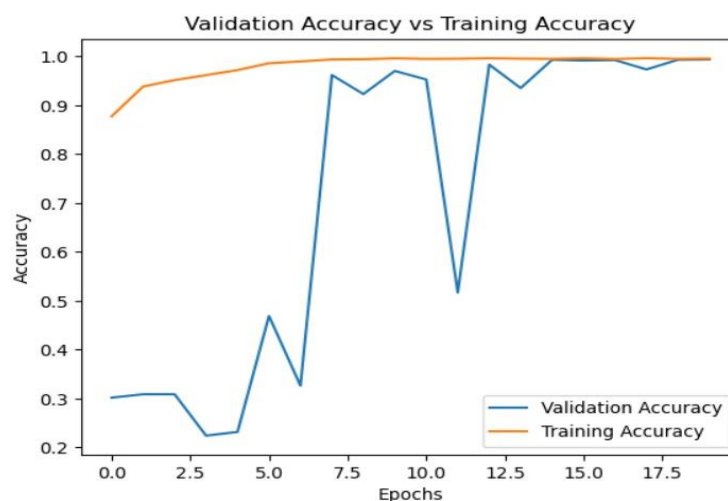


Figure 6. The Accuracy rate between the Validation and Training

3.7 Classified Output: In this research, the outcome is the extraction of final classified results as Glioma, Meningioma, No-tumor, and Pituitary tumors from the MRI dataset, and the objective is to increase the accuracy and decrease the running rate to improve the performance of the model using InceptionResNetV2 architecture.

3.8 Efficiency Analysis: Accuracy is a parameter used to measure the performance of a model. A confusion matrix has been utilized to calculate the performance of a classifier. The performances are described by four components of the confusion matrix, such as true positive (TP), true negative (TN), false positive (FP), and false negative (FN) to make accurate predictions.

4. RESULT

4.1 Confusion Matrix: The confusion matrix in Figure 7. shows Predicted Labels of brain tumor types on the x-axis while True Labels are on the y-axis. The diagonal (from top left to bottom right) represents accurate values. The maximal value shows high accuracy. The diagonal values of Glioma-68, Meningioma-78, No Tumor-132, and Pituitary-68 state that No Tumor has high accuracy. Other than Diagonal are misclassifications. The sum of each row corresponds to the actual count of each brain tumor type. The sum of each column is the predicted count of each brain tumor type. The actual count of each tumor type is Glioma-300, Meningioma-306, No Tumor-405, and Pituitary-300, and the predicted count of each tumor type is Glioma-296, Meningioma-307, No Tumor-405, and Pituitary-303.

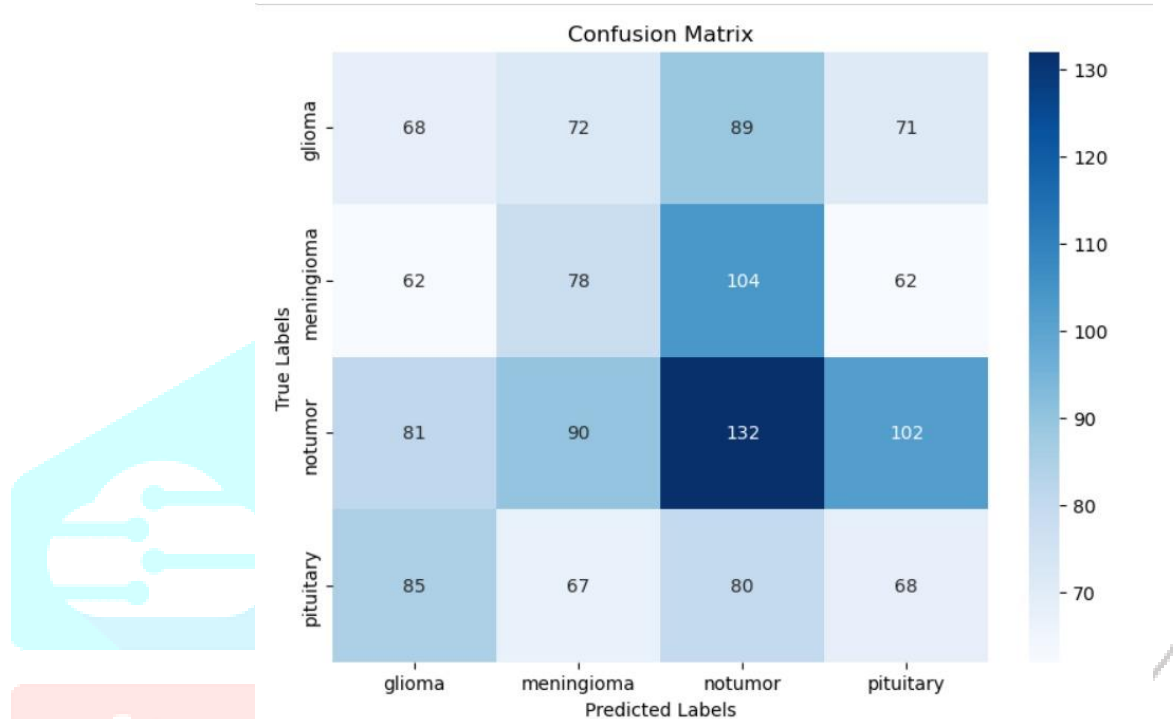


Figure 7. Confusion Matrix

4.2 Comparative Analysis: Figure 8 shows the comparative analysis of the model accuracies of AlexNet, GoogleNet, SqueezeNet, and MobileNet with our InceptionResNetV2. Comparatively, as per our experimental design and paradigm, InceptionResNetV2 performs better than AlexNet, GoogleNet, SqueezeNet, and MobileNet. InceptionResNetV2 achieved an accuracy of 0.99, whereas AlexNet achieved 0.97, GoogleNet achieved 0.98, SqueezeNet achieved 0.96, and MobileNet achieved 0.98, which are comparatively less than InceptionResNetV2 as shown in the Figure 9.

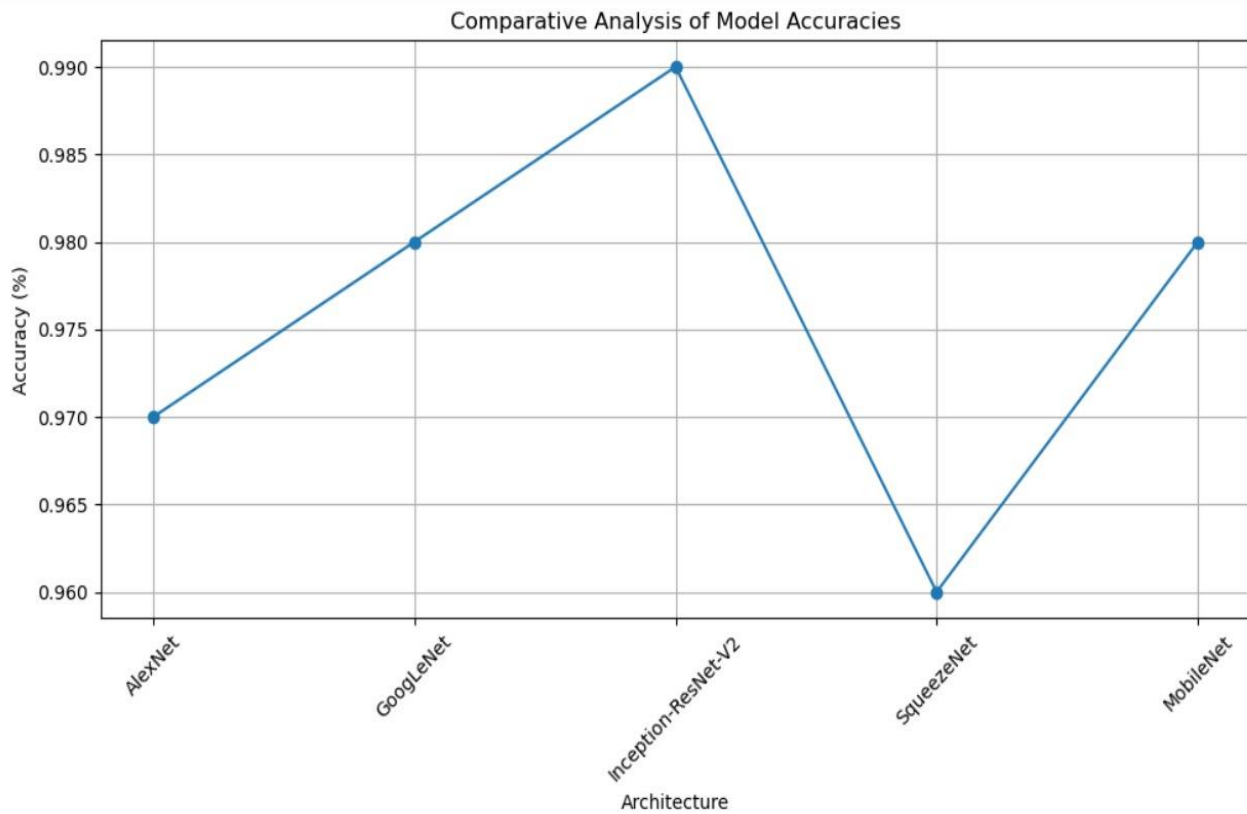


Figure 8. Comparative Analysis of Model Accuracies

Table1.AccuracyComparison chart

Model	Accuracy (%) Brain Tumor public dataset Full Brain MRI
AlexNet [10]	97
GoogleNet [12]	98
SqueezeNet [14]	96
MobileNet[15]	98
InceptionResNetV2	99

Table1 compares the accuracy of a model to the accuracy of a full brain MRI for identifying brain tumors. The Table 1 shows four different models: AlexNet, GoogleNet, SqueezeNet, and MobileNet. It also shows one model, InceptionResNetV2. The accuracy of each model is listed as a percentage. The table shows that InceptionResNetV2 has the highest accuracy, at 99%. The accuracy of the other models ranges from 96% to 98%.

5. CONCLUSION

Inception-Re-sNetV2, a powerful blend of Inception and ResNet designs excels in identifying brain tumors. This fusion balances detailed and broad feature capture via inception modules, ensuring optimum computational speed via 1x1 convolutions. It uses residual connections to counter the issue of vanishing gradients, thereby enabling the proficient training of deep networks. The model's flexible nature gracefully adjusts to changes in tumor attributes, ensuring consistent results in the field of medical imaging. The mastery of InceptionResNetV2 to amalgamate the virtues of Inception and ResNet renders it an ideal choice for precise brain tumor categorization.

REFERENCES

1. K. Denys, "The processing of visual shape in the cerebral cortex of human and nonhuman primates: A functional magnetic resonance imaging study," *J. Neurosci.*, vol. 24, no. 10, pp. 2551–2565, Mar. 2004.
2. Khan Muhammad, S. Khan, J. D. Ser and V. H. C. d. Albuquerque, "Deep Learning for Multigrade Brain Tumor Classification in Smart Healthcare Systems: A Prospective Survey," in *IEEE Transactions on Neural Networks and Learning Systems*, vol. 32, no. 2, pp. 507-522, Feb. 2021, doi: 10.1109/TNNLS.2020.2995800.
3. M. W. Dusenberry, D. Tran, E. Choi, J. Kemp, J. Nixon, G. Jerfel, K. Heller, and A. M. Dai, "Analyzing the role of model uncertainty for electronic health records," in *Proc. ACM Conf. Health, Inference, Learn.*, Apr. 2020, pp. 204–213.
4. A. A. Abdullah, M. M. Hassan, and Y. T. Mustafa, "A Review on Bayesian Deep Learning in Healthcare: Applications and Challenges," in *IEEE Access*, vol. 10, pp. 36538-36562, 2022, doi: 10.1109/ACCESS.2022.3163384
5. M. Havaei et al., "Brain tumor segmentation with deep neural networks," *Med. Image Anal.*, vol. 35, pp. 18–31, Jan. 2017
6. H. Selvaraj, S. T. Selvi, D. Selvathi, and L. Gewali, "Brain MRI slices classification using least squares support vector machine," *International Journal of Intelligent Computing in Medical Sciences & Image Processing*, vol. 1, no. 1, pp. 21–33, 2007.
7. A. Sarkar, M. Maniruzzaman, M. S. Ahsan, M. Ahmad, M. I. Kadir, and S. T. Islam, "Identification and classification of brain tumor from MRI with feature extraction by support vector machine," in *2020 International Conference for Emerging Technology (INCET)*, pp. 1–4, Belgaum, India, 2020.
8. Hu H, Mu Q, Bao Z, Chen Y, Liu Y, Chen J, Wang K, Wang Z, Nam Y, Jiang B, Sa JK. Mutational landscape of secondary glioblastoma guides MET-targeted trial in brain tumor. *Cell*. 2018 Nov 29;175(6):1665-78.
9. MsoudNickparvar "Brain Tumor MRI Dataset" DOI: 10.34740/kaggle/dsv/2645886
10. Alok Sarkar, Md. Maniruzzaman, Mohammad Ashik Alahe, Mohiuddin Ahmad, "An Effective and Novel Approach for Brain Tumor Classification Using AlexNet CNN Feature Extractor and Multiple Eminent Machine Learning Classifiers in MRIs", *Journal of Sensors*, vol. 2023, Article ID 1224619, 19 pages, 2023. <https://doi.org/10.1155/2023/1224619>
11. N. Bhardwaj, M. Sood and S. Gill, "Deep Learning Framework using CNN for Brain Tumor Classification," *2022 5th International Conference on Multimedia, Signal Processing and Communication Technologies (IMPACT)*, Aligarh, India, 2022, pp. 1-5, doi: 10.1109/IMPACT55510.2022.10029043
12. A. Sekhar, S. Biswas, R. Hazra, A. K. Sunaniya, A. Mukherjee and L. Yang, "Brain Tumor Classification Using Fine-Tuned GoogLeNet Features and Machine Learning Algorithms: IoMT Enabled CAD System," in *IEEE Journal of Biomedical and Health Informatics*, vol. 26, no. 3, pp. 983-991, March 2022, doi: 10.1109/JBHI.2021.3100758.
13. M. A. Hafeez, C. B. Kayasandik and M. Y. Dogan, "Brain Tumor Classification Using MRI Images and Convolutional Neural Networks," *2022 30th Signal Processing and Communications Applications Conference (SIU)*, Safranbolu, Turkey, 2022, pp. 1-4, doi: 10.1109/SIU55565.2022.9864962
14. R. Islam et al., "Enhanced Brain Tumor Classification using Squeeze and Excitation Attention-Guided Modified EfficientNetB2 Architecture," *2023 26th International Conference on Computer and Information Technology (ICCIT)*, Cox's Bazar, Bangladesh, 2023, pp. 1-6, doi: 10.1109/ICCIT60459.2023.10441029.
15. J. Raju, K. Anand, D. Krishna Kumar and D. Sivaganesan, "Brain Tumor Identification and Classification Using Enhanced Convolution Neural Network," *2023 5th International Conference on Inventive Research in Computing Applications (ICIRCA)*, Coimbatore, India, 2023, pp. 471-478, doi: 10.1109/ICIRCA57980.2023.10220641.
16. Arora, A.; Jayal, A.; Gupta, M.; Mittal, P.; Satapathy, S.C. Brain Tumor Segmentation of MRI Images Using Processed Image Driven U-Net Architecture. *Computers* 2021, 10, 139. <https://doi.org/10.3390/computers10110139>