Intelligent Tumor detection using Deep Learning

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Abstract: This paper describes how to use deep learning (CNN) to detect brain tumor in medical images, solving the problem of tumor differentiation and unraveling the complexity of the distributed grid. Four prominent CNN architectures and two additional models (MobileNet) are assessed for their performance in brain tumor classification. The research employs a varied dataset of brain MRI scans, incorporating different tumor types, sizes, and locations. Pre-processing techniques, such as image normalization and augmentation, enhance model robustness. Each CNN is fine-tuned and trained, with experiments evaluating accuracy, sensitivity, specificity, and computational efficiency. The comparative analysis identifies strengths and weaknesses, providing insights into the models' suitability for real-world clinical applications.

Convolution Neural Networks, Deep learning, ResNet-50, VGG-16, DenseNet-121,Mobile-Net and Inception V3

1- Introduction

Brain tumor is a complex and diverse class of medical conditions, pose a significant challenge in the field of healthcare due to their varied characteristics and potential negative effects on human well-being. These abnormal growths within the brain can manifest in diverse sizes, shapes, and locations, making their search and classification are important tasks in medical analysis.[1]

Identification and classification of brain tumors when done manually is not only time-consuming but can lead to inaccurate results, emphasizing the need for advanced technologies to enhance diagnostic precision. The application of Deep Learning techniques, especially CNNs, show great promise in detecting of brain tumors medical images, notably Magnetic Resonance Imaging (MRI) scans. [2]

In this research endeavor, we focus on four prominent CNN architectures: ResNet-50, Mobile-Net,VGG-16, DenseNet-121, and Inception V3. [3] Each of the above models represents a unique approach to extract features and classify problem, contributing to the evolving landscape of deep learning applications in medical imaging

1- VGG-16 (Visual Geometry Group 16): VGG-16 is characterized by its deep architecture with 16 weight layers. It is renowned for its simplicity and uniformity, employing 3x3 convolutional filters throughout the network.VGG-16 has demonstrated success in various computer vision tasks.

2-ResNet-50 (Residual Network): ResNet-50 introduces the concept of residual learning, mitigating the vanishing gradient problem in deep networks. The architecture includes shortcut connections that enable the direct flow of information across layers. ResNet-50 has exhibited exceptional performance in image classification tasks. [4]

3-Inception V3: Inception V3 employs a unique architecture with multiple parallel paths for feature extraction. It incorporates 1x1, 3x3, and 5x5 convolutions. Inception V3 is recognized for the efficiency and has been successful in image recognition tasks. [5]

4-DenseNet-121 (Densely Connected Convolutional Networks): DenseNet-121 features dense connectivity, where each layer receives input from all previous layers. This architecture encourages feature reuse and facilitates gradient flow. DenseNet-121 has demonstrated effectiveness in various image analysis applications.

In the later sections of this paper, we delve into the methodology employed for training and evaluating these models, presenting results and insights gained from their application in the automated brain tumor identification. The comparative analysis of these models aims to discern their individual strengths and contributions in advancing image analysis for improved brain tumor diagnosis. This article, propose an efficient and effective method based on traditional products and neural networks to identify and segment brain tumors without human assistance.

I. LITERATURE REVIEW

To get the classification of the brain tumors by traditional biopsy, the early detection of brain tumors is vital. This procedure is performed exclusively through definitive brain surgery. For physicians to identify and categorize brain tumors non-invasively, computational intelligence-based techniques offer a promising avenue. Brain Tumor have more than 200 diverse varieties that may affect humans, Early detection of Brain Tumor can lead to early initiation of treatment, for the survival of the patient as the number of lives lost has increased by 300 % in the last three decades as per the NBTF report. Hence the use of neural networks can play very important role in quick detection of tumor in medical field.
In the paper proposed by Driss Lamrani1 in 2022 [6], The CNN model has been proposed to segment MRI images into tumors and non-tumors. They used 3,000 high-resolution

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MRI images for training. Various criteria were used to calculate the performance of the model. Their model outperforms other models with 98% accuracy, 96% overall accuracy, 96.5% F1 score, and 98% sensitivity. They experimented on the model using ANN methods, transfer learning algorithms, random forest classifiers, and CNN and found that CNN outperformed other methods. For more accurate detection and classification of tumor cells, CNN shows the best performance in curve analysis and measurement. Since the results they obtained in the test are higher and higher in the CNN method than in other methods, their model ranks high with the best accuracy compared to other methods. The final result is a tumor prediction using CNN, and the working model has shown that it can be used with transformation data from brain MRI images.

In the paper proposed by D C Febrianto, I Soesanti and H A Nugroho in 2020 [7], Their paper presents experiments with 2065 images, 1085 tumor samples, and 980 non tumor samples. The data is further split, with 70% of the data used for training, 15% of the data for validation, and 15% of the data for testing. Currently, 10 experiments with 25 epochs and 32 groups have been performed on the data using the proposed CNN model. The results were compared with standard deviation, mean, negative, true and f1 methods. In the first model of the CNN, an average accuracy rate of 94% was achieved with an average loss of 0.14181 on the training data, and an average accuracy rate of 85% was achieved with an average loss of 0.44037 on the test data, in this case only one argument is used in the Procedure. They achieved better results using 2 convolution models, with a 96% accuracy rate and 0.10046 loss for the training data, and a 93% accuracy rate and 0.23264 loss for the test data. The second model took longer to train than the first model and its f1 score was 92%. The conclusion of the paper is the effectiveness of the CNN model in detecting brain tumors using MRI images; The final result of the paper test is 93% accuracy and 0.23264 missing. The article also noted that accuracy can be improved when we add convolutional methods, but such models still take a long time to train, so methods that enhance images can be used to improve the product's differences over existing products, which can lead to a higher level of accuracy. to classification.

In the paper proposed by Mohammad Omid Khairandish, Ruchika Gupta & Meenakshi Sharma in 2020 [8], this research includes studies of both benign and malignant tumor types. Two separate methods are used to train and evaluate input data; one is Fast R-CNN and the other is SVM model, which takes advantage of both models. The proposed CNN model has many layers and methods to train and test the input data, and to better classify the data, the full connection method of Fast R-CNN passes the output as input to the SVM layer. This hybrid technology achieves better results compared to existing technologies. A combination of these two different methods with equal detail is used to aid in the removal of the skull. Image noise was removed using the image averaging technique and tumor was enlarged using threshold-based segmentation. The fast R-CNN method in this model helps in finding features using RPN and displaying features in MRI images. The hybrid model achieved 98.81% accuracy, while SVM alone achieved 63.57% accuracy for benign and 68.88% for malignant, while R-CNN achieved 97.82% accuracy for benign and 68.88% for malignant. achieved 68.85% accuracy. The average value of the composite sample for benign and malignant is 98.787% and 98.677%, respectively. The article concludes that the hybrid model provides better results than existing methods.

II. PROPOSED WORK

A. MODEL

In this project, there are multiple stages of research as can be seen from Fig. 1. In the form of research framework. In the proposed research framework: This is the basic structure of the CNN the model that we are going to use in our project and compare the accuracies of various models and then conclude which model is the best. [9]

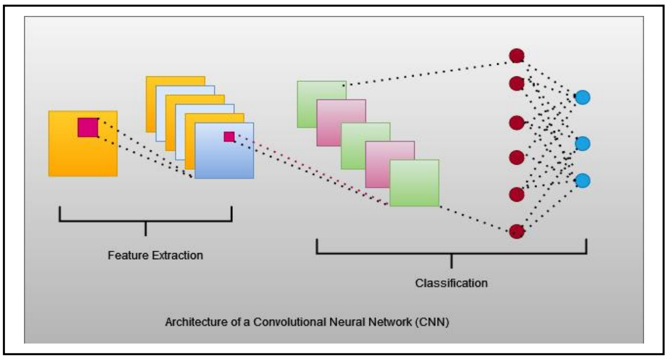


Figure 1.Convolutional Neural Networks (CNNs)

In figure no 2 we will propose the required flowchart that describe the entire working of the model and then we will run all the models in our computer system and find accuracies and compare various models and find out which one deep learning model is the best.[10].

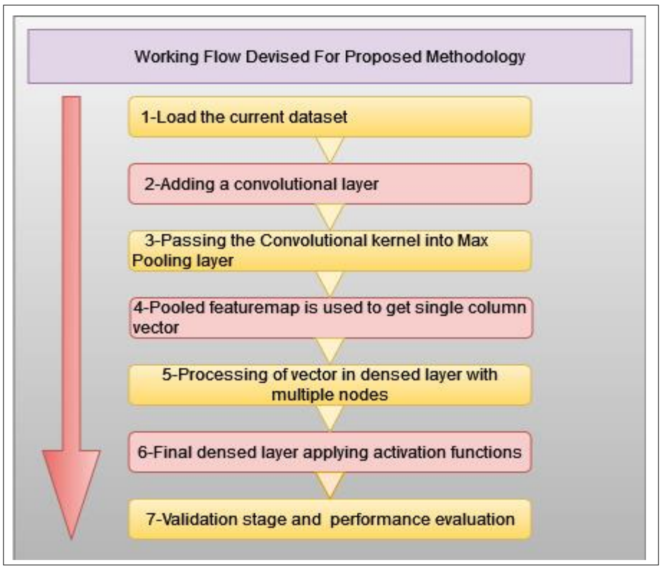


Figure 2: Flowchart that explains working of proposed work

In clinical picture analysis, CNNs have emerged as a transformative technology, particularly noteworthy for their efficacy in tasks such as the automated detection of brain tumors. This section provides a concise overview of the CNN architecture within the context of our research paper, focusing on its role in deciphering complex patterns in medical images. The CNN architecture is characterized by a hierarchical structure designed to autonomously learn spatial hierarchies of features from input data, making it particularly adept at handling intricate visual information present in medical images.[11]

Architecture: Main elements of CNN architecture such as convolution layers, activation functions, pooling layers, a flattening layer, and fully connected layers, culminating in an output layer for making predictions.[12]

Convolutional Layers: The convolutional layer plays a key role in extracting important Features are obtained by creating local connections in the data structure of the access process. The feature vector is obtained through convolutional operations, represented by the equation

$$Feature\ Vector = \sum (Input_{k\ x\ k} + Weights_{k\ x\ k}) + B$$

where Input_(k x k) is the local receptive field, Weights_(k x k) are filter weights, and B is the filter bias. This convolutional operation involves sliding the filter over image pixels, adding them together to create feature maps.

Pooling Layers: Feature Map's each channel gets 2-D filter applied over it and features get summarized within the region.[13]

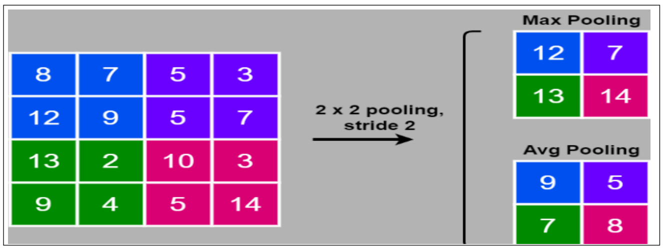


Fig 3. Pooling

Fully Connected Layers: The conversion of the previous layer's 3-D matrix into 1-D vector is done using a fully connected layer with full convolution operation.
Mathematical Operation:

$$Z_{V_o \times 1} = Weight_{V_o \times V_1} I_{V_i \times 1} . Bias_{V_o \times 1}$$

In our research, these layers finally classify the MRI images as either tumor-present or tumor-absent.[14]

Activation Functions: Crucial parameter in a CNN model, which is employed Examine and predict relationships in networks. Simply put, it decides which messages should be opened up front and which messages should not be opened at the network end, introducing non-linearity. Common activation functions include ReLU, Softmax, tanH, and Sigmoid.Their brief description is as follows.[15]

Softmax Function- Combination of Multiple sigmoids

Formula*:*

$$\sigma(\vec{z})_i = \frac{e^{z_i}}{\sum_{j=1}^{K} e^{z_j}}$$

ReLU Function (Rectified Linear Activation Function): It is a piecewise function where positive input get outputted directly or else output will be zero.

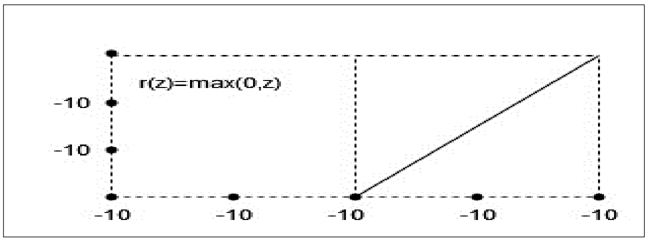


Figure:3 Graph of Relu Function

Binary Cross Entropy: Binary Classification task's default loss function. [16]

Formula:

$$L = -\frac{1}{m}\sum_{i=1}^{m} y_i \,.\log(\hat{y}_i)$$

Training Process: Training the CNN involves leveraging labeled datasets, where the network learns to adjust its internal parameters through a process known as backpropagation. In the specific context of our research, the CNN learns to distinguish patterns indicative of brain tumors from the provided medical images. This iterative process the network's parameters to optimize its ability to accurately detect tumors.[17]

Significance in Brain Tumor Detection: The application of CNNs in brain tumor detection represents a paradigm shift in medical image analysis. By autonomously learning complex patterns and spatial relationships within MRI images, CNNs offer the potential for more efficient, accurate, and consistent tumor detection. Our research builds upon this foundation, employing CNNs with varying architectures— ResNet-50, VGG-16, Mobile-Net, DenseNet-121, and Inception V3—to comprehensively evaluate their performance in the context of automated brain tumor detection.[18]

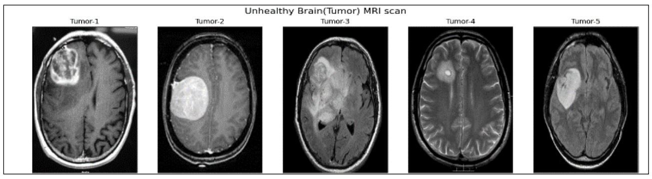


Figure 4: MRI images of Unhealthy Tumor

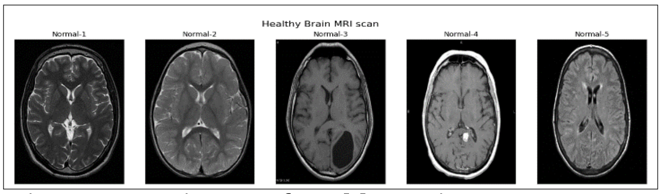
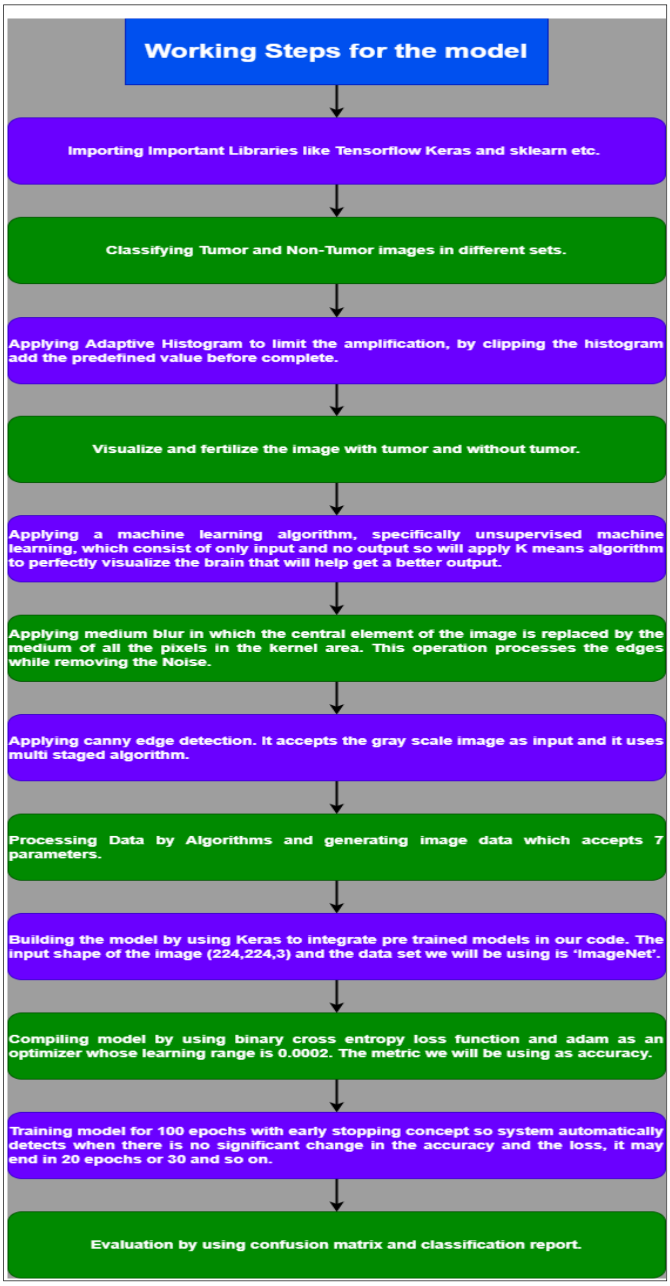


Figure 5: MRI images of Healthy Brain

Here we get to know that healthy images will not contain tumor and both of them will be used for training and testing purposes.



F1 score ,accuracy and precision recall will be determined by classification report and our ML model's performance will be summarized by confusion on test data set. [19]

Models :

VGG16: VGG16, or Visual Geometry Group 16, a powerful CNNetwork acclaimed for the efficacy in image recognition and analysis. Its unique architecture, featuring 16 weight layers, utilizes compact 3x3 convolution filters, proven more effective than previous configurations. VGG16 excels in object detection and classification, achieving an impressive 92.7% accuracy. Its user-friendly design supports easy implementation through transfer learning. The consistent layer structure includes convolution layers with 64 to 512 filters and 3 fully-connected layers. [20]

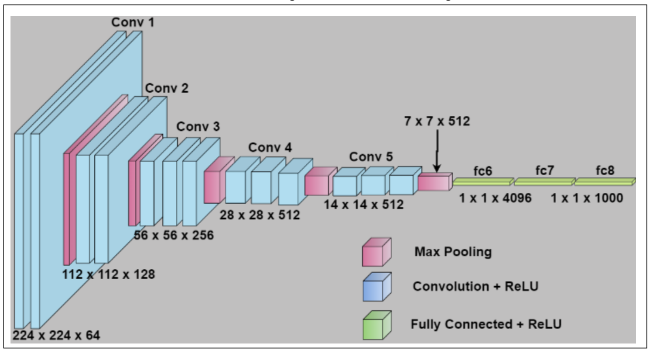


Figure 6: Architecture of VGG16

MOBILE NET: MobileNet, optimized for mobile vision applications, stands out in object detection and fine-grained classifications due to its efficiency and lightweight design. The innovation lies in depth-wise separable convolution, featuring two crucial layers: depthwise and pointwise convolution. The depthwise convolution processes each input channel independently, significantly reducing computational costs. The pointwise, via a 1×1 convolution, computes a linear combination of depthwise outputs, enhancing feature generation. This strategic use of depth-wise separable convolutions ensures high performance with minimal computational demands. MobileNet's efficiency in resource-constrained environments makes it a practical choice, showcasing robust performance in tasks like object detection and classifications in real-world applications.[21]

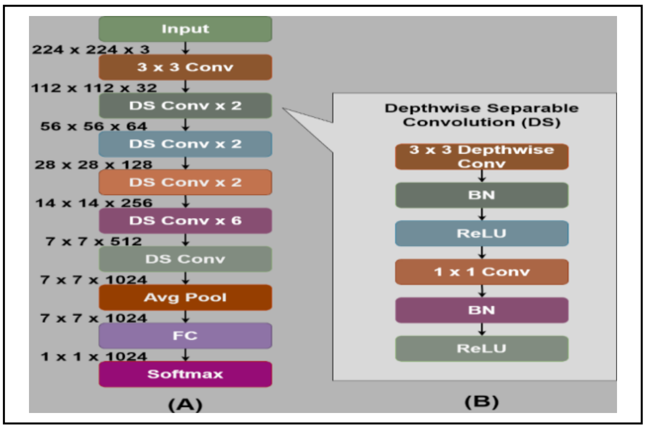


Fig 7. Mobile-Net Architecture

DENSENET: Dense blocks enhance comprehensive feature learning, aiding the model in discerning intricate patterns. Transition layers manage computational complexity and ensure smooth stage transitions. As the architecture progresses, a global average pooling layer condenses feature map dimensions, followed by a fully connected layer for classification, producing class probabilities.[22]

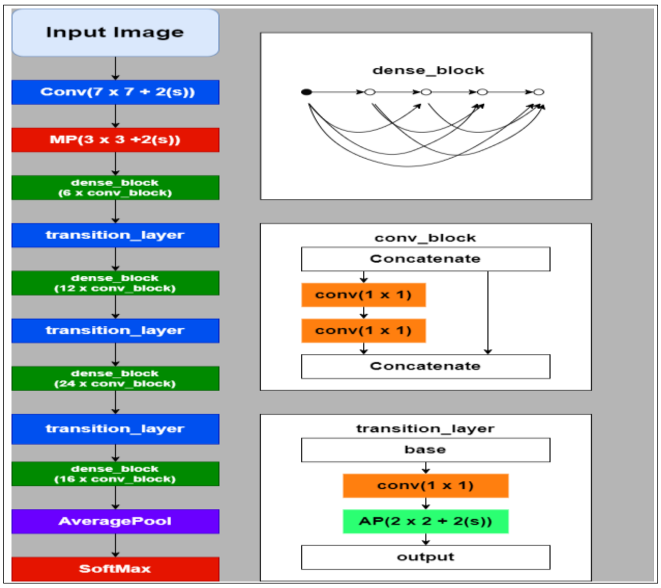


Fig 8. Dense-Net architecture

DenseNet models, such as DenseNet-121, DenseNet-169, and DenseNet-201, offer adaptability in layers and parameters, catering to diverse applications and computational resources. This flexibility optimizes model performance based on specific requirements. Dense connectivity within DenseNet contributes to feature learning, parameter efficiency, and overall accuracy, making it a versatile and powerful choice for various deep learning tasks.[23]

RESNET: The architecture is composed of convolutional layers, pivotal identity, and convolutional blocks, and concluding with fully connected layers. Identity blocks intelligently integrate input into the output, while convolutional blocks use a 1x1 convolutional layer to enhance feature extraction. Trained on the vast ImageNet dataset—comprising over 14 million images and 1000 classes—ResNet50 boasts exceptional performance with a low 22.85% error rate, approaching human-level accuracy at 5.1%.[24]

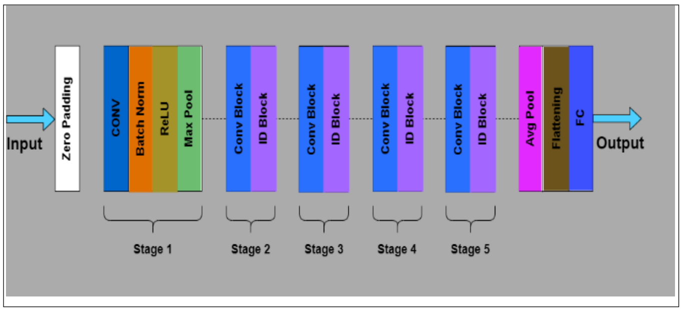


Fig 9. Resnet Architecture

INCEPTION V3: A 48-layer deep CN network, offers pre-trained versions capable of classifying images into 1000 categories. Notably, its architecture evolved from Inception V1 to address certain drawbacks. Issues with Inception V1 included occasional information loss due to 5x5 convolutions, which prompted a shift to factorization, breaking down 3x3 convolutions into 1x3 and 3x1 for computational efficiency. The auxiliary classifier, introduced for convergence in V1, showed limited effectiveness. In Inception V2, improvements were made by replacing 5x5 convolutions with two 3x3 convolutions, enhancing computational efficiency. Feature bank expansion addressed representational bottlenecks. Inception V3 further refined the architecture, introducing RMSprop optimizer, batch normalization for the auxiliary classifier, 7x7 factorized convolution, and label smoothing regularization. These enhancements contribute to improved optimization and performance across various tasks.[25]

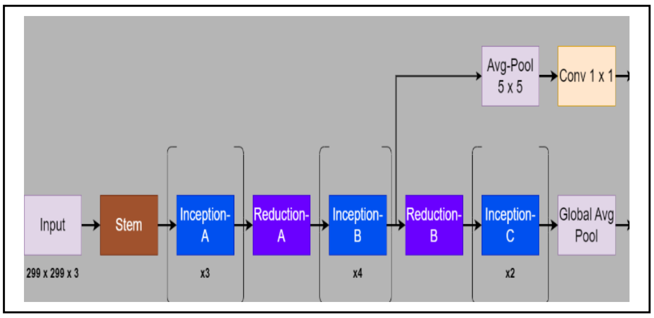


Figure 10 : Architecture of Inception V3

OBSERVATIONS :

Here after running various models, we get readings considering Factors such as large training data, heterogeneity of testing data, time required to complete test scores, and network complexity.

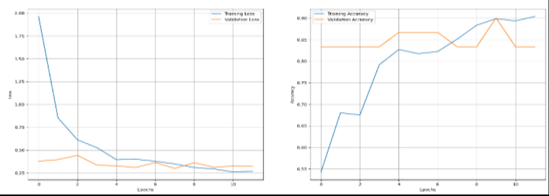
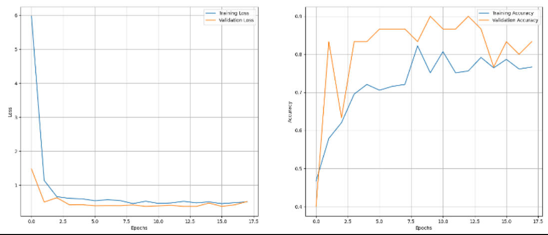
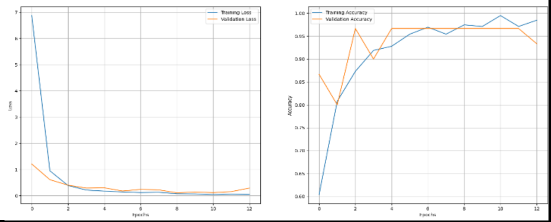
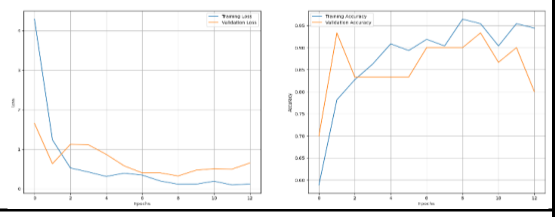
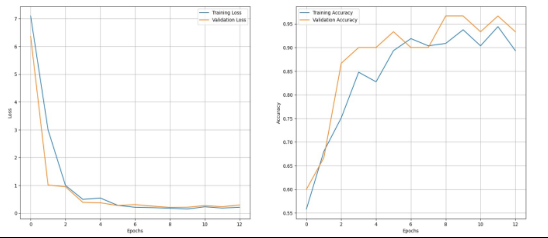
Table 1:

MODELS	TUMOR /NO TUMOR	PRECISION	RECALL	F1-SCORE	ACCURACY
VGG 16	TUMOR	0.81	0.94	0.87	0.833
	NO	0.89	0.67	0.76	
RESNET 50	TUMOR	0.81	0.94	0.87	0.8129
	NO	0.89	0.67	0.76	
INCEPTION	TUMOR	0.94	0.89	0.91	0.9
	NO	0.85	0.92	0.88	
DENSENET	TUMOR	0.94	0.94	0.94	0.933
	NO	0.92	0.92	0.92	
MOBILE NET	TUMOR	0.95	1.0	0.97	0.966
	NO	1.0	0.92	0.96	

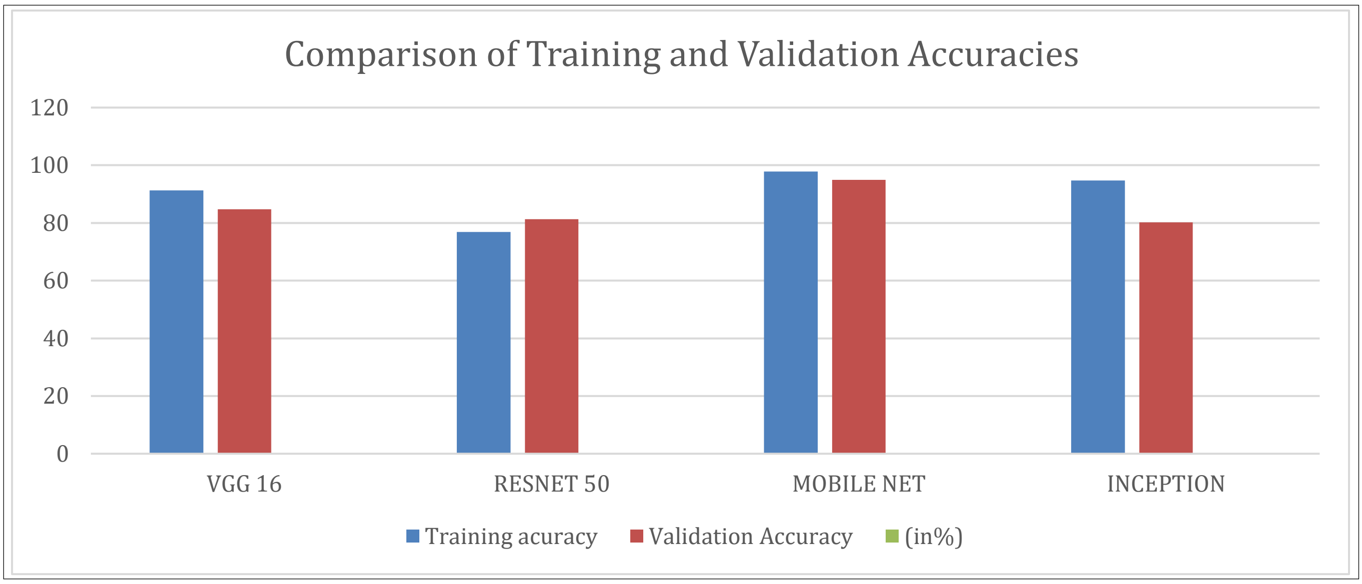
DISCUSSION:

This study evaluated 5 deep learning models to detect brain tumor. Table 2 highlights that models, including customized CNN, VGG-16, MobileNet, DenseNet, ResNet50 and Inception-V3, achieved high test scores with small datasets, converging faster. However, ResNet-50 excelled at higher epochs, showcasing the impact of network complexity on accuracy. Notably, network complexity played a crucial role in accuracy, with models like customized CNN and VGG-16 outperforming those with more convolutional layers. Reduction in layers enhanced efficiency and operating time. The suggested model demonstrated effective feature learning with fewer convolutional layers than pretrained models. Examining Table 2, it becomes apparent that these models can attain high testing scores even with less training datasets, provided there is sufficient variance between the datasets used for training. Notably, customized models of CNN, VGG-16, MobileNet, DenseNet, ResNet50 and Inception-V3 demonstrated faster convergence is done in the previous semester and does not require any additional time to achieve high test scores. In comparison, the ResNet-50 model performs better at higher times, emphasizing the role of network complexity in influencing model accuracy time. Interestingly, we found that network complexity plays a pivotal role in model accuracy, with the modified CNN, VGG-16 model, boasting 5 and 16 convolutional layers, respectively, outperforming models with more convolutional layers. This reduction in convolutional layers not only enhances computational efficiency but also shortens the operational time of the applied models for experiment.

TABLE : 2

MODELS	LOSS	VALIDATION LOSS	TRAINING ACCURACY	VALIDATION ACCURACY	GRAPHS
VGG 16	0.2663	0.3206	0.9129	0.8472	
RESNET50	0.5062	0.5159	0.7691	0.8131	
MOBILENET	0.0468	0.2864	0.9778	0.9489	
INCEPTION	0.1209	0.6533	0.9477	0.8023	
DENSENET	0.2987	0.2908	0.8988	0.9433	

Now we will compare accuracies of the models.



RESULT:

Here we can conclude that Mobile Net's validation Accuracy is best among all models.

REFERENCES:

[1] Sakib, Adnan, et al. *Brain Tumor Detection and Classification Using Deep Learning Approach*. Department of Computer Science & Engineering (CSE), BUBT, 2023.

[2] Methil, Aryan Sagar. "Brain tumor detection using deep learning and image processing." *2021 international conference on artificial intelligence and smart systems (ICAIS)*. IEEE, 2021.

[3] Grampurohit, Sneha, et al. "Brain tumor detection using deep learning models." *2020 IEEE India Council International Subsections Conference (INDISCON)*. IEEE, 2020.

[4] Choudhury, Chirodip Lodh, et al. "Brain tumor detection and classification using convolutional neural network and deep neural network." *2020 international conference on computer science, engineering and applications (ICCSEA)*. IEEE, 2020.

[5] Gore, Deipali Vikram, and Vivek Deshpande. "Comparative study of various techniques using deep Learning for brain tumor detection." *2020 International conference for emerging technology (INCET)*. IEEE, 2020.

[6] Lamrani, Driss, Bouchaib Cherradi, Oussama El Gannour, Mohammed Amine Bouqentar, and Lhoussain Bahatti. "Brain tumor detection using mri images and convolutional neural network." International Journal of Advanced Computer Science and Applications 13, no. 7 (2022).

[7] Febrianto, D. C., I. Soesanti, and H. A. Nugroho. "Convolutional neural network for brain tumor detection." In IOP Conference Series: Materials Science and Engineering, vol. 771, no. 1, p. 012031. IOP Publishing, 2020.

[8] Khairandish, Mohammad Omid, R. Gurta, and Meenakshi Sharma. "A hybrid model of faster R-CNN and SVM for tumor detection and classification of MRI brain images." Int. J. Mech. Prod. Eng. Res. Dev 10, no. 3 (2020): 6863-6876.

[9] Dipu, Nadim Mahmud, Sifatul Alam Shohan, and K. M. A. Salam. "Deep learning based brain tumor detection and classification." *2021 International conference on intelligent technologies (CONIT)*. IEEE, 2021.

[10] Dipu, Nadim Mahmud, Sifatul Alam Shohan, and KM A. Salam. "Brain Tumor Detection Using Various Deep Learning Algorithms." *2021 International Conference on Science & Contemporary Technologies (ICSCT)*. IEEE, 2021.

[11] Sravya, V., and S. Malathi. "Survey on brain tumor detection using machine learning and deep learning." *2021 International Conference on Computer Communication and Informatics (ICCCI)*. IEEE, 2021.

[12] Wang, Zijie J., et al. "CNN explainer: learning convolutional neural networks with interactive visualization." *IEEE Transactions on Visualization and Computer Graphics* 27.2 (2020): 1396-1406.

[13] Sun, Yanan, et al. "Automatically designing CNN architectures using the genetic algorithm for image classification." *IEEE transactions on cybernetics* 50.9 (2020): 3840-3854.

[14] Minaee, Shervin, et al. "Image segmentation using deep learning: A survey." *IEEE transactions on pattern analysis and machine intelligence* 44.7 (2021): 3523-3542.

[15] Pan, Haihong, et al. "A new image recognition and classification method combining transfer learning algorithm and mobilenet model for welding defects." *Ieee Access* 8 (2020): 119951-119960.

[16] Hartanto, Cahyo Adhi, and Adi Wibowo. "Development of mobile skin cancer detection using faster R-CNN and MobileNet v2 model." *2020 7th International Conference on Information Technology, Computer, and Electrical Engineering (ICITACEE)*. IEEE, 2020.

[17] Mascarenhas, Sheldon, and Mukul Agarwal. "A comparison between VGG16, VGG19 and ResNet50 architecture frameworks for Image Classification." *2021 International conference on disruptive technologies for multi-disciplinary research and applications (CENTCON)*. Vol. 1. IEEE, 2021.

[18] Foong, Chai C., Goh K. Meng, and Lim L. Tze. "Convolutional neural network based rotten fruit detection using resnet50." *2021 IEEE 12th Control and System Graduate Research Colloquium (ICSGRC)*. IEEE, 2021.

[19] Tong, Wei, et al. "Channel-attention-based DenseNet network for remote sensing image scene classification." *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing* 13 (2020): 4121-4132.

[20] Al Husaini, Mohammed Abdulla Salim, et al. "Automatic breast cancer detection using inception V3 in thermography." *2021 8th International Conference on Computer and Communication Engineering (ICCCE)*. IEEE, 2021.

[21] Rajbongshi, Aditya, et al. "Rose diseases recognition using MobileNet." *2020 4th International Symposium on Multidisciplinary Studies and Innovative Technologies (ISMSIT)*. IEEE, 2020.

[22] Tian, Chunwei, et al. "A heterogeneous group CNN for image super-resolution." *IEEE transactions on neural networks and learning systems* (2022).

[23] Montaha, Sidratul, et al. "Timedistributed-cnn-lstm: A hybrid approach combining cnn and lstm to classify brain tumor on 3d mri scans performing ablation study." *IEEE Access* 10 (2022): 60039-60059.

[24] Duvvuri, Kavya, Harshitha Kanisettypalli, and Sarada Jayan. "Detection of brain tumor using CNN and CNN-SVM." *2022 3rd International Conference for Emerging Technology (INCET)*. IEEE, 2022.

[25] Mishra, Biswaranjan, et al. "A CNN model with activation to classify MRI images for brain tumor." *AIP Conference Proceedings*. Vol. 2981. No. 1. AIP Publishing, 2023.