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Enhancing Brain Tumor Classification: A CNN-Based Approach with InceptionV3 and Xception

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Abstract*: Brain tumors are among the most aggressive and deadly diseases, with a very short life expectancy at the highest grade. To combat this, early detection and treatment are crucial.In this approach, MRI images are used to analyze brain abnormalities. The manual investigation of brain tumor classification is a time-consuming task, and there might be possibilities of human errors. Hence, accurate analysis in a short span of time is essential. This approach presents the automatic brain tumor classification algorithm using a highly accurate Convolutional Neural Network (CNN), InceptionV3 and Xception algorithm for classification of Glioma, Meningioma and No tumor. The brain part is initially segmented by a thresholding approach followed by a morphological operation. The brain MRI is classified using CNN, Inceptionv3, and Xceptionv3 algorithms. The system's performance is evaluated using precision, recall, F1 score, and accuracy parameters***.

Keywords: Brain Tumor, MRI, CNN, Machine Learning.

I. INTRODUCTION

MRI's exceptional spatial resolution and ability to distinguish between soft tissues make it a vital tool in medicine and surgery. Ensuring patient safety during diagnostics is its capability to provide vivid contrasts while avoiding harmful ionizing radiation. Magnetic resonance imaging (MRI) helps radiologists find cancerous tumors. The human eye's sensitivity declines with increasing MRI image processing volumes, which increases the risk of incorrect diagnoses, particularly when dealing with several slices. This highlights the importance of automated systems for the rapid and precise categorization and interpretation of medical images. The diagnostic decisions based on MRI images need accurate feature extraction due to the wide range of possible abnormalities shown in these images. To aid in diagnosis and treatment planning, feature extraction is used in image processing to condense large amounts of input data into a manageable set of essential qualities.

Tumors are abnormal lumps in the brain. Tumors may form due to unchecked cell growth, ineffective cell death, or both. Brain cancer may be either primary or secondary. Cells originating in the original organ or tissue make up primary cancers. It is from brain cells that primary brain cancers develop. Some cancers may metastasize if they develop too quickly. "Malignancy" is often understood to refer to cancer. Secondary cancers develop when cells metastasize from one part of the body to another. The cells that make up secondary brain tumors are cancer cells that have spread to the brain [3]. As the global population rises, cancer has emerged as the leading cause of worry. The diagnosis of brain tumors relies heavily on imaging. Tumors are caused by unchecked cell division. Nomenclature of brain tumors is based on cell type. Different types of brain tumors, both primary and secondary. Tumor cells in their early stages resemble

The original tissue or organ. It is from brain cells that primary brain cancers develop. Rapidly spreading malignant tumors may engulf vast amounts of tissue. Secondary malignancies arise when cells metastasize from another section of the body. Tumors in the brain that originated in another part of the body and metastasized there are known as secondary tumors. Radiologists rely on the images' sharpness to detect cancer in MRI scans. In the radiological reorganization, the multi-parametric imaging profile is king. Radiologists risk making an error while processing large MRI datasets because, as the number of instances increases, the human eye becomes less sensitive to even little slices that may be affected. This highlights the necessity for efficient solutions for the automated interpretation and classification of medical images. To avoid brain injury or death, it is essential to detect and treat brain tumors early. The best course of treatment depends on precise tumor size and location. Brain cancers may be seen and classified using magnetic resonance imaging (MRI). MRI is now a standard medical diagnostics and brain imaging tool in modern hospitals and clinics. There is soft tissue contrast with MRI, and it is non-invasive. Magnitentiography does not employ ionizing radiation. Imaging the brain using MRI is helpful since it is painless, non-invasive, and does not involve radiation.

Numerous programs use classifiers like KNN, SVM, ANN, PNN, and HMM to sort images into categories. There are advantages and disadvantages to every classifier.

II. LITERATURE SURVEY

Brain tumors are becoming a pressing priority for machine learning algorithms because of their significant impact on individuals' lives. Swift and accurate diagnosis is crucial in lowering the mortality rate, which has lately surged to concerning levels. Common technologies like MRI and CT scanning provide high-quality brain pictures from many perspectives, making them extensively used in contemporary medicine. A knowledgeable specialist accurately diagnoses the specific brain tumor. Taking many images is not only tiresome but also time-consuming. Furthermore, errors might result in incorrect treatment or decisions. This led to the creation of many techniques for independently efficient and precise categorization of tumor kinds beyond human understanding. This paper thoroughly examines techniques for detecting and classifying brain tumors. [1]

This study delves into the processing of medical images to categorize the grade of brain tumors using MRI. The study was published in Biomedical Signal Processing and Control in 2018. The article thoroughly summarizes contemporary techniques for assessing medical images derived from magnetic resonance imaging (MRI). The researchers thoroughly examine the methodologies utilized to assess the difficulties of brain tumor grading in this study. This work enhances our comprehension of the current advancements, upcoming paths, and challenges in medical image processing using magnetic resonance imaging (MRI) for classifying brain tumors by consolidating information from diverse sources. [2]

The researchers investigated advanced medical imaging methods to identify and analyze brain tumors to add to the field. The study investigated the intricacies of brain tumor detection with advanced methods and instruments. The group aimed to enhance understanding in the computer science and information security industry by providing a comprehensive overview of their work, using medical imaging methods to improve the analysis and diagnosis of brain tumors. [3]

Brain tumors are a significant health issue affecting both young individuals and those in middle age. Various types of brain tumors exist, such as benign, pituitary, malignant, and others. MRI scans provide extensive data pictures. The radiologist reviews the images, although there is a possibility of errors due to the complexity of tumors. Propose comparing and enhancing accuracy by using several ML and DL algorithms. To establish the appropriate model for tumor classification, assess the accuracy of many models and identify the kind of brain tumor in MRI data. [4]

This study introduces a novel method that utilizes statistical characteristics and machine learning techniques. The preprocessing step involves converting grayscale photos to RGB images and eliminating salt-and-pepper noise with the median filter. This kind of noise is often seen in MRI images. Histogram equalization was used in the preprocessing phase to enhance the quality of individual RGB channels. After evaluating several classification algorithms on these characteristics, it was found that decision trees yielded the most favorable results based on their output. Hence, the decision tree has been reviewed for further analysis. The proposed technique outperformed numerous popular algorithms in terms of simplicity and accuracy. [5]

Brain tumors are clusters of aberrant cells. Human mortality increases as a consequence. Following fusion, noise is eliminated using a partial differential diffusion filter (PDDF). The tumor area is segmented using a global thresholding approach, and a convolutional neural network (CNN) model is used to distinguish between tumor and non-tumor regions. The results show that fused pictures perform better than separate sequences on benchmark datasets. [6]

Uncontrolled cell growth and abnormal brain cell distribution are key characteristics of a brain tumor, which is the most lethal kind of cancer. Deep Learning (DL) neural network technology has made tremendous advancements in aiding the healthcare sector in diagnosing various life-threatening conditions using medical imaging. Learning image identification visually may result in error detection, a task that machine learning is adept at managing. Evaluating the performance of the suggested CNN model using the transfer learning technique. This model surpasses an existing model in performance while using fewer computer resources, being more straightforward, and achieving higher accuracy, all with a very small dataset. [7]

Developing deep 3D convolutional neural network topologies for brain MRI data classification. The effectiveness of simple convolutional neural networks and residual networks trained on the ADNI dataset, which is the most extensive publicly accessible compilation of structural MRIs from healthy persons and those with Alzheimer's disease. Proved that the recommended models provide comparable results to other approaches when used for an MRI classification challenge. Handcrafted feature creation is unnecessary, and the technology is simple, which are its primary benefits. The suggested method, which involves automatically analyzing incoming images for skull stripping and normalization, is expected to be advantageous for quickly predicting any MRI scan. [8]

A convolutional neural network is used with image augmentation techniques to achieve this task. The study's findings demonstrate a high level of accuracy, namely 97.84 percent, after a thorough evaluation of the suggested framework. This study's findings show that the model has excellent generalizability, making it a useful and reliable tool for medical practitioners. This method undoubtedly aids physicians in diagnosing brain tumors with more speed and accuracy. Intended to enhance medical imaging technology to enhance patient care. To accomplish this objective, we will construct 3D networks to analyze diverse medical images and create technologies for real-time detection of brain tumors. [9]

It is uncommon to do a biopsy before definitive brain surgery for categorizing brain tumors. Technological developments in machine learning enable radiologists to assist patients with noninvasive tumor diagnosis. The CNN is a machine learning technique with significant image classification and segmentation potential. Two datasets and two 10-fold cross-validation processes were used to evaluate the network's performance. Using record-wise cross-validation on the improved dataset, the 10-fold cross-validation method yielded the highest accuracy of 96.56%. The newly developed CNN architecture has the potential to serve as a valuable decision-support tool for radiologists in medical diagnostics because of its rapid execution speed and great generalizability. [10]

III. PROPOSED SYSTEM

3.1 Block Diagram of the System

Due to the intricacy and variability of tumors, the work of MRI brain tumor identification is hard. This method involves utilizing a thresholding technique to identify a tumor in a brain MRI scan and then using a convolutional neural network to categorize the scans as either glioma, meningioma, or showing no tumor.

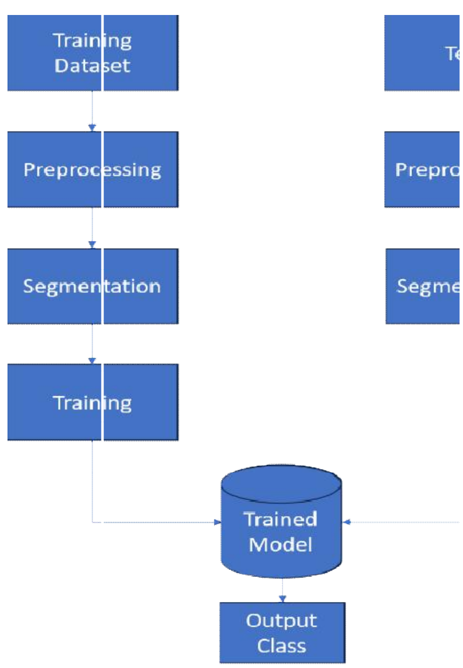

Fig.1 Block Diagram of the System

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Dataset

The clinical MRI database of the brain is used in this method. The database includes gliomas, meningiomas, and tumor MR images. After dividing the data into training and testing sets, the database includes preprocessed raw photos, segmentation, and augmentation techniques.

Preprocessing

Many patient data are written in the database photos, and they are raw and noisy. One thing to keep in mind is that the pictures are in RGB format. The weighted average approach is used to transform the RGB color into grayscale. When dealing with salt and pepper noise, bipolar and unipolar impulses, and other similar types of noise, the median filter works well. This method uses the median filter to eliminate noise early to get to the judgment step confidently. There is also the issue of low contrast in medical imaging. Using power-law transformation helps improve the low-contrast photos. The formula for it is as follows:

$$S = Cr \qquad (3.1)$$

the gamma transformation is named after the variable r, representing the input image's intensities. The range of values is from zero to one. S stands for the produced image's grayscale. C stays the same.

MRI Segmentation and Tumor Identification

The segmentation process is essential to removing the brain from the skull. This method segments the brain using thresholding. The thresholding procedure is used to segment the preprocessed pictures I(x, y) as follows:

$$f_g(x,y) = \begin{cases} 1 & I(x,y) > T \\ 0 & else \end{cases} \qquad (3.2)$$

The binary image $f_g(x,y)$ and the grayscale value of the pixel $I(x,y)$. Assign a value of 1 to a grayscale pixel if its value is higher than the stated threshold; otherwise, set it to 0. After that, a morphological operation, such as erosion or dilation, is again applied to the threshold picture to get the correct form and boundary. This process culminates in convolving the original picture with the binary mask.

The thresholding approach is used to identify the tumor component. We use the weighted average approach to turn the colored MRI picture into a grayscale one. Thresholding with median filtering is used to transform the grayscale picture into binary. Smoother borders are achieved by applying morphological filters, including erosion and dilation, to the binary picture. We go on with tumor identification using the contour approach. After counting the number of binary items using the contour approach, the max area object is treated as a tumor.

Data Augmentation

Data augmentation artificially creates fresh training data from existing data. Using domain-specific approaches to training data examples creates fresh and varied training examples. Image data augmentation, the most common kind, transforms training dataset images into the same class as the original image. Images may be transformed using shifts, flips, zooms, and more.The goal is to add credible instances to the training dataset. This implies that the model may perceive variants of the training set picture. Data augmentation strategies may be tested in isolation and together to evaluate whether they increase model performance, potentially using a tiny prototype dataset, model, and training run.

CNN and other deep learning algorithms can learn visual attributes that are location-invariant. Augmentation may help the model learn transform-invariant properties. This is distinct from data preparation like picture resizing and pixel scaling, which must be done uniformly across all model-interacting datasets.

Training and testing Using CNN, InceptionV3, and XceptionV3.

The explanation of each algorithm is explained below

Convolutional Neural Network (CNN)

Image classification and identification are CNN's strengths. CNNs have many feedforward layers. CNNs employ learnable weights, parameters, and biases for filters, kernels, or neurons. Each filter may introduce non-linearity after convolution. A typical CNN architecture is given in Fig.4. CNN's layers are convolutional, pooling, ReLU, and connected.Image classification and identification are CNN's strengths. CNNs have many feedforward layers. CNNs

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employ learnable weights, parameters, and biases for filters, kernels, or neurons. Each filter may introduce non-linearity after convolution. Fig.2 shows a typical CNN design. CNN uses convolutional, pooling, ReLU, and fully linked layers. Consider the CNN architectural blocks below.

Convolutional Neural Network-based Inception V3 deep learning characterizes images. Inception V3 enhanced the 2014 GoogLeNet model Inception V1. As its name says, Google constructed it. INception v3, released in 2015, has 42 layers and less errors. Let us analyze Inception V3 upgrade optimizations.

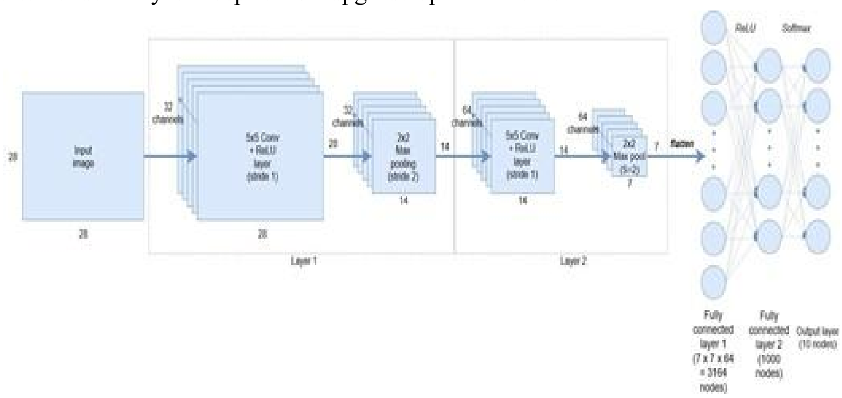

Fig. 2 Architecture of CNN

Inception V3

Convolutional Neural Network-based Inception V3 deep learning characterizes images. Inception V3 enhanced the 2014 GoogLeNet model Inception V1. As its name says, Google constructed it. Inception v3, released in 2015, has 42 layers and less errors. Let us analyze Inception V3 upgrade optimizations.The Inception V3 model underwent considerable improvements, including smaller convolution factorization and asymmetric spatial factorization.

The following steps build an Inception v3 network's architecture:

- Reduces network parameters and computing efficiency using factorized convolutions. It monitors network efficiency.
- Replacement of larger convolutions with smaller ones speeds up training. Instead of 25 parameters, two 3 x 3 filters may replace a 5 x 5 convolution with 18 (3*3 + 3*3) parameters, as shown in Fig.3.

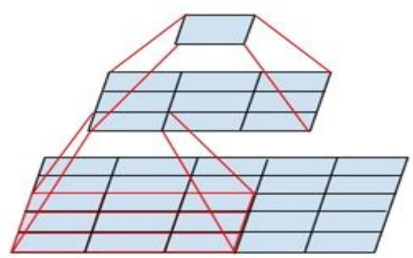

Fig. 3 Process of convolution

The center is a 3x3 convolution, and the bottom is entirely linked. Since both 3x3 convolutions share weights, calculations may be simplified.

- Asymmetric convolutions: Replace a 3x3 convolution with a 1x3 followed by a 3x1 convolution. Using a 2x2 convolution instead of a 3x3 convolution results in slightly more parameters than the suggested asymmetric convolution.
- An auxiliary classifier between training layers increases network loss. GoogleLeNet employed auxiliary classifiers for a deeper network; Inceptionv3 used regularizers. Pooling shrink's grids. We propose a more effective way to overcome computational cost restrictions.The final architecture incorporates all the ideas above.

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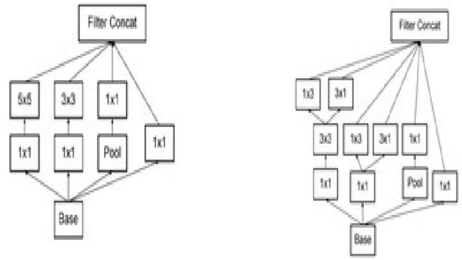

Fig. 4 Asymmetric convolution

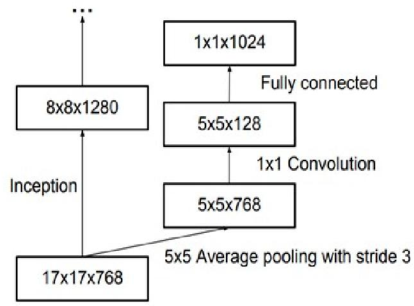

Fig. 5 Auxiliary classifier

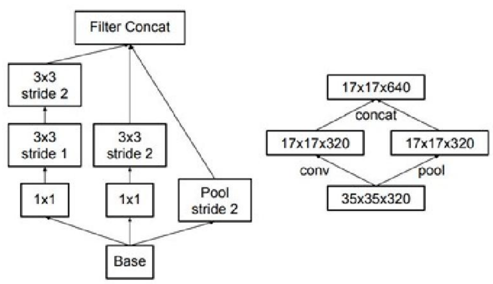

Fig. 6 Grid size reduction

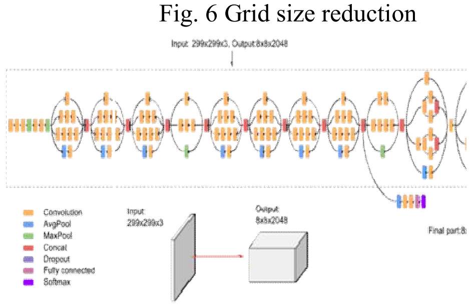

Fig. 7 Overall Architecture of Inception V3 model

Xception

Francois Chollet presented the Xception architecture in 2016 as a deep learning CNN. This variant of the Inception architecture improves CNN performance by addressing their constraints. The Xception architecture replaces CNN convolutional layers with depthwise separable convolutions.

In a typical CNN, a convolutional layer filters the input volume and computes a dot product between filter weights and input values at each spatial point. This procedure needs several calculations, particularly with big input volumes. The Inception design factorized a convolutional layer into 1x1, 3x3, and 5x5 convolutions to simplify calculations and

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capture information at multiple scales. Xception's depthwise separable convolutions break the convolutional layer into two processes. Two stages make up depthwise separable convolutions.

Fig.8 shows the Xception module's three primary pieces. Entry, Middle (eight times), and Exit flows. ReLU activation follows two convolutional layer blocks in the entrance flow. The figure also shows strides, filter size (kernel size), and number of filters.

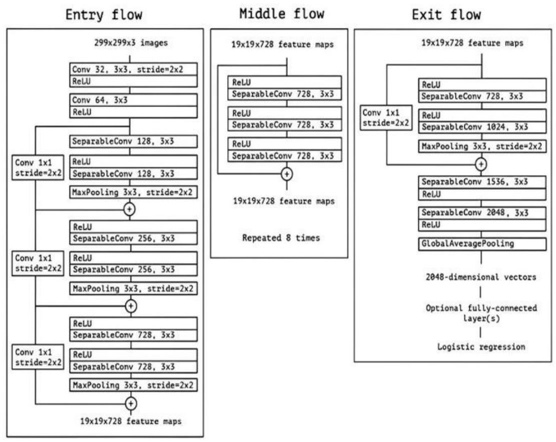


Fig. 8 Overall Architecture of the Xception Model

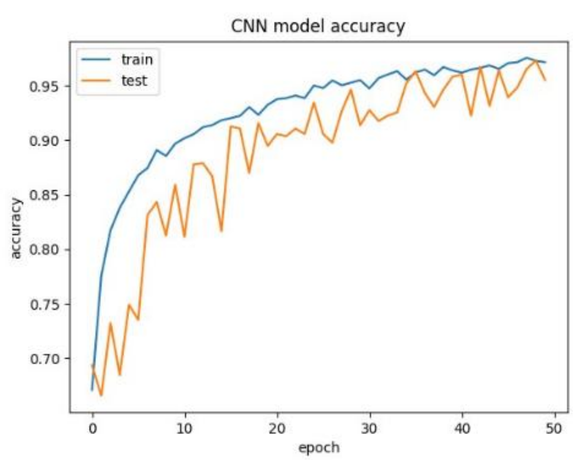
There are also separable convolutional layers. Max Pooling layers exist. When strides vary, they are stated. In skip connections, we utilize 'ADD' to combine two tensors. The input tensor shape of each flow is also shown. The picture size changes from 299x299x3 to 19x19x728 following the entering flow.Fig.8 illustrates the image size, layers, number of filters, filter shape, pooling type, repetitions, and opportunity to add a fully connected layer for the Middle and Exit flows later.

IV. RESULT

This section presents the results and analysis of the proposed system using CNN, Inceptionv3, and the Xception algorithm.

4.1 Analysis of CNN

Fig.9 shows the CNN brain MRI classification training progress graph forthe classification of brain MRI into Glioma, Meningioma, and No-tumor.



(a)

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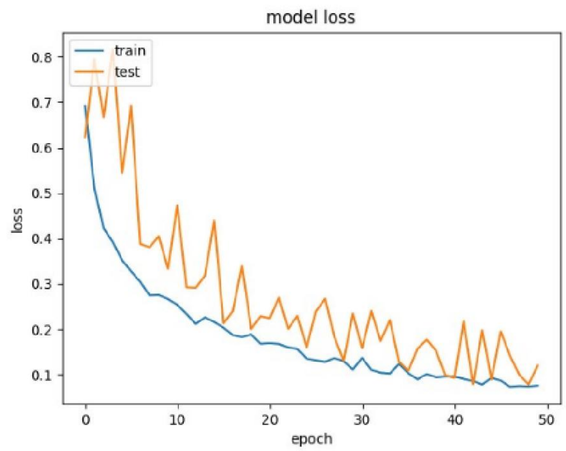
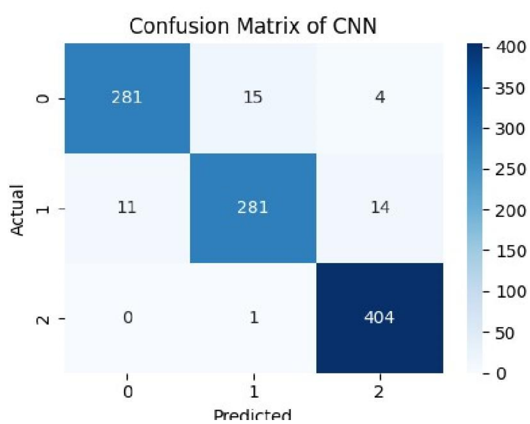


(b)

Classification Report

	precision	recall	f1-score	support
glioma	0.96	0.94	0.95	300
meningioma	0.95	0.92	0.93	306
notumor	0.96	1.00	0.98	405
accuracy			0.96	1011
macro avg	0.96	0.95	0.95	1011
weighted avg	0.96	0.96	0.96	1011

(c)



(d)

Fig.9 CNN algorithm training graph for (a) accuracy,(b)loss, (c)classification report, (d) confusion matrix

The training progress graph indicates that epochs enhance training and validation accuracy. No gap between training and validation accuracy means no overfitting.

A classification model's performance across brain tumor classification classes is assessed in the classification report. Each row in the report corresponds to a specific class, representing different types of brain tumors, including ”glioma tumor,”meningioma tumor,” and ”Pituitary,” along with a class indicating ”no tumor.”Each class's model performance is measured by precision, recall, and F1-score.

The CNN algorithm achieved a precision, recall, F1-score, and accuracy of 0.96,0.96, 0.96 and 0.96.CNN models have shown promising results in brain cancer recognition.

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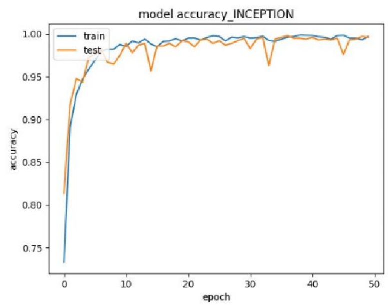
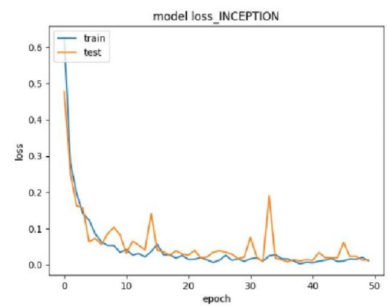
4.2 Analysis of Inception V3

The validation analysis of the Inceptionv3 algorithm forthe classification of brain MRI into Glioma, Meningioma, and No-tumor is shown in Fig.10



(a)



(b)

Classification Report

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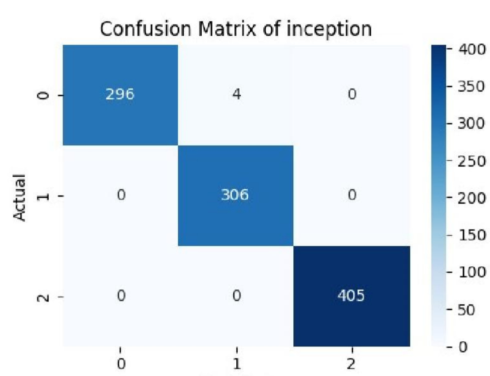
weighted avg	1.00	1.00	1.00	1011

(c)



(d)

Fig. 10 Training progress graph of Inceptionv3 algorithm for (a) accuracy, (b)loss, (c)classification report, (d) confusion matrix

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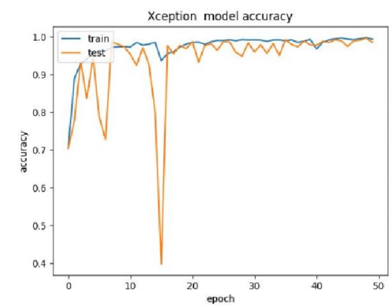
A classification model's success in predicting dataset classes is described in the classification report. The report's rows represent the model's target categories, while the columns measure its accuracy and performance. Effectiveness.

The study defines precision as the model's ratio of genuine positive predictions to total positive predictions. The model's positive predictions for each class have fewer false positives with high accuracy ratings. Recall, or sensitivity, is the fraction of positive predictions that match all positive dataset occurrences.

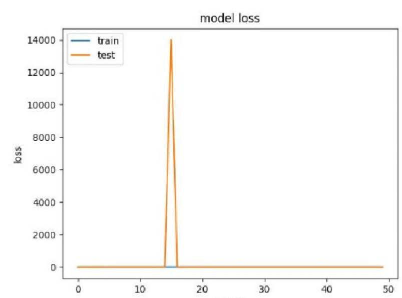
The Inception algorithm achieved a precision, recall, F1-score, and accuracy of 1. Inception models have shown promising results in brain cancer recognition.

4.3 Analysis of Xception V3

Fig. 11 shows the performance of the Xception algorithm for brain MRI classification.



(a)



(b)

Classification Report

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(c)

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(d)

Fig. 10 Training progress graph of Inceptionv3 algorithm for (a) accuracy, (b) loss, (c) classification report, (d) confusion matrix

The classification report assesses an automated brain tumor categorization method across tumor classifications. The report contains precision, recall, and F1-score, which measure the system's tumor classification accuracy. The report also provides the support parameter, which shows the number of each tumor type in the dataset.

The Xception algorithm achieved a precision, recall, F1-score, and accuracy of 0.99,0.99, 0.99 and 0.99. Xception models have shown promising results in brain cancer recognition.

The comparative analysis of the presented CNN, Inception, and Xception algorithms with existing algorithms for the classification of brain MRI into Glioma, meningioma, and No-tumor classification is presented in Table 2 and Fig12.

Table 2: Comparative analysis of the Proposed approach with state-of-the-art methods

Contribution	**Type of classifier**	**Accuracy**
Proposed approach	CNN	0.96
Proposed approach	Inception	0.95
Proposed approach	Xception	0.95
Pashaei et al. [11]	CNN	0.9368
Gumaei et al. [12]	FNN (feedforward neural network)	0.9423

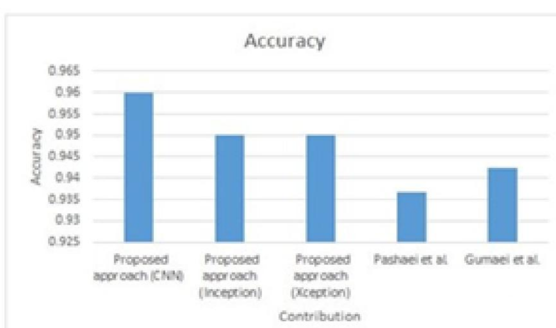

Fig. 12: Comparative analysis of different deep learning algorithms for brain MRI classification

From a comparative analysis of the proposed system with state-of-the-art methods, we observed that the proposed system shows better accuracy than others.

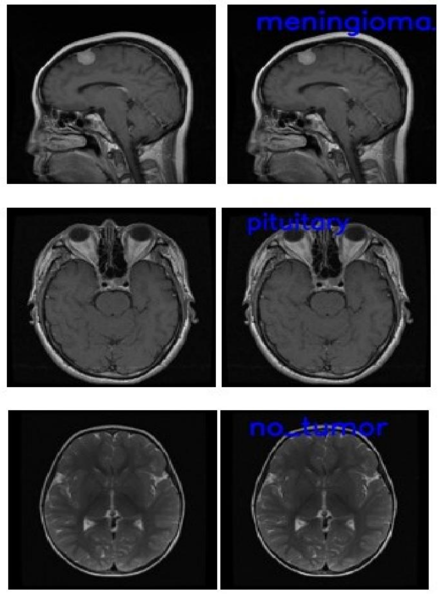

Fig. 13Testing results of the proposed system

V. CONCLUSION AND DISCUSSION

InceptionV3 and Xception CNNs have been used to automate brain tumor classification in medical imaging. The method reduces manual brain MRI image analysis time and errors. The system segments resizes, and normalizes MRI images for CNN models. Pre-trained models like InceptionV3 and Xception can learn complex patterns and characteristics from large datasets, making them suitable for image classification. The automated brain tumor classification system is evaluated by precision, recall, F1 score, and accuracy. This indicates that the technology identifies brain tumors with minimal false positives and negatives. Automatic brain tumor classification speeds diagnosis, minimizes errors, and enhances efficiency. The system's limitations and large annotated datasets for training and ongoing validation and improvement must be addressed.

CNN models predict brain tumors using preprocessed pictures. Categorization depends on prediction thresholds. Professionals diagnose and schedule treatment using classification. The automated brain tumor classification system is also assessed using precision, recall, F1 score, and accuracy. These values show how well the system detects brain tumors with few false positives and negatives. Automatic brain tumor categorization improves efficiency, reduces mistakes, and may speed diagnosis. The system's limitations, such as the need for large annotated datasets for training and constant validation and development, must be acknowledged.

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