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Detection of Brain Tumor using Convolution Neural Network algorithm

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Abstract

Brain tumors, especially in their aggressive forms, significantly reduce life expectancy. This study aims to advance the early identification and classification of brain tumor by utilizing a comprehensive approach encompassing binary classification tumor or no tumor. Employing advanced techniques such as deep learning algorithms, including Convolutional Neural Networks (CNNs) with transfer learning, employing pre-trained models such as the Visual Geometry Group 16-layer network (VGG16) and the 50-layer Residual Network (ResNet50), custom CNN model 8 -layer network.

The appearance of deep learning technologies has markedly advanced the field of medical diagnostics through enhanced medical imaging capabilities, particularly in identifying and diagnosing various diseases. Within this context, the CNNs have evolved as the leading machine learning algorithm for tasks involving visual learning and image recognition. Our study presents a novel CNN framework that is specifically tailored to classify brain cancers using T1-weighted contrast enhanced MRI into 2 categories: tumor, or no tumor. The results show that our CNN model Achieved (97%) accuracy which is approaching one of the best models VGG-16

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(99%), while others score about ResNet-50 (91%), still our model have a good accuracy with minimum computational overhead which is advantages.

Keyword (Brain Tumor, Medical Imaging, Deep Learning, Convolutional Neural Networks (CNNs), VGG16, ResNet50, Custom CNN Model, MRI (Magnetic Resonance Imaging)).

اكتشاف أورام الدماغ باستخدام خوارزمية الشبكات العصبية الالتفافية

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الملخص

تُعد أورام الدماغ، لا سيما في أشكالها العدوانية، من الأمراض التي تؤدي إلى انخفاض كبير في متوسط العمر المتوقع. تهدف هذه الدراسة إلى تحسين الكشف المبكر عن أورام الدماغ وتصنيفها من خلال اعتماد نهج شامل للتصنيف الثنائي، أي وجود ورم أو عدم وجود ورم. وقد تم توظيف تقنيات متقدمة في مجال التعلم العميق، وبالأخص خوارزميات الشبكات العصبية الالتفافية (Convolutional Neural Networks – CNNs) مع استخدام التعلم بالنقل(Transfer Learning) ، وذلك بالاعتماد على نماذج مدربة مسبقًا مثل شبكة **VGG16**ذات الستة عشر طبقة، وشبكة **ResNet50**ذات الخمسين طبقة، بالإضافة إلى تصميم نموذج CNN مخصص يتكون من ثماني طبقات.

أدى ظهور تقنيات التعلم العميق إلى إحداث تطور ملحوظ في مجال التشخيص الطبي من خلال تحسين قدرات تحليل الصور الطبية، لا سيما في الكشف عن الأمراض

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وتشخيصها بدقة عالية. وفي هذا الإطار، برزت الشبكات العصبية الالتفافية باعتبارها من أكثر خوارزميات التعلم الآلي فاعلية في مهام التعلم البصري والتعرف على الصور. تقدم هذه الدراسة إطارًا جديدًا لشبكة CNN تم تصميمه خصيصًا لتصنيف أورام الدماغ باستخدام صور الرنين المغناطيسي المعززة بالصبغة-T1-weighted Contrast) (Enhanced MRIإلى فئتين: وجود ورم أو عدم وجود ورم.

أظهرت النتائج أن النموذج المقترح حقق دقة بلغت **97%**، وهي قريبة من دقة نموذج **VGG16**التي بلغت **99%**، في حين حقق نموذج **ResNet50**دقة تقارب **91%.** وعلى الرغم من ذلك، يتميز النموذج المقترح بكفاءة عالية من حيث الحمل الحسابي المنخفض، مما يجعله خيارًا مناسبًا وفعالًا للتطبيقات العملية في المجال الطبي.

الكلمات المفتاحية: أورام الدماغ، التصوير الطبي، التعلم العميق، الشبكات العصبية الالتفافية(CNNs)، VGG16، ResNet50، نموذج CNN مخصص، التصوير بالرنين المغناطيسي.(MRI)

Introduction

The healthcare industry used to rely solely on the hard work of human laborers and the precision of medical practitioners. The process of diagnosing, recording, and treating patients was a multi-tasking challenge that wholly depended on physical checks, patient's medical history, and laboratory tests like blood work. Oftentimes, the medical professionals made decisions based on their education and experience using their judgment. At first, the computerization of the medical field was characterized by the manual processing of data, limited diagnosis, and a strong dependence on the clinical skill and the professional's experience. The lack of advanced technology not only held back medical treatments but also made them inefficient and prone to errors [1].

Computer-based systems have ultimately been beneficial for the healthcare industry. The transition marked the beginning of modern medicine with the layering of technologies over-practice of simply drafted and recorded decisions. The medical imaging area in particular has undergone a drastic change with the pulling and pushing of the different aspects of diagnosis and treatment, often involving the fusion of the most complex and richest areas of image

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processing. For instance, tumor detection or cancer diagnosis are some areas of research that are widely explored. The International Agency for Research on Cancer (IARC) estimates that there are over 1,000,000 new cases of brain tumor diagnosis each year globally with the death rate still increasing. Brain tumors are among the most lethal cancers, especially affecting infants and the age group of over 34 years [2].

In the past, tumor diagnoses involved painful procedures for patients. Today, non-invasive techniques like CT scans (Computed Tomography) and MRI (Magnetic Resonance Imaging) are commonly used to detect abnormalities in the body. MRI-based clinical analyses of brain tumors have recently gained attention, requiring advanced computer hardware for image comparison and visualization. Automated detection of brain tumors from MRI images is now playing a vital role in reducing the need for manually processing large amounts of data, improving both accuracy and efficiency in diagnosis [2].

Tumor diagnosis in those days meant also making the patients go through some hard and painful procedures.

Brain tumor is a consequence of the excessive growth of abnormal cells in the brain. Brain tumors are divided into several types, which can be either non-cancerous, malignant, or carcinogenic. Malignant tumors are subdivided into two groups: primary tumors that arise from the brain and secondary tumors called brain metastases, which are spread from other body parts [3].

Types of brain tumors

1. Benign Tumor

Brain tumors are usually grouped as a bunch of cells that do not adhere to the normal division and growth rules thus, becoming invisible microscopic cells that do not look like cancer [4].

The following are the features of a benign tumor:

• Most benign tumors appear in brain computerized tomography (CT) or magnetic resonance imaging (MRI) scans.

• They are characterized by slow growth, no invasion of adjacent tissue or metastasis to distant tissues, and sometimes they can be identified on the CT scan due to their visible borders or boundaries.

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• They can be life-threatening due to their location; thus, the term "benign" can be misleading since they can block brain tissue and other structures in the skull.

2. Malignant Tumor

Malignant brain tumors comprise cancerous tumors and very often lack distinct boundaries. They are regarded as fatal because of their rapid invasiveness and the consequent devastation of the surrounding brain tissue [5].

Their signs include the following of a malignant tumor:

- Cancer that is characterized by rapid growth and spread to other parts of the brain and spinal cord.
- Malignant brain tumors are classified as grade 3 or 4, while grade 1 or 2 tumors are usually termed benign or non-cancerous.
- Usually this is serious and often life threatening. Figure 1 shows the tumor types Benign Tumor and Malignant Tumor.

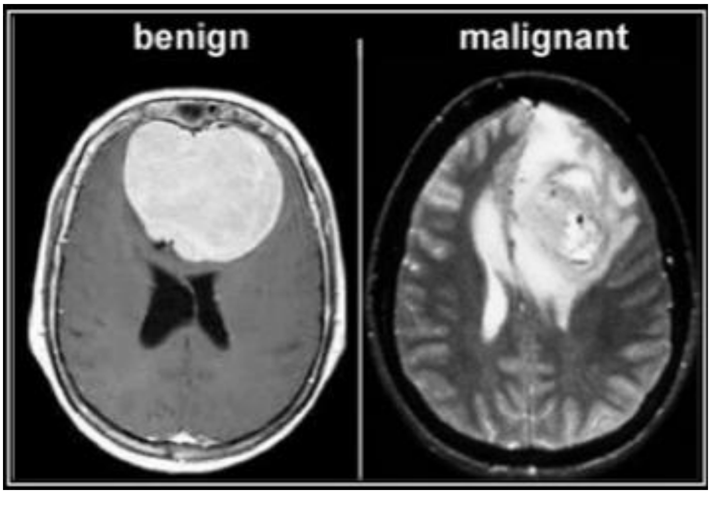

Figure 1 Benign Tumor (left) and Malignant Tumor (Right) [6]

Medical Image

Medical imaging is a technique that makes it possible to see the human body or specific organs, tissues, and so forth (or a little

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part of it) for the purposes of clinical diagnosis, treatment, and monitoring of diseases. Radiography, nuclear medicine, and optical imaging are some of the methods involved. All these processes to a significant extent; even image-guided intervention has been deemed as one of the various techniques belonging to the same concept.

1. Computed Tomography (CT)

The creation of computed tomography or CT (which is the term commonly used now) opened the door to two-dimensional medical imaging before the surgical axial tomography which had been a lengthy process and could yield body images in cross-section with very clear detail. In addition, it was compared with a process of cutting bread since one could actually get the layers of the body that were mainly given by the exposure of the area to x-rays from different angles. This great innovation of Sir Godfrey Hounsfield and Allan Cormack in the 1950s is considered the foundation of the current medical imaging technology. CT scanning has become the most common method of patient diagnosis and treatment selection and even conducting operations. Consequently, the scans are highly demanded in these situations especially in accidents, infections, and heart diseases.

2. Magnetic Resonance Imaging (MRI)

The term "MRI" stands for "Magnetic Resonance Imaging" and it was a landmark step in the evolution of medical imaging which commenced and lasted until 1969 when it was first publicly demonstrated. MRI is based on the physical laws; it is a non-invasive, magnetic field, and radio wave technique that generates high-resolution images of the human body.

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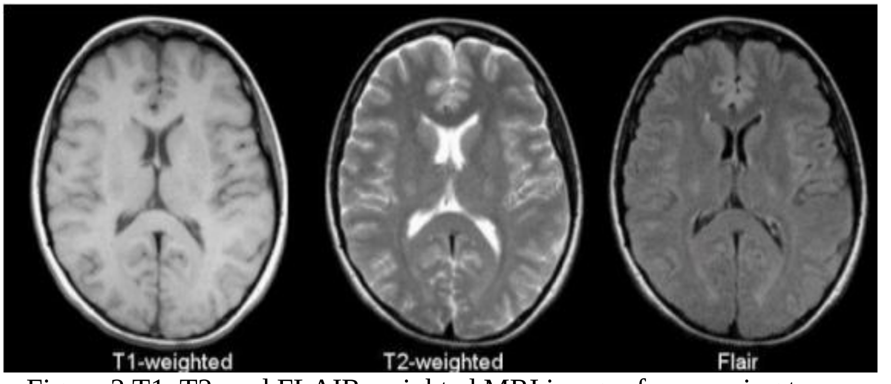

Figure 2 T1, T2, and FLAIR weighted MRI images for mapping tumor-induced change [7]

Back ground and Related Work

Convolutional neural network (CNN) is one of the main approaches built upon deep learning. It inputs an image as a whole and sorts out the contents of the image depending on the assigned relevance through weights and biases, which it applies accordingly. However, a CNN applied in a model will require much less pre-processing than the other techniques for classification. Antique methods used to manually create filters. CNN learns them along with properties if there is enough training provided. The neurons' interconnections in the human brain can be likened to a CNN setup. By filtering the picture, the CNN determines the temporal and spatial relationships between elements in the image [8].

The aforementioned CNN structure proves to be more beneficial when dealing with pictures due to the reduction of parameters and easing of weight utilization. As a result, the network can even more so grasp the intricacy of the image during the training phase. The convolutional operation is intended to reveal the most sophisticated features such as edges from the original image. To put it differently, the very first CNN layer is responsible for detecting the most basic features such as edges, color, and the degree of exposure of the gray area. The successive layers are then prepared to obtain features of higher abstraction since the architecture is now in a state of processing the images in a way that knows exactly the dataset. The human brain is such a comprehensive network that it can receive the same images and produce the same understanding as the dataset [10]. The convolution function leads to either a reduction or an increase in the dimensionality of the points being convolved as compared to the input. The reduction is achieved through the application of Valid Padding while the increase or no change at all is executed through Same Padding. Figure 3 illustrates An Example of CNN architecture.

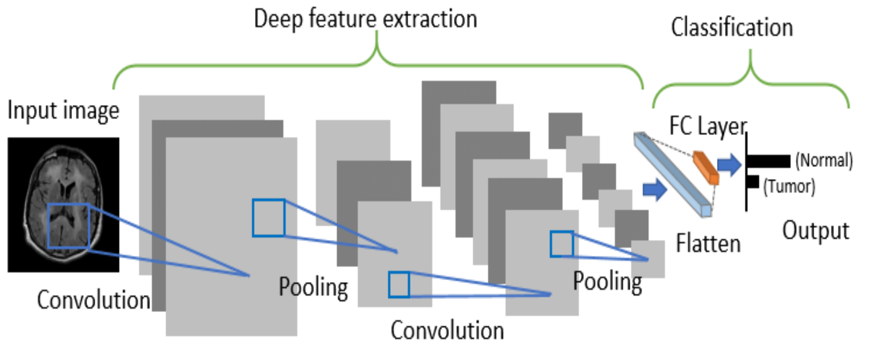

Figure 3 An Example of CNN architecture [8]

The pooling layer, akin to the convolutional layer, performed the same function by reducing the spatial extent of the convolved feature. By reducing the number of dimensions, the pooling layer also lessened the requirement for the computer to process the data again therefore conserving energy and time. It transmits only the most pronounced features, which are rotation and position invariant, thus the training of the model is backed up. There are two main types of pooling, one is average pooling and the other is max pooling. The first operation is max pooling and it gives the maximum value from the part of the image occupied by the kernel. Then, it is the turn of average pooling which calculates the average of all the operations from the image part whose area is covered by the kernel. Moreover, max pooling does an excellent job of getting rid of the noise in the signal. The noisy activation is cut off, and the signal is allowed to go through the dimensionality reduction. In contrast, average pooling dims the signal in an identical way to that of a noise suppression method. Hence, we can conclude that max pooling is better than the average pooling. The Pooling Layer and the Convolutional Layer are the i-th layers of a CNN algorithm. Depending on the image complexity it is sometimes possible to stack up more layers of the same type to gain even more low-level

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details, though it would come at the expense of demanding more resources for processing. Eventually, the output is flattened and presented to a traditional neural network for classification. It is a usual practice to insert a fully-connected layer which facilitates the learning of non-linear combinations of the high-placed features as illustrated by the output of the convolutional layer. The Fully-Connected layer is training a potentially non-linear function in such space [9].
The input image was reshaped and then it was turned into a

1. The VGG-16 Model

Convolutional Neural Networks (CNNs) are among the most significant breakthroughs in deep learning, and their primary benefit is the capability to automatically extract and classify features directly from the input images. This has lessened the preprocessing effort required for CNNs in contrast to other classification methods, which has in turn led to quicker model training. VGG-16 is one of the major applications of this type of architecture, which consists solely of sixteen convolutional layers—indeed, a very deep architecture [11].

The depth of the model is a double-edged sword; on the one hand, it leads to a more robust model, while on the other hand, it results in longer training times since the data has to go through many layers and the processing is thorough. The VGG-16 model, to be precise, has been superb in how it groups the images into various classes from object detection to recognizing tumors' presence or absence in medical images. Besides creating the model, the researchers have evaluated the VGG-16 model on the ImageNet database and obtained a top-5 accuracy score of 92.7%, which is regarded as a landmark achievement [11]. In the area of tumor detection, the VGG-16 model is applied to classify MRI scans as either containing a tumor or not, which showcases the model's power in medical image analysis and its field of application.

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2. The ResNet50 Model

The ResNet50 model, which is a version of the Residual Network architecture, is a significant milestone in deep learning, and it was developed by Microsoft in 2015 [9]. The model is referred to as ResNet50 due to the fact that it consists of fifty layers and almost twenty-six million parameters which the model is trained on. In addition to this, the designers of ResNet50 have taken different routes to address the concerns in Residual Network is its use of residual learning, where the network focuses on learning the residuals or differences between the input and output features, rather than the features themselves. This is achieved through the implementation of skip connections, which directly link the input of an n the layer to the (n + x) th layer

Related Work

They have proposed a new convolutional neural network (CNN) architecture for the automatic detection of brain tumors in magnetic resonance imaging (MRI) images in [14]. The model is deep CNN, problem-based one, which has been trained from the beginning on 3,394 MRI images belonging to 4 different classes-glioma, meningioma, pituitary, and no tumor. After preprocessing steps, the proposed model was found to provide better results than other very popular deep CNN models like VGG16, VGG19, and a hybrid CNN-SVM approach concerning accuracy, sensitivity, and specificity. The proposed model demonstrated impressive performance, bestowing ROC (AUROC) values of 0.990 to glioma, 0.988 to meningioma, 0.967 to pituitary, and 0.974 to normal class.
In [15] they have proposed the improved YOLOv7 model which is capable of accurately detecting three types of brain tumors (meningioma, glioma, and pituitary) in MRI images. Model was optimized by using Convolutional Block Attention Module (CBAM), which combines channel and spatial attention mechanisms, as its core and thus captures both global and local contextual information. The proposed model was proved to get very high precision (99.5%), recall (99.3%), sensitivity (99.3%), specificity (99.4%), accuracy (99.5%), and F1-score (99.4%) on 613 MRI images dataset.
In [16] a deep convolutional neural network (CNN) architecture was presented for accurate tumor detection using MRI data lumbar.

Their proposed "23-layers CNN" excelled, with the Fig share dataset being 97.8% overall accuracy detection which contains 3,064 MRI slices of 233 patients diagnosed with meningioma, glioma, and pituitary cancer. Besides comparing the performance of the proposed "23-layers CNN" with a fine-tuned VGG16 model, the authors concluded that the custom CNN architecture outperform This paper presents a comprehensive study on brain tumor detection using Transfer learning VGG16, ResNet50, and a custom CNN model. By leveraging the well-established VGG16 model for its robust feature extraction capabilities and the ResNet50 model for its effective handling of deep network training through residual learning, the research evaluates their performance on brain tumor datasets. Additionally, the custom CNN model is developed to address specific limitations observed in standard models, offering a tailored approach with specialized layers and parameters optimized for tumor detection. The goal of this thesis lies in its comparative analysis of these models, highlighting their strengths and weaknesses, and providing insights into how advanced neural network architectures can enhance the accuracy and reliability of automated brain tumor diagnosis, ultimately aiming to improve diagnostic practices and patient outcomes.

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Methodology

If one wants to live a long and healthy life, it is very important to have a good knowledge of brain tumors and their types. The "Materials and Methods" part discusses all the steps taken in data gathering and processing that relate to deep learning and cognitive brain research. Among other things, this section explains how MRI images were collected and prepared for the study, including data augmentation and preprocessing. Moreover, it discusses the different algorithms and techniques that were used for data analysis, such as convolutional neural networks and feature extraction. An important point brought up by this section is the need for a large and varied dataset for effective training and validation of the models. Figure 4 depicts the proposed method's workflow, which illustrates the sequence of activities from data acquisition to model evaluation and deployment.

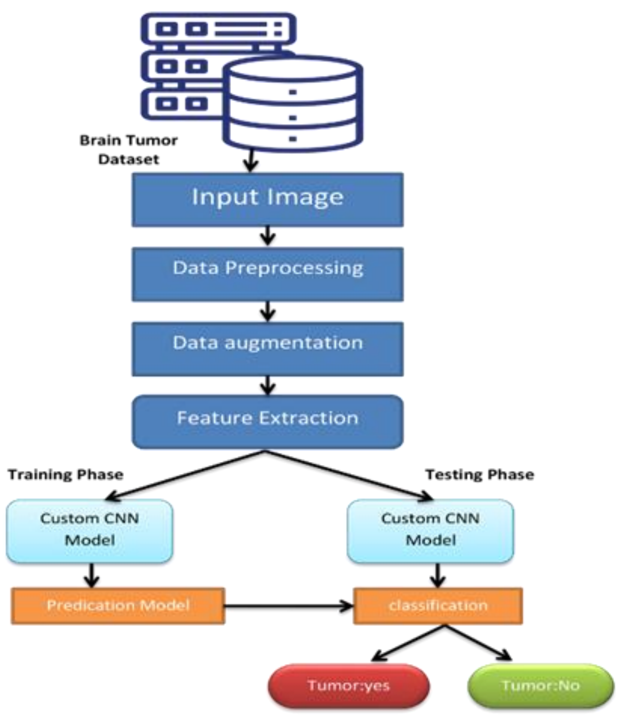

Figure 4 The workflow of the proposed method

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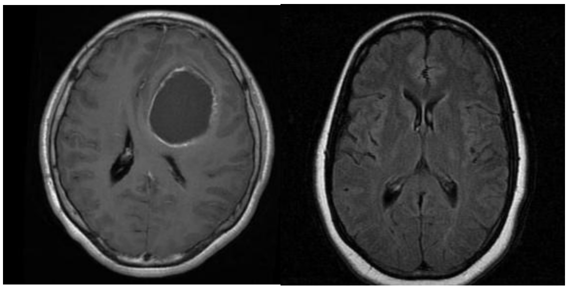
1. Data Collection

Data set formation has always been the most significant factor concerning the improvement of a deep learning model and the generation of an Android application for tooth decay detection. One such aspect was the truth labels made available for T1-weighted, T2-weighted, and FLAIR MRI images of brain tumors, among others. DATASET DETAILS The entire dataset counts 902.5 MB. Dataset images of a Normal Brain (left side) and a Brain with Tumor (right side) are shown in Figure 5.



Normal Brain (left) and Brain with Tumor (right)5Figure

2.Data Preprocessing

The most critical factor that influences the performance of deep-learning models and the site is data quality. Various preprocessing methods were implemented so that they covered the entire pipeline for MRI detection in the specific preprocessing stage. The very first images that the model receives are RGB images with three color channels. Then, input shape is determined as (224, 224, 3).

3.Data augmentation

This technique is considered the one that significantly increases the training set by the generation of new data from the existing data. The process is accomplished by applying various transformations that allow the new data, though altered to some degree, to be recognized as very close to the original data. It has indeed been used

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in workout videos for the purpose of making one's body strong and fit. Thus, the following operations were applied: rotation, resizing and height processing, cropping of heights, zooming, and flipping.

4. Data Splitting

The data was separated into three parts: training, validation, and testing. The training set was intended for neural network modeling, while the validation set was responsible for supervision and hyperparameter tuning during the training period. Finally, the testing set was employed to assess the model's performance as well as that of the website.

5. Custom CNN Model Building

A CNN model was custom-built from scratch and subsequently, the dataset was employed for its training. For 30 epochs, the training occurred with the test dataset being the one that decided the accuracy. Our experiment was carried out on Kaggle and we utilized TensorFlow and Keras as the primary Python libraries for a cumulative training time of about three hours across all models. Moreover, the same pre-processed dataset was used for the training of the existing models, ResNet50, VGG-16, and a custom model.

Layers, Activation Function and Optimizers

he Convolutional Neural Network (CNN) model entails various critical layers and functions. The Conv2D layer is responsible for the feature extraction of the local regions in the image, whereas the MaxPooling2D layer minimizes the spatial dimensions and also by selecting the maximum pixel values prevents overfitting.

The Dense (fully connected) layer acts as a classifier and connects all neurons at once.

GlobalAveragePooling2D facilitates the reduction of dimensions through the averaging of the feature maps.

Among the activation functions, ReLU f(x)=max (0, x) brings in non-linearity and speed of convergence while Sigmoid f(x)=1/(1+e-x) gives outputs for classification in the form of probabilities between 0 and 1.

The Categorical Cross-Entropy loss function is responsible for quantifying the difference between the actual and the predicted class distributions. The optimizer Adam, at last, is the one who updates

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weights in a very effective way thanks to the application of adaptive learning rates and momentum, thus allowing the model to converge faster and more stably.

The **Dense** (fully connected) layer serves as the classifier, linking all neurons together.

GlobalAveragePooling2D further reduces dimensions by averaging feature maps.

Activation functions such as **ReLU $f(x)=\max(0, x)$** introduces non-linearity and accelerate convergence, whereas **Sigmoid $f(x)=1/(1+e^{-x})$** outputs probabilities between 0 and 1 for classification tasks.

The **Categorical Cross-Entropy** loss function measures the difference between true and predicted class distributions. Finally, the **Adam optimizer** efficiently updates weights using adaptive learning rates and momentum, ensuring faster and more stable convergence.

1. Structure of proposed Custom CNN model

To build a CNN, six indispensable operations must be carried out: convolution, fully connected layers, pooling, Global Average Pooling 2D, ReLU, and Sigmoid function. During the filtering operation at the convolution stage, the input image is examined for potential characteristics. ReLU acts to retain the positive values and switch the negatives to zero thus speeding up the training process. Pooling, by down sampling, cuts down the parameter count and sharpens the result. A number of layers are applied to these processes in a manner that each one can detect more and more specific characteristics. The arrays are then squeezed to provide a linear vector which is accessible to the fully connected layers. The fully connected layers take along the features of the convolutional ones. The final decision of the classification is then made using the Sigmoid function.

2. Proposed Custom CNN model architecture

Proposed Custom CNN Model Architecture In this thesis work, a CNN model intended for MRI image analysis has been proposed and described. The model receives enhanced data of size 224x224 with 32 batch sizes and RGB color channels as input. The first layer of the model consists of a convolutional layer having 16 filters and a kernel size of 3×3, which is specifically designed to capture the brain MRI images' lines, corners, and edges. Subsequently, the

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addition of a max-pooling layer with a kernel of 2×2 brings in a lower perspective of the image. Then, the model is escalated to a higher level of recognition of larger patterns by increasing the number of convolutional layers and filters to 32, 64, 128, and 512 while using a 3×3 kernel for all the conv layers. The max-pooling layers are also included in each convolutional layer to get the best results. Finally, the fully connected dense layer with 1024, 512 neurons and a sigmoid output layer gives the probability score for each class which helps in classifying, tumor or no tumor.
The architecture of the proposed CNN model is depicted in
Figure 6

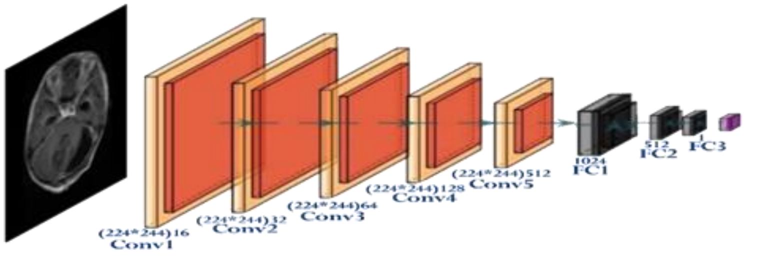

Figure 6 shows the suggested CNN model's design

Hyperparameter	Value/Description
Image rescale	1./255
rotation range	20 degrees
Width shift range	0.2(20% of image width)
Height shift range	0.2 (20% of image height)
range Shear	0.2 (20% shear angle)
Zoom range	0.2(20% zoom)
flip Horizontal	True (random horizontal or vertical)
Fill Mode	"nearest" (file pixels that are newly created)
Input Image Size	(244,244)

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Batch Size	32
Optimizer	Adam
Loss function	Binary Cross entropy
Metrics	Accuracy
Learning rate	Default value as per Adam optimizer
Epochs	30
Model Architecture	Custom CNN with layers including Conv2D, MaxPooling2D,Dense,andGlobalAveragePooling2D layers
Activation function	ReLU for hidden layers, Sigmoid for output layer

Proposed Custom CNN model Hyperparameter

To get the most out of the deep learning models in terms of performance, different data augmentation methods were used. The application of these methods increased the model's robustness and generalization since it was trained on a large variety of image variations, which were, to a certain extent, quite different from one another.

The present research applies a custom CNN (Convolutional Neural Network) model that is thoroughly layered to ensure the extraction of strong features and the classification of brain tumors. The total number of parameters in the model is 1,738,401, which are derived from the weights and biases of the different layers and therefore, it indicates a proper blend of complexity and efficiency to learn and predict brain tumor presence from MRI images accurately.

Training of Proposed Custom CNN Model

In order to transform the data, the CNN model will be adapted and exposed to a number of epochs or repetitions. Timing just means a way of getting the best performance in model training. Thus, it would be quite the opposite if there was a lot of lifting or extended timing as the error of the training data would be very low. On the other hand, if the training data is very large, the model may get confused and produce wrong predictions while going through it. It can be said that the validation error is an indicator for the system being overwhelmed. Setting a limit on the number of epochs and stopping the training when the error rate is checked may be one of the ways. Usually, the same time is allocated to all the training runs. The submitted dataset version is the final one. Getting there takes a long time. The number of model iterations is restricted to 30 because larger numbers can lead to a decreasing learning rate. Between epochs 17 and 21 there was a small decrease in model validation but that could be a positive sign. Furthermore, if the model is evaluated with the overfitted data, it loses its strength. So, the model loses its precision as the breadth is restricted. For this reason, it is vital to monitor sample loss constantly and to appraise the accuracy of the displayed results after each run. The parameters for which the statistics are prepared and the results and analysis obtained from the graphs are correct, training loss, validation, and validation loss. The whole process took about an hour for the model to be submitted on Kaggle and run through all training scenarios. It means that the model is ready for testing on new data and its performance can be assessed through the model's accuracy and prediction scores. In addition, weights are saved automatically.

System Development

User Interface (Frontend) and Backend Server

The User Interface (Frontend) of the brain tumor detection system has been created using HTML, CSS, and JavaScript which makes the system simple and responsive. It lets the users upload MRI images, see prediction results, and interact with the system in a clean and user-friendly interface that adjusts to different screen sizes. The Backend Server which is built using Flask, takes care of the image uploads, preprocessing, and communicating with the trained CNN model. The uploaded images are resized and normalized and then they go to the model for inference. Flask takes care of the user requests in a timely manner and integrates perfectly with the Python-based libraries for image classification and tumor diagnosis.

Deep learning Model

The web application has a deep Learning Model that is a custom CNN model which is capable of detecting brain tumors with a high degree of accuracy and loaded and used for inference. This model

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can be in the form of .h5 (for Keras) and it has to be integrated with the backend server. The training of the model is based on the latest deep learning techniques and it has a large MRI dataset which also means that the model can easily tell the difference between tumor-related and normal areas of the image. The application can analyze and categorize new MRI images that are based on the already learned patterns through this pre-trained CNN. The model's structure, commonly characterized by convolutional and pooling operation layers followed by dense layers, permits to acquire and classify features efficiently, thus delivering dependable tumor detection results which are essential for precise diagnosis.

Dataset

The dataset was at the forefront of the whole application for brain tumor classification since inception. Along with this, it consists of the global collection of the largest brain MRI images in the world which have T1-weighted, T2-weighted, and FLAIR modalities included. The total amount of uncompressed images is 902.5 MB, and all of them can be accessed at Kaggle. After this, the dataset was split into two equal parts for training and testing, respectively, of the CNN (Convolutional Neural Network) model. The dataset underwent a pre-processing step which hardened and made it more diverse by applying normalization and augmentation techniques. As a result, the model got trained not only for generalization but also for being powerful in tumor detection.

GUI of Detecting brain tumor

The tumor detection application can be presented with a web-based GUI (Graphical User Interface) which is made up of HTML, CSS, and JavaScript. CSS adds the visual appeal while HTML provides the basic arrangement of the site. This not only allows for interaction but also enhances the site’s friendliness to the user. Subsequently, JavaScript comes in for a more dynamic and interactive content updating of the website. At the upper page section, there is a top navigation bar that links to the Home, About, Services, and Contact pages. The proposed website GUI is depicted in Figure 7.
What the user comes to see first when he/she steps into the home page is the "Choose File" button. The "Choose File" button is the one that has been very tactically and graciously placed up there and

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is invitingly posted for the user to click on it. What follows next is that the file selection dialog box will sh. Figure 8 ,9shows Image upload process.

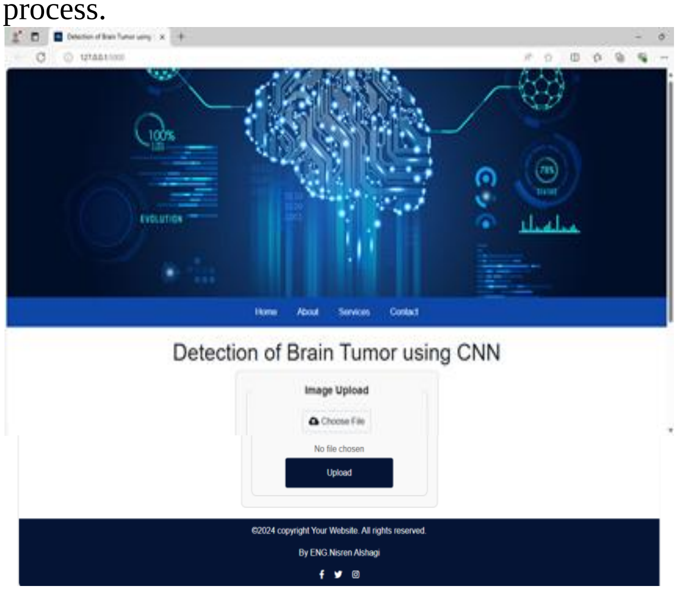

Figure 7 GUI for the proposed website

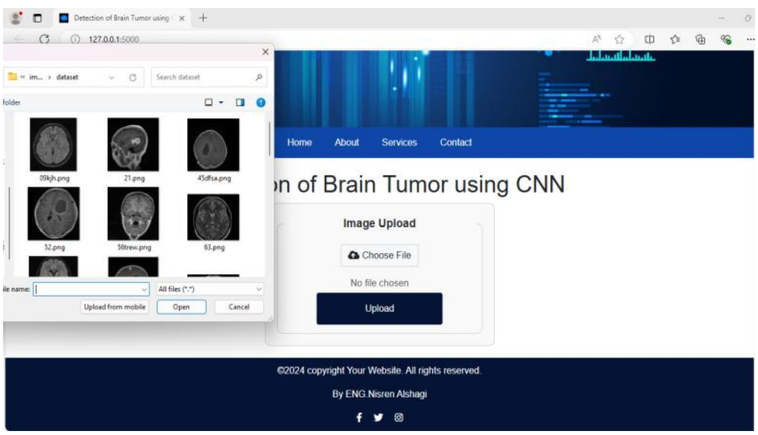

Figure 8 GUI Image upload process

Clicking the upload button opens a new page displaying the uploaded image along with its tumor prediction and inference time. Figure 9 shows GUI Result detection of image.

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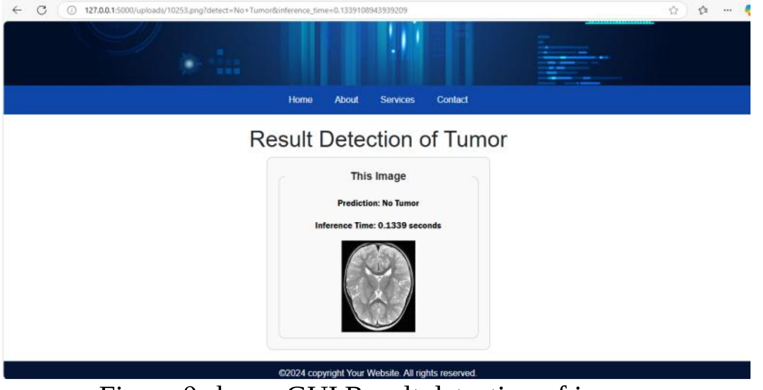

Figure 9 shows GUI Result detection of image.

Model Performance

Based on the specified criteria of input data size, model complexity, accuracy, model loss, accuracy graph, and confusion matrix, three deep learning models underwent evaluation to identify and binary classification brain Tumor. The experiments were conducted utilizing the Python programming language on a Kaggle by using 1000GPU. The parameters and number of convolutional layers for each model are detailed in Table 1. Comparative analysis revealed that the suggested CNN model boasts the fewest layers and network parameters among the pre-trained models considered. Notably, the ResNet50 model stands out with 73times more network parameters and three times greater depth compared to the suggested model. While the architectures of the custom CNN model align closely with that of VGG-16 model, they exhibit VGG-16 model greater depth and number of layers. Despite this, the suggested CNN model maintains lower complexity in terms of parameter count relative to other pre-trained models.

Comparing the suggested CNN model with models that have already been trained

The suggested CNN model was compared in two ways to other pre-trained models, namely,

1. The accuracy, validation accuracy and loss, validation loss of the model graph
2. confusion matrix
3. Inference time

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4. Number of total parameters

The Accuracy and Loss of the Model Graph

The loss and accuracy graphs for all the pre-trained models used in this experiment have been plotted using the Matplotlib library. Each graph represents the performance of the respective model over 30 epochs. Figure 10 show illustrates a comparison of model loss and validation loss between the proposed CNN model, VGG-16, and ResNet50. Additionally, a comparison of model accuracy and validation accuracy for the proposed CNN model, ResNet50, and VGG-16 is also presented in this experiment.

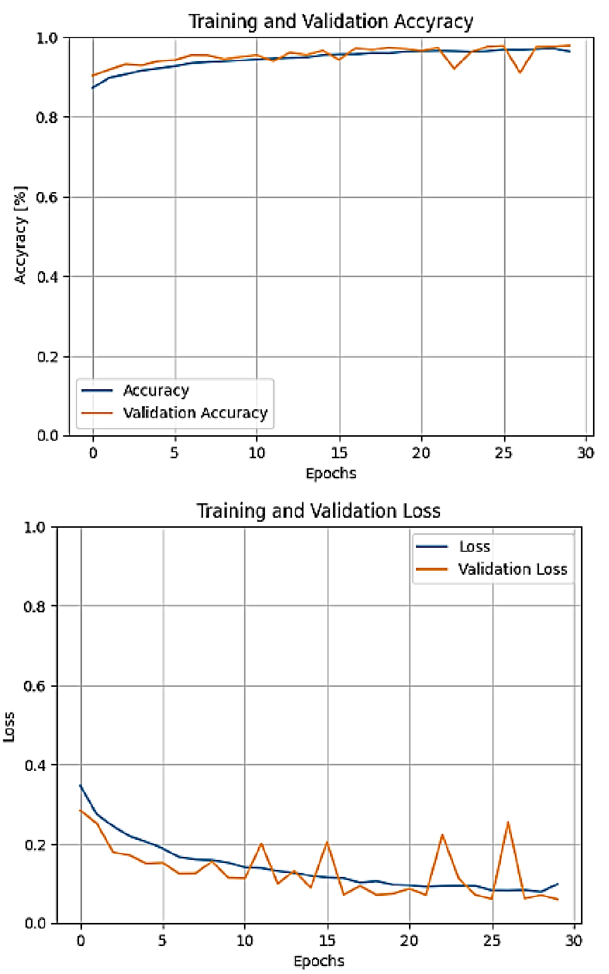

Figure 10 shows the comparison graph between proposed CNN (validation accuracy-validation loss)

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The accuracy increases with a reduced loss function. In the beginning, epochs proposed CNN model's loss function is high than VGG16, but when it trains through more epochs, the loss function decreases enormously than ResNet50 model. After running it for 30 epochs, 0.0279 loss function has been achieved for the proposed model Figure11 show comparison graph between ResNet50 (validation accuracy-validation loss).

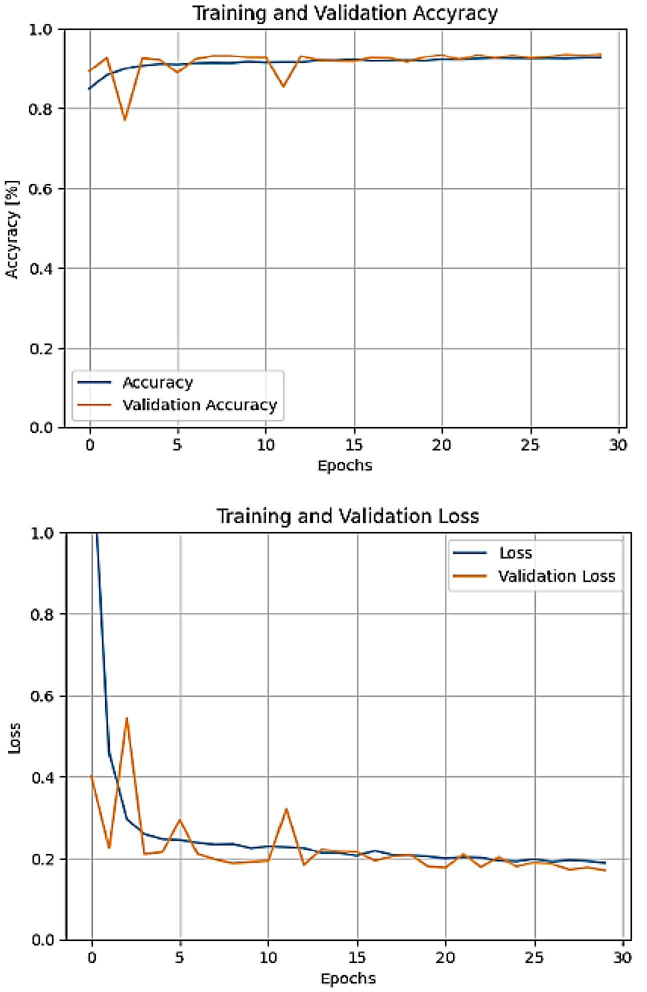

Figure 11shows the comparison graph between ResNet50 (validation accuracy-validation loss)

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The accuracy increases with a reduced loss function. In the beginning, epochs proposed CNN model's loss function is high than VGG16, but when it trains through more epochs, the loss function decreases enormously than ResNet50 model. After running it for 30 epochs, 0.1802 loss function has been achieved ResNet50 model.

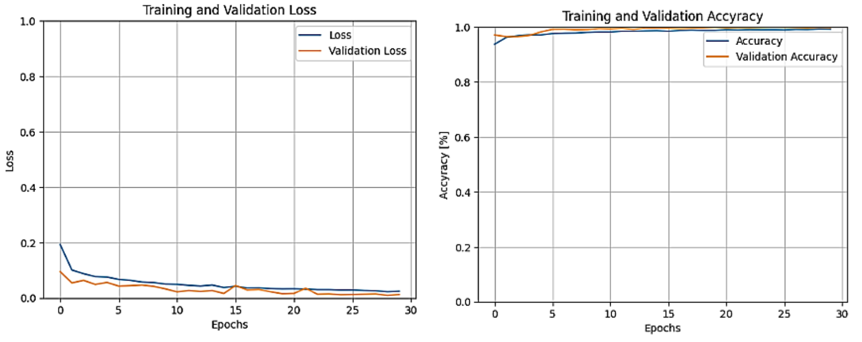
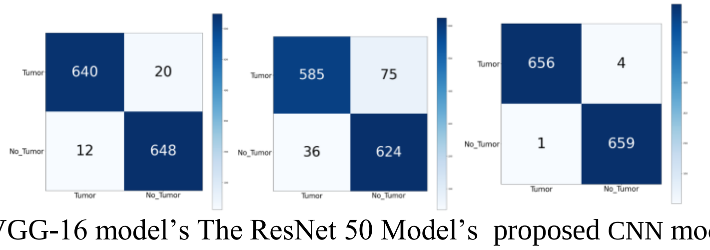


Figure 12shows the comparison graph between VGG16 (validation accuracy-validation loss)

The correlation between the loss function and the model's accuracy was at a very high level, which implied that the loss function decreasing was equal to the accuracy increasing. The VGG16 model was the first to be singled out with lossy function among all the other models and this became especially evident during the first training phase where the loss function had a wider range for these epochs. Presenting the training through epochs, the VGG16 loss decreased significantly more compared to others but still had the highest range at the beginning. After a 30-epoch training, the loss function of VGG16 was 0.0279 which is illustrated by the graph, show figures

Transfer Learning Models Confusion Matrix



The VGG-16 model's The ResNet 50 Model's proposed CNN model's Confusion Matrix

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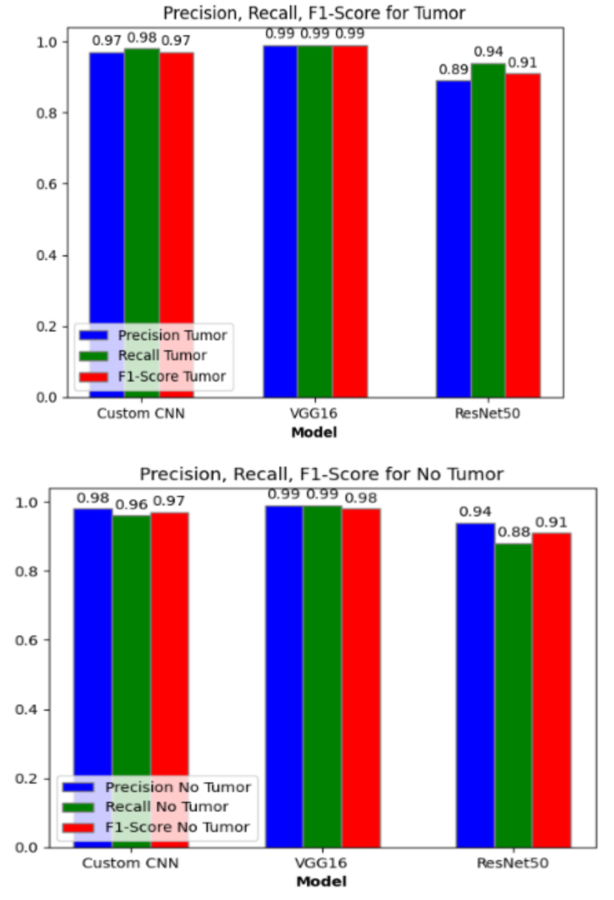

Figure 13 shows Precision Recall f1-score all model (Tumor-NO Tumor)

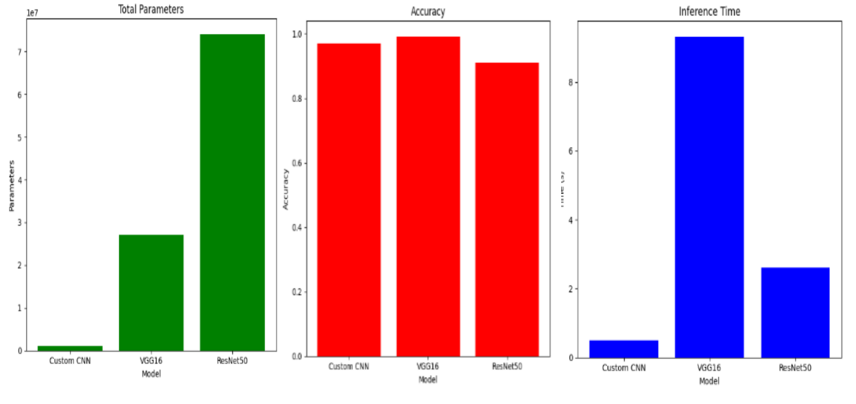

Figure 14 comparison all the Models total parameters, Inference time, Accuracy

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Table 1. Comparative analysis all the Models presented

All the Model	Inference time	Number of total parameters	Accuracy
Custom CNN Model	0.51526977 s	1,738,401	97%
VGG16	9.33099758 s	27,560,769	99%
ResNet50	2.62929707s	74,968,961	91%

Conclusion

Detection of brain tumor applications generally encounter many challenges, due to the complication of the requirements itself and the difficulty of handling image objects instead of numerical values. However, many algorithms and libraries have been developed to help deep learning models being trained at images data and finding patterns in image processing applications to extract feature.

The research offers a novel method for binary classifying of brain tumors from MRI images. This inventive technique first defines the region of interest using picture edge recognition methods, then employs data augmentation to enhance the size of the training dataset. Next, a Convolutional Neural Network (CNN) model is proposed and a website for brain tumor detection using MRI images. We collected and preprocessed a dataset of MRI images of brain tumors and developed a deep learning model based on convolutional neural networks using Python, TensorFlow, and Keras. We also developed a website using HTML, CSS and JavaScript to allow users to upload MRI images and receive a prediction of the presence or absence of a brain tumor for precise and efficient classification of brain tumors. In addition, the results demonstrate that the suggested CNN model Fewer parameters and shorter inference time outperform pre-trained models. Such as VGG-16, and ResNet-50, even with the use of a small dataset. It also attains flawless precision.

Additionally, the CNN model has faster training times because of its lower parameter needs, which contribute to its higher computing efficiency. The prognostic relevance of brain tumors in patients may be significantly impacted by the suggested system. Better preprocessing methods and thorough hyper-parameter tuning can lead to even greater gains in the model's efficiency., the suggested system is capable of binary classifying the tumor or no tumor. To assess how well the suggested model performed in comparison to other pre-trained models, the model's accuracy and loss graphs as well as its confusion matrix were plotted.

Future Works

Research into brain tumor detection and classification, in general, is an active area of research that has many new technical directions to contribute to the performance and applicability of the proposed system.

The size of the dataset will be significantly expanded: The generalization of the model will be improved a lot, the problem of overfitting will be lesser and the total accuracy will be increased if there will be a significant increase in the number and diversity of MRI images.

Analysis of 3D Images: In future works, the use of 3D MRI images instead of 2D slices will lead to more detailed spatial analysis of the tumors and hence, better localization of the tumors.

Inclusion of Traditional Classifiers: The performance of the classification may turn out to be better if the deep learning approach is used along with the traditional machine learning classifiers such as Support Vector Machines (SVM), Random Forests or k-Nearest Neighbors (k-NN).

Tumor Detection and Classification: Future systems might not only detect tumors but also classify them as benign or malignant, thereby providing more clinically relevant information.

Tumor Type Identification: The model can be further trained to identify the types of cancerous tissues (like glioma, meningioma, and pituitary tumors) which will help doctors in making the right diagnosis and treatment.

Testing of advanced deep learning methods: The investigation of the advanced and hybrid deep learning architectures that comprise different CNN variants, transfer learning models, and attention networks among others may lead to the highest accuracy in detection and classification.

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