RESEARCH PAPER

Automated Brain Tumor Detection from Medical DICOM Images Using ResNet50 and VGG16

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Abstract:
Brain tumours are one of the most frequent illnesses in India, and their prevalence is mostly attributable to lifestyle. With shifting trends and technology, early detection and treatment are rising. Early illness detection improves therapy. Image processing helps discover tumours early. MRI imaging can identify tumours and their severity. In our work we have used Digital Imaging and Communication in Medicine (DICOM) format images as input to deep learning models for determining the presence of a brain tumour in a patient. The existence of brain tumours is detected using ResNet50 and VGG16 models. The performance parameter of accuracy is used to compare the results of both models. The results indicate that ResNet50 achieves a brain tumour detection accuracy of 95.86%, whereas VGG16 achieves an accuracy of 92.31%. This shows a increase of 3.13% improvement. Therefore, our paper concludes that ResNet50 achieves superior accuracy as compared to VGG16 in the detection of brain tumours.

Keywords: DICOM, Deep Learning, Convolutional Neural Network, VGG16, ResNet50, Neural Network.
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I. Introduction

A brain tumour is the most common kind of brain illness. It is an uncontrolled proliferation of brain cells. Brain tumours are consistently categorized as either primary or secondary brain tumours. The former originates in the brain and often remains localized, whereas the latter originates as cancer in another part of the body and metastasizes to the brain. Tumors may be classified into two distinct types: malignant and benign. A benign tumour is a slow-growing tumor that does not invade neighboring tissues, whereas a malignant tumor is a highly aggressive tumour that metastasizes to other locations. The World Health Organisation (WHO) classifies brain tumours into four grades: I, II, III, and IV. Tumours classified as category I and II are considered to have a modest growth rate, but tumours classified as category III and IV are usually malignant and have a more unfavourable prognosis [1-4].

Various imaging techniques, including X-ray, Magneto Encephalo Graphy (MEG), Computed Tomography (CT), Ultrasonography, Electro Encephalo Graphy (EEG), Single-Photon Emission Computed Tomography (SPECT), Positron Emission Tomography (PET), and Magnetic Resonance Imaging (MRI), have been developed in recent decades. These techniques provide detailed and comprehensive information about brain tumours, enabling doctors to accurately diagnose the tumour and determine the appropriate treatment approach. MRI is often regarded as the most prevalent imaging tool for identifying brain tumour. MRI is a non-ionizing imaging technology that provides crucial information about the shape, location, and size of brain tumours, without exposing patients to excessive ionizing radiation. It also offers great contrast for visualising soft tissues[5-7].

Artificial intelligence (AI) has shown great potential in several fields, including its ability to aid in illness detection and accurate medical diagnostics. To tackle real-world issues, academics and governments prioritize machine learning, a subfield of artificial intelligence.

Our research presents a comparative analysis of two deep learning models, ResNet50 and VGG 16, in terms of their performance in detecting brain tumours. The models are trained using two datasets. The collection includes DICOM pictures of patients with brain tumours while another dataset contains images of people without brain tumours. The paper is divided into Section II, which includes a review of deep learning models used for brain tumor detection as a literature survey. Section III includes the proposed methodology; Section IV includes the result and the final Section V includes the conclusion of our work.

II. Literature Review

In their study, B. Srikanth et al[10]. introduced a 16-layer VGG-16 deep neural network (NN) that takes enhanced pictures from a previous pre-processing stage as input. The network then passes these images through the convolution layer to extract features and downsample them using Convolution, ReLU, and Max-Pooling techniques. Their suggested methodology enhanced the accuracy of multi-classification of brain tumour MR images. In order to

mitigate the issue of overfitting, the use of fully connected and SoftMax layers is implemented. Finally, after 20 training rounds, their suggested model attains the optimal results, exhibiting a 98 percent accuracy.

About a three-class brain tumour classification, the authors Kokkalla S et.al [11], proposed the use of a deep inception residual network. The output layer of the ResNet V2 network has been modified by including a dense network and a softmax layer. The proposed approach aims to optimize the accuracy of brain tumour categorization. The suggested model underwent testing using a publicly available dataset of brain tumour images, consisting of 3064 photographs. The suggested model demonstrates a level of accuracy that surpasses the current state-of-the-art methodologies by 99.69%.

Referring to the theory of transfer learning, the authors Özlem P et.al [12], developed a brain tumour classification approach using MRI scans. The VGG16, ResNet50, DenseNet, and VGG19 networks use transfer learning to accurately identify the most prevalent types of brain tumours. The deep transfer learning algorithms are trained and assessed using the Figshare dataset, which is a publicly accessible collection of 3064 T1-weighted MRI scans. This dataset includes images from 233 people, with three prevalent forms of brain tumours: glioma (1426 images), pituitary tumour (930 images), and meningioma (708 images). The proposed model significantly improves the classification performance by 99.02% when compared to both ResNet50 and Adadelta.

Another author, Tummala S et.al[13], presented ImageNet-based Vision Transformer (ViT) models (B/16, B/32, L/16, and L/32) that have undergone training and fine-tuning specifically for brain tumour classification. Validation and testing were conducted on a brain tumour dataset consisting of 3064 T1w contrast-enhanced (CE) MRI slices from figshare. The dataset included gliomas, meningiomas, and pituitary tumours, which were classified into three distinct groups. The L/32 model had the greatest performance, with a total test accuracy of 98.2% at a resolution of 384×384. The collective models of all four ViT algorithms demonstrated an average testing accuracy of 98.7% when evaluated at the identical resolution. This surpassed the individual performance of each method at both resolutions, as well as their combined performance at a resolution of 224×224.

In their work author Mahmud et.al[14], examined several models, including ResNet-50, VGG16, and Inception V3, and compared the suggested architecture with these models. To evaluate the effectiveness of the models, they assessed several measures including accuracy, recall, loss, and area under the curve (AUC). After conducting a thorough analysis of several models, they determined that their suggested model outperformed the others based on these measures. By analysing a dataset consisting of 3264 MR images, they determined that the CNN model achieved an accuracy of 93.3%, an AUC (Area Under the Curve) of 98.43%, a recall rate of 91.19%, and a loss value of 0.25.

III. Proposed Methodology

A. Python and Deep Learning

Python has several deep learning modules for various techniques and methods. Mostly, tensorflow trained and evaluated VGG16 and ResNet50 models. Designing, arranging, and displaying each level with a detailed dataset on a PC is tiresome. Thus, Python's modules make complicated computations easy, especially in transfer learning using pretrained models. Keras is a TensorFlow-based module. Layers, activation functions, optimizers, and picture and text data are available for deep learning.

B. Dataset

All the MRI pictures used in this work were sourced from Jun Cheng's Brain Tumour Dataset, which employs cutting-edge procedures to acquire various kinds of MRI scans. The brain tumour database comprises 3064 T1-weighted contrast-enhanced pictures obtained from 233 people diagnosed with three distinct forms of brain tumours: meningiomas (708), gliomas (1426), and pituitary tumours (930). As a result of the storage space's file size restriction, we partitioned all files into four segments and saved them in four .zip archives, with each archive comprising 766 segments. Additionally, a 5-fold cross-validation index is provided. This file is available in the MATLAB file format, specifically as a .mat file.

C. Image Preprocessing

Preprocessing optimizes visual data by eliminating distortion and emphasizing key features for later processing. Enhancing an image can improve it.

The images must possess certain attributes and meet the requirements of the model. Afterward, images were enlarged to "224 X 224" using cv2, a Python tool for image processing. Additionally, we applied grayscale to the images to modify the hues. Since the models are preloaded from the vgg16 and ResNet50 libraries, adding a new component to the model would enhance its capabilities. In vgg16, the architecture consists of a final pooling layer and 4 fully connected layers. Finally, the dataset is ready to be used for training the models.

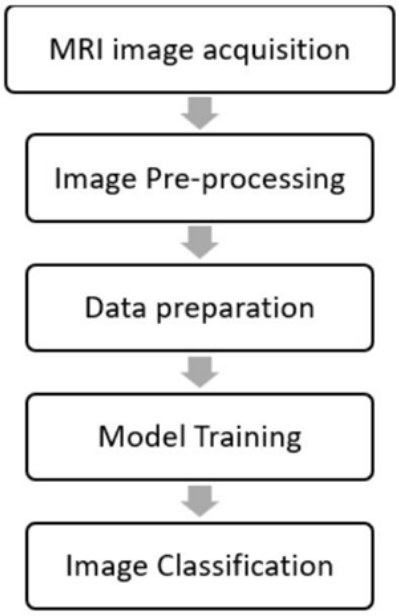


Figure 1: Flow of the proposed work

D. Model Training

Model training is the process of training a machine learning model to identify patterns and generate predictions using input data. This procedure entails providing the model with labelled data, which comprises input-output pairs, and repeatedly modifying its internal parameters to minimise the disparity between the model's predictions and the actual labels in the training data. The objective of model training is to develop a model that can effectively extrapolate from the training data to make accurate predictions on novel, unobserved data. We have trained two models ResNet50 and VGG16 for identifying the presence of brain tumor. VGG16 is a widely used convolutional neural network (CNN) architecture in computer vision. It was developed by the Visual Geometry Group and consists of 16 layers, including 13 convolutional and 3 fully connected layers. VGG16 is known for its simplicity and effectiveness, and it has had a significant impact on image classification tasks. Its design is straightforward, with small convolutional filters (3x3) and deep stacking, allowing it to learn complex features hierarchically. Despite its depth, VGG16's architecture is easy to understand, which has made it a popular choice for transfer learning. Many researchers and practitioners utilise pre-trained VGG16 models on large image datasets, fine-tuning them for specific applications beyond the original ImageNet classification task.

ResNet50 enables the training of a large number of layers, ranging from hundreds to thousands, while achieving favourable outcomes. Its robust representation characteristics make it very effective in enhancing many computer vision applications, including but not limited to picture categorization, object identification, and face recognition. The universal approximation theorem states that a multilayer feedforward network can do any task as long as it has enough power. Conversely, this particular layer might potentially be too massive, resulting in the network becoming overly specialised to the given data, a phenomenon known as overfitting. The well recognised issue of extinction poses a challenge to deep training: when gradients propagate back to earlier layers, the iterative process causes the gradients to diminish significantly. Consequently, when the network expands in size, the throughput will reach its maximum capacity, even if it doesn't decline significantly. functionality. The outcomes are same. Consequently, the training error of the deep model may not be higher than the training error of the shallow model. In order to address this issue, a novel design was developed that capitalises on the connection speed by establishing direct connections to every tier. In this new approach, each layer's input consists of a distinct map that includes all the information from the previous levels. The output of each layer is then sent to the succeeding layers. The deep join operation is used to merge or combine functions.

IV. Result

The two models ResNet50 and VGG16 are trained on DICOM images and after training the model is run on 5 epochs. The results of the model are shown in Table 1(a) and Table(b).

Table 1(a): Shows the accuracy and loss values of ResNet50

Epochs	Accuracy	Loss
1	57.99	2.05
2	68.05	0.87
3	82.25	0.38
4	91.12	0.24
5	**95.86**	**0.14**

Table 1(b): Shows the accuracy and loss values of VGG16

Epochs	Accuracy	Loss
1	53.25	8.00
2	64.56	1.04
3	78.11	0.54
4	87.57	0.27
5	**92.23**	**0.23**

A comparison of the two models based on accuracy and loss can be shown in Figure 2 and Table 2.

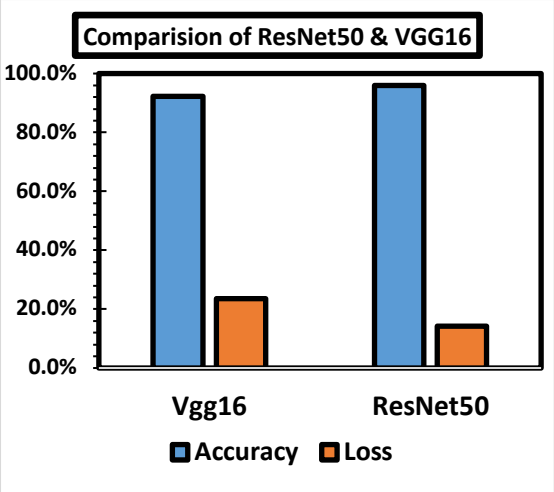


Figure 2: Comparison of ResNet50 & VGG16

Table 2: Comparison of ResNet50 and VGG16

Model	Accuracy	Loss
Vgg16	92.31%	23.45%
ResNet50	95.86%	14.26%

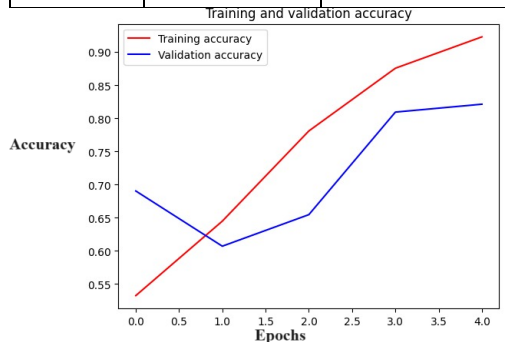


Figure 3: Accuracy Vs Epochs Graph of VGG16

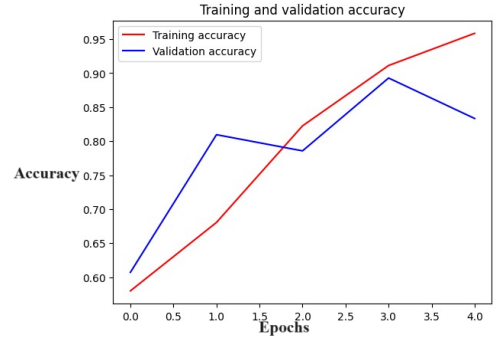


Figure 4: Accuracy Vs Epochs Graph of ResNet50

V. Conclusion

In our work we used ResNet50 and the VGG16 models to identify the presence of brain tumours. Based on the performance parameter of accuracy, a comparison of the outcomes of both models was carried out. According to the findings, ResNet50 obtains an accuracy of 95.86% when it comes to the identification of brain tumours, whereas VGG16 achieves an accuracy of 92.31%. Therefore, the conclusion that our work reaches is that ResNet50 obtains a higher level of accuracy in the diagnosis of brain tumours when compared to VGG16.

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