Enhancing The Efficacy Of Several Deep Learning-Based Models For Identifying Brain Tumours From Magnetic Resonance Images

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Abstract: It is essential to classify brain MRI scans as soon as feasible in order to diagnose brain tumours. There are numerous diagnostic imaging modalities that can be used to identify brain tumours. MRI's high-quality picture production makes it a popular choice for this application. The development of state-of-the-art methods for the automated diagnosis of medical pictures has been greatly influenced by artificial intelligence (AI), more especially by Deep Learning (DL). The aim of this study was to develop an accurate and efficient method for classifying brain tumours using magnetic resonance imaging (MRI). In this work, we leverage well-known deep learning architectures to create a brain tumor diagnosis system. The deep features from brain MRI data are extracted using pre-trained models such as Xception, NasNet Large, DenseNet121, and others.

Keywords: InceptionResNetV2, DenseNet121, Deep Learning (DL), Magnetic Resonance Imaging (MRI), Artificial Intelligence

1 Introduction

The brain is one of the most intricate anatomical structures in the human body, with billions of cells cooperating to regulate the whole nervous system. The human brain is incredibly sensitive.

It regulates fundamental processes and is responsible for things like memory, emotion, perception, and reaction in humans. These abilities will be significantly impaired if brain tumors begin to grow. This tumor originates in brain tissue and is therefore called a primary brain tumor, as opposed to secondary tumors that go

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to the brain via the circulation from elsewhere in the body.
Due to its short survival rate and aggressive character, a brain tumor is one of the worst diseases there is. Malignant brain tumors are cancerous, but benign brain tumors are not. Benign tumors don't spread cancer and develop more slowly than malignant ones. Usually, it doesn't spread to other parts of the brain. The rapid metastasis of malignant tumors to different brain tissues worsens the patient's situation.

2.Literature Review

Pre-trained deep learning models such as XCEPTION, DENSENET121, INCEPTIONRESNETV2, and NASNET are used in the proposed paper because they are proficient at features extraction from MRI images and thus can aid in better and more accurate prediction of brain tumors, which can save lives if caught early. When compared to other algorithms, XCEPTION performs best across the board in terms of accuracy, precision, RECALL, and FSCORE. The author conducted extensive training on both a big and a small MRI dataset obtained from the KAGGLE website, with the former producing subpar results.
A deep learning model is a computer model that is trained using training samples and deep learning neural networks to perform various tasks such as object detection, pixel classification, detect changes, and objects classification.
deep learning models into three categories in ArcGIS:

- **ArcGIS pretrained models**
- **Models trained using ArcGIS**
- **Custom models**

Python raster function framework is the foundation upon which ArcGIS's deep learning model inferencing is built.**Many deep learning models trained outside of ArcGIS can be used in ArcGIS for inferencing; however, this requires the inference function to be customized and the correct packages to be installed that support the model.**

3.Proposed Methodology

Xception
employs Depthwise Separable Convolutions in its deep convolutional neural network architecture. Francois Chollet, a Google employee, is credited with launching this network.

Inception-ResNet-v2
. Based on the Inception family of designs, this convolutional neural network replaces the filter concatenation step that Inception utilizes with residual connections.

A DenseNet is a type of convolutional neural network that makes use of Dense Blocks, which link every layer directly with every other layer (that is, with equal feature-map sizes). To keep the feed-forward structure intact, each layer absorbs more data from the layers underneath it while feeding its own feature maps to the levels above it.

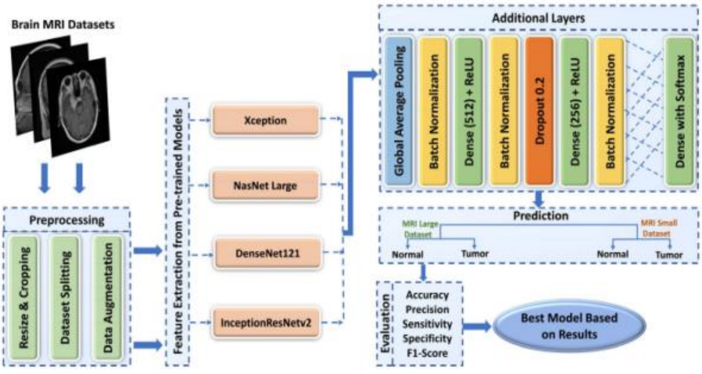

Fig1.ArchitectureDiagram

4 Results and Discussions

The code and output screens for this project, which we created using a JUPYTER notebook, are shown here with blue-colored comments.The dataset is divided into train and test segments, with 80% of the images used for training and 20% for testing.

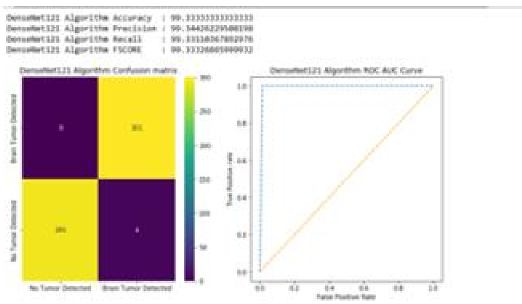

Fig .2. Output for DesNet123 Algorithm

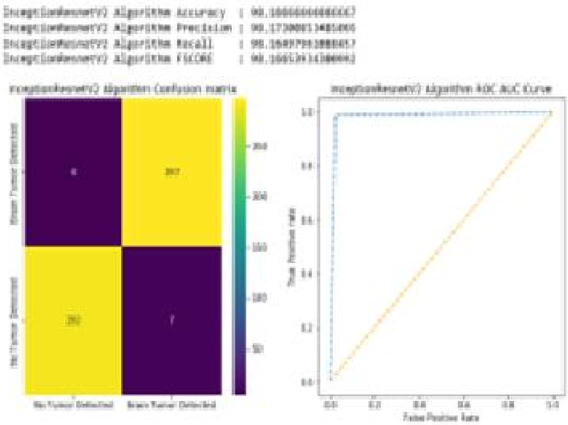

Fig. 3. Output for InceptionResNetV2 Algorithm

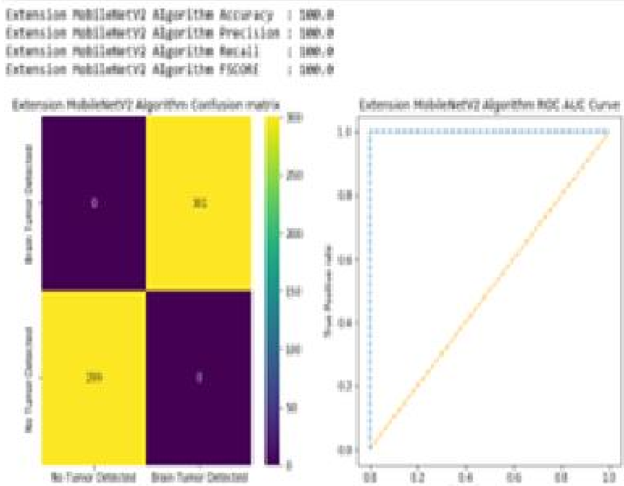

Fig. 4. Output for Algorithm

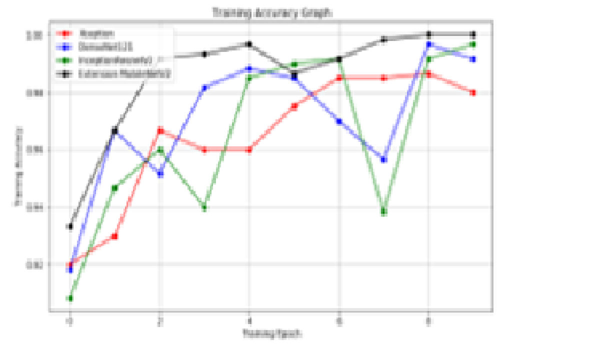

Fig. 5. Comparison of Training Accuracy Graph

Figure 5. The aforementioned graph shows the training epoch on the x-axis, accuracy on the y-axis, and the following lines: black for the extension mobileNetV2, blue for Densenet121, green for InceptionResnetV2, and red for XCEPTION. MobileNetV2 extension achieved good accuracy

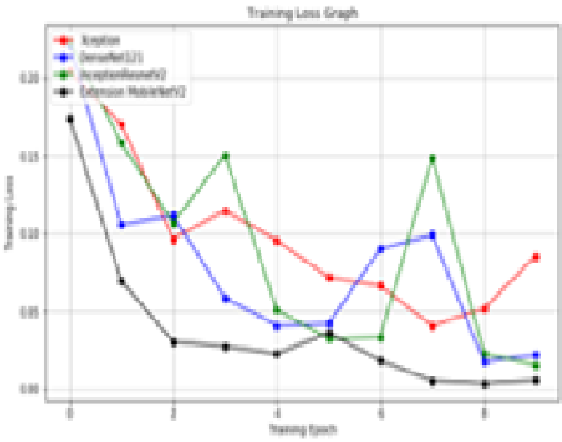

Fig. 6. Comparison for Training Loss Graph

Figure 6.In above graph we are showing loss or error value and in all algorithms Extension MobileNetV2 got less loss. Any algorithm must have high accuracy and less loss to be consider as perfect

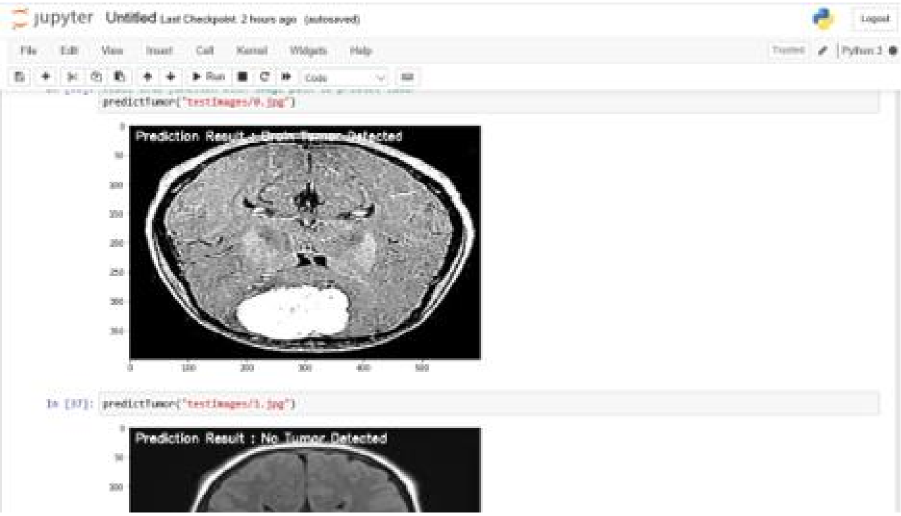

Fig. 7. Results

Table 1. Comparison of metrics for all algorithms

Algorithm used	Accuracy	Precision	Recall	F score
Xception	98.83333	98.836615	98.834967	98.833333
Densenet123	99.33333	99.344262	99.331164	99.333267
InceptionResNetV2	98.166667	98.173009	98.160000	98.366639
Extension MobileNetV2	100.00000	100.00000	100.00000	100.00000

5 Conclusion

In order to automatically diagnose brain tumors using MR images, we employed transfer learning to train a CNN model. The weights in transfer learning come from networks that have already been trained on millions of data points. The proposed study implements four distinct transfer learning models with different optimizers (ADAM, SGD, RMSprop), and extensive tests were performed on the two datasets with the biggest number of MR images currently accessible. These four models use transfer learning to extract features, and then use three dense layers and a softmax layer to classify data. The suggested deep TL models displays fast learning by employing the Adam optimizer, and the dropout method overcomes the problem of overfitting.

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