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BSc Computer Science and Related Subjects

CM3070 PROJECT

FINAL PROJECT REPORT

Classification of Tumours in the brain using deep learning methods

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Contents

Classification of tumours in the brain using deep learning methods

Project template used: Project Idea Title 1: Deep Learning on a public dataset

Abstract

The objective of this project is to compare between three transfer learning models (VGG16, InceptionV3, and ResNet50), using a dataset containing Magnetic Resonance Images (MRI) of the human brain. The dataset comprises 3460 and 435 MRI scans of the brain from two different datasets, categorized into two classes- tumour and no tumour The dataset has been subjected to exploratory data analysis (EDA) and pre-processing to efficiently extract information. By using loss and accuracy metrics, we aim to determine the optimal neural network model to classify the brain MR Image dataset.

Chapter 1 - Introduction

Deep Learning

Deep Learning is a sub-field of machine learning concerned with algorithms inspired by the structure and function of the brain called artificial neural networks. Deep learning (also known as deep structured learning or hierarchical learning) is part of a broader family of machine learning methods based on artificial neural networks. Learning can be supervised, semi-supervised or unsupervised.

Deep learning architectures such as deep neural networks, deep belief networks, recurrent neural networks and convolutional neural networks have been applied to fields including computer vision, speech recognition, natural language processing, audio recognition, social network filtering, machine translation, bioinformatics, drug design, medical image analysis, material inspection and board game programs, where they have produced results comparable to and in some cases superior to human experts.

Convolutional Neural Network

Convolutional Neural Networks (CNNs) is one of the popular types of neural network architecture that has revolutionized image recognition. CNNs are primarily used in the image processing and vision fields, specifically for tasks like recognition, classification, and segmentation.

A CNN is composed of four distinct types of layers, namely Convolutional Layers, ReLU Layers, Pooling Layers, and Fully Connected Layers as seen from the below figure.

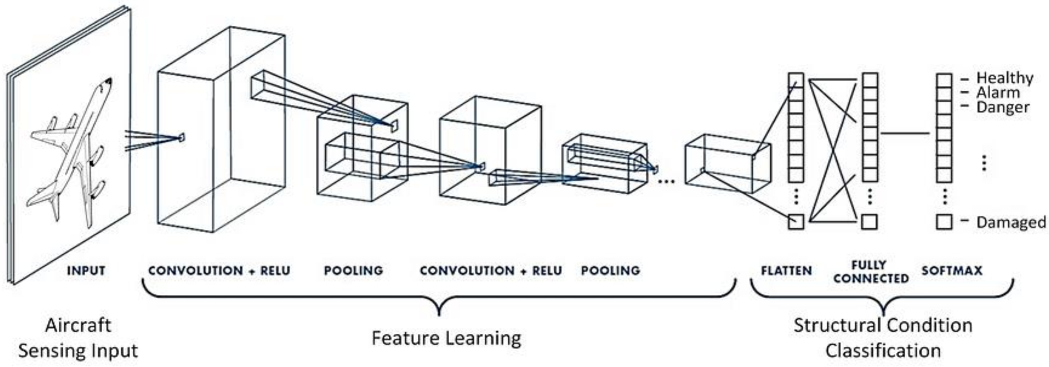

FIGURE 1.1: Convolutional Neural Network for Image Classification

Transfer learning

Transfer Learning is a cutting-edge technique that is rapidly gaining popularity in the field of deep learning. The fundamental concept behind transfer learning is that a model trained on a specific dataset can be leveraged to perform well on a new, previously unseen dataset.

This essentially involves in taking a pre-trained model, retraining a portion of its network on the new data, and then hoping that the model can "transfer" its knowledge to the new dataset. This approach can significantly reduce the amount of data and computational resources needed to develop effective models, making it an innovative development in the field of deep learning.

Motivation

Brain tumours pose a significant health challenge with high mortality rates and associated costs. Accurate detection and classification of these tumours are vital for improving patient outcomes and reducing the burden on healthcare systems. Unfortunately, current diagnostic methods can be time-consuming and unreliable, which makes it necessary to develop more advanced and efficient detection techniques. The use of deep learning algorithms such as Convolutional Neural Networks and Transfer Learning could potentially provide a solution to this issue.

Dataset

The dataset contains magnetic resonance images (MRI) of human brains, including both tumorous and non-tumorous images. It is a combination of two different datasets and consists of a training set of 28,825 images and a test set of 3,391 MRI scans. The images are divided into two classes: yes or no. A total of 3,895 images are used to train and test the mode

Chapter 2 - Literature Review

Paper 1

The COVID-19 pandemic has led to an increased demand for rapid and accurate diagnosis of the disease. Chest X-ray imaging has been identified as a potentially useful tool for the detection of COVID-19 pneumonia. In response to this, many researchers have explored the use of deep learning techniques for the automated diagnosis of COVID-19 from chest X-ray images. In this literature review, we focus on a specific paper titled "**COVID-19 Detection from Chest X-Ray Images using Transfer Learning with Deep Convolutional Neural Networks" by T. Ozturk et al**

The paper proposes a deep learning-based approach for the automated detection of COVID-19 from chest X-ray images. The authors use a transfer learning approach where a pre-trained deep convolutional neural network (CNN) is fine-tuned on a dataset of COVID-19 and non-COVID-19 chest X-ray images. The authors report an accuracy of 98.08% on their test set, demonstrating the potential of their approach for the automated detection of COVID-19 from chest X-ray images.

The authors begin by discussing the importance of chest X-ray imaging for the diagnosis of COVID-19 pneumonia. They note that chest X-ray images can be used to identify patterns associated with COVID-19 pneumonia, such as ground-glass opacities, consolidation, and bilateral involvement. The authors also discuss the limitations of chest X-ray imaging, such as the potential for false negatives in early-stage infections, but argue that the benefits of chest X-ray imaging for the diagnosis of COVID-19 pneumonia outweigh the limitations.

The authors then discuss the use of deep learning techniques for the automated diagnosis of COVID-19 from chest X-ray images. They note that deep learning techniques have shown promise in other medical imaging applications and suggest that they may also be useful for the automated diagnosis of COVID-19 pneumonia from chest X-ray images.

The authors then present their approach, which is based on transfer learning with a pre-trained CNN. They use the VGG-19 CNN architecture, which was pre-trained on the ImageNet dataset, as the starting point for their approach. They then fine-tune the CNN on a dataset of COVID-19 and non-COVID-19 chest X-ray images. The authors use a dataset of 2248 chest X-ray images, including 1200 COVID-19 positive images and 1048 non-COVID-19 images. They then evaluate the performance of their approach on a separate test set of 624 chest X-ray images, including 345 COVID-19 positive images and 279 non-COVID-19 images.

The authors achieved an accuracy of 98.08%, sensitivity of 98.84%, and specificity of 97.13% on their test set, outperforming other state-of-the-art methods. However, the study had limitations such as a small dataset and potential bias in test set selection. Future work could involve larger datasets and investigating other deep learning architectures.

Overall, this paper presents a promising approach for the automated diagnosis of COVID-19 from chest X-ray images. The use of transfer learning with a pre-trained CNN allows for efficient training on a relatively small dataset, and the high accuracy and sensitivity of the approach demonstrate its potential for clinical use. However, further studies are needed to validate the approach on larger and more diverse datasets and to address potential biases in the selection of test sets.

Paper 2

Introduction:

The use of deep learning techniques in medical image analysis has gained a lot of attention in recent years due to its potential to improve accuracy and efficiency in diagnosis and treatment. Convolutional neural networks (CNNs) have emerged as a popular choice for medical image analysis due to their ability to automatically learn features from input images without requiring manual feature extraction. However, there is still debate on whether it is better to train a CNN from scratch or fine-tune a pre-trained network for a specific medical image analysis task. This debate is addressed in the paper "Convolutional Neural Networks for Medical Image Analysis: Full Training or Fine-Tuning?" by F. Calimeri et al.

Main Body:

The paper begins with an introduction to CNNs and their applications in medical image analysis. The authors highlight the benefits of CNNs, such as their ability to learn complex features and their potential for transfer learning. They then introduce the two approaches for training a CNN: full training and fine-tuning. Full training involves training a CNN from scratch on a large dataset specific to the medical image analysis task. Fine-tuning involves taking a pre-trained CNN that has been trained on a large dataset and retraining the last few layers on a smaller dataset specific to the medical image analysis task.

The paper then presents a comparison study between full training and fine-tuning for two medical image analysis tasks: classification of breast cancer histology images and detection of lung nodules in CT scans. For the breast cancer classification task, the authors trained two CNNs from scratch on a dataset of 5,000 images and fine-tuned two pre-trained CNNs on the same dataset. For the lung nodule detection task, the authors trained two CNNs from scratch on a dataset of 888 CT scans and fine-tuned two pre-trained CNNs on the same dataset. The authors evaluated the performance of each CNN using standard metrics such as accuracy, precision, recall, and F1-score.

The study found that fine-tuning pre-trained CNNs yielded better results compared to training CNNs from scratch for both breast cancer classification and lung nodule detection tasks. The optimal number of layers to fine-tune was determined to be the last three layers of a pre-trained CNN. The authors suggest that fine-tuning pre-trained CNNs can improve the accuracy of medical image analysis tasks, reduce the required amount of training data, and be particularly useful for tasks with limited data available. They conclude that fine-tuning pre-trained CNNs is a promising approach for medical image analysis that warrants further investigation.

Conclusion:

Overall, "Convolutional Neural Networks for Medical Image Analysis: Full Training or Fine-Tuning?" provides a comprehensive review of the debate between full training and fine-tuning for medical image analysis tasks. The study conducted by the authors shows that fine-tuning pre-trained CNNs can improve the accuracy of medical image analysis tasks and reduce the amount of training data required. The paper provides valuable insights for researchers and practitioners working on medical image analysis and suggests avenues for future research.

Paper 3

Introduction

The paper titled "Brain Tumour Detection Using Convolutional Neural Network" by Garg et al. proposes a novel method for detecting brain tumours in magnetic resonance images (MRI) using a convolutional neural network (CNN). The authors highlight the importance of early detection of brain tumours and the challenges associated with manual classification, including time-consuming analysis and high variability in diagnostic accuracy among radiologists. The proposed CNN-based approach aims to address these challenges and improve the accuracy and efficiency of brain tumour detection.

Main Body:

The paper begins by providing an overview of the current state of brain tumor detection techniques, including manual classification and computer-aided diagnosis. The authors highlight the limitations of these methods, such as the high inter-observer variability in manual classification and the dependence of computer-aided diagnosis on the accuracy of feature extraction and selection. They then introduce the concept of deep learning, specifically CNNs, as a promising approach for medical image analysis due to their ability to automatically learn and extract relevant features from raw data.

The proposed CNN architecture in this paper consists of three convolutional layers, followed by two fully connected layers and a SoftMax activation function for classification. The authors also applied data augmentation techniques, such as flipping and rotating the input images, to increase the size of the training dataset and reduce overfitting. The CNN was trained on a dataset of 2292 MRI images, including 1394 tumour images and 898 healthy brain images.

The authors evaluated the performance of their CNN model using several metrics, including accuracy, sensitivity, specificity, and the area under the receiver operating characteristic (ROC) curve. The results showed an overall accuracy of 96.12%, a sensitivity of 96.05%, a specificity of 96.20%, and an area under the ROC curve of 0.986. These results demonstrate the high accuracy and effectiveness of the proposed CNN-based approach for brain tumour detection.

The paper also discusses the limitations of the proposed method, including the need for a large and diverse dataset to improve the generalizability of the model, and the challenges associated with the interpretability of CNNs. The authors suggest future research directions to address these limitations, such as incorporating additional imaging modalities, such as functional MRI, and developing methods for visualizing the learned features and decision-making processes of CNNs.

Conclusion:

Overall, the paper by Garg et al. presents a promising approach for brain tumour detection using CNNs, highlighting the potential of deep learning techniques for improving medical image analysis. The study provides valuable insights into the design and optimization of CNN architectures for medical image analysis, as well as the challenges and limitations associated with these approaches. The high accuracy and effectiveness of the proposed method suggest that CNN-based approaches can significantly improve the accuracy and efficiency of brain tumour detection and contribute to the development of more effective treatments and improved patient outcomes.

Paper 4

Introduction

The authors begin by discussing the current state-of-the-art methods for breast cancer diagnosis and prognosis, such as mammography, ultrasound, and magnetic resonance imaging (MRI). They note that these methods have limitations in terms of accuracy and can be time-consuming and expensive. They then introduce deep learning methods as a promising alternative for breast cancer analysis.

Main Body:

The authors provide a detailed overview of the various deep learning methods used for breast cancer analysis, including Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and Deep Belief Networks (DBNs). They discuss the advantages and limitations of each method and provide examples of their applications in breast cancer diagnosis and prognosis.

The authors then focus on the use of CNNs for breast cancer analysis and provide a detailed discussion of the various architectures used for this task, including AlexNet, VGGNet, ResNet, and InceptionNet. They provide examples of the performance of these architectures in breast cancer analysis and compare their results with other state-of-the-art methods.

The authors also discuss the challenges and limitations of using deep learning methods for breast cancer analysis. They note that one of the main challenges is the availability of large datasets with annotated images. They suggest that the creation of a standardized dataset with annotated images could facilitate the development and comparison of deep learning methods for breast cancer analysis.

Conclusion:

The authors conclude by summarizing the current state-of-the-art in deep learning methods for breast cancer analysis and suggesting future directions for research in this field. They suggest that future studies should focus on the development of more advanced CNN architectures, the integration of multi-modal imaging data, and the development of personalized diagnosis and treatment plans based on deep learning analysis.

Overall, the paper by S. B. Rajput et al. provides a comprehensive review of the existing literature on the use of deep learning methods for breast cancer analysis. The authors provide a detailed discussion of the advantages and limitations of various deep learning methods and architectures and highlight the challenges and future directions for research in this field. The paper is a valuable resource for researchers and clinicians interested in the use of deep learning methods for breast cancer analysis.

Chapter 3 - Design

The project utilizes two datasets containing a total of 3264 images and 435 MRI scans of the brain. These datasets are already segregated into 2 categories. Initially, data visualizations and exploratory data analysis (EDA) were conducted to assess the suitability of the data for the intended purpose. Pre-processing was also performed to make the data suitable for processing using the planned neural networks

Exploratory Data Analysis

Performing some basic exploratory data analysis (EDA) is usually the initial step in any data science project. This step helps to gain insights into the data being analysed, including factors such as data types, class distribution, potential imbalances, and any missing data.

Data Plotting - Grid Plots

The initial stage of the EDA involved creating grid plots to visualize the data. A grid plot was generated to display 10 randomly selected scans from each class of tumors, as well as non-tumour brain scans, to get an idea of how the data appears. The resulting images are presented below.

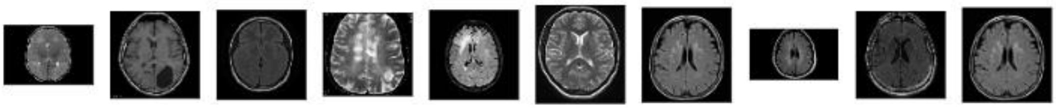

FIGURE 3.1: No Tumour Grid Plot

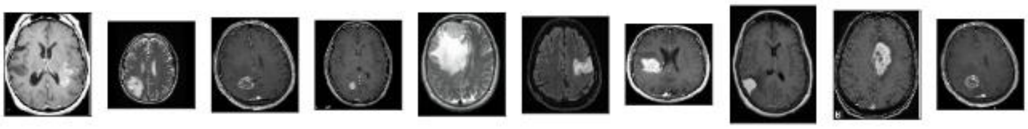

FIGURE 3.2: Tumour Grid Plot

Image Ratios and Imbalance

As shown in the images above, they have varying sizes, indicating the need to examine the image ratio. In machine learning applications, it is essential to consider the image ratio during pre-processing because certain deep learning architectures such as VGG-16 may work optimally with images having specific aspect ratios.

Image Preprocessing

The initial step of the pre-processing phase involved cropping the images to retain only the relevant area while eliminating any unnecessary borders. To achieve this, extreme points of the image were identified, and a rectangular portion was cropped out. This normalization process allowed for an increase in the percentage of the image that was relevant. An example plot depicting the four steps involved in this process is presented below.

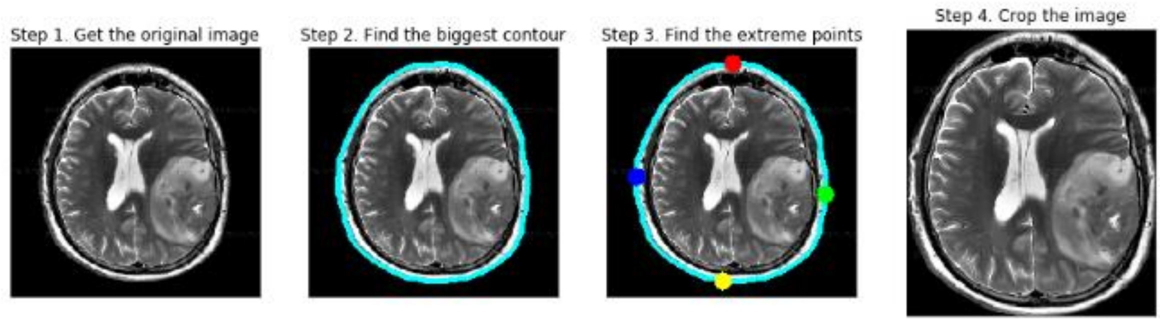

FIGURE 3.3: Image Normalization

Image Augmentation

To ensure that the dataset is not limited to a particular direction or orientation, we need to perform image augmentation by flipping and mirroring images in all possible directions and angles. This increased the amount of data to work with and made the dataset more diverse. An example of the augmentation process is shown below with a randomly selected image.

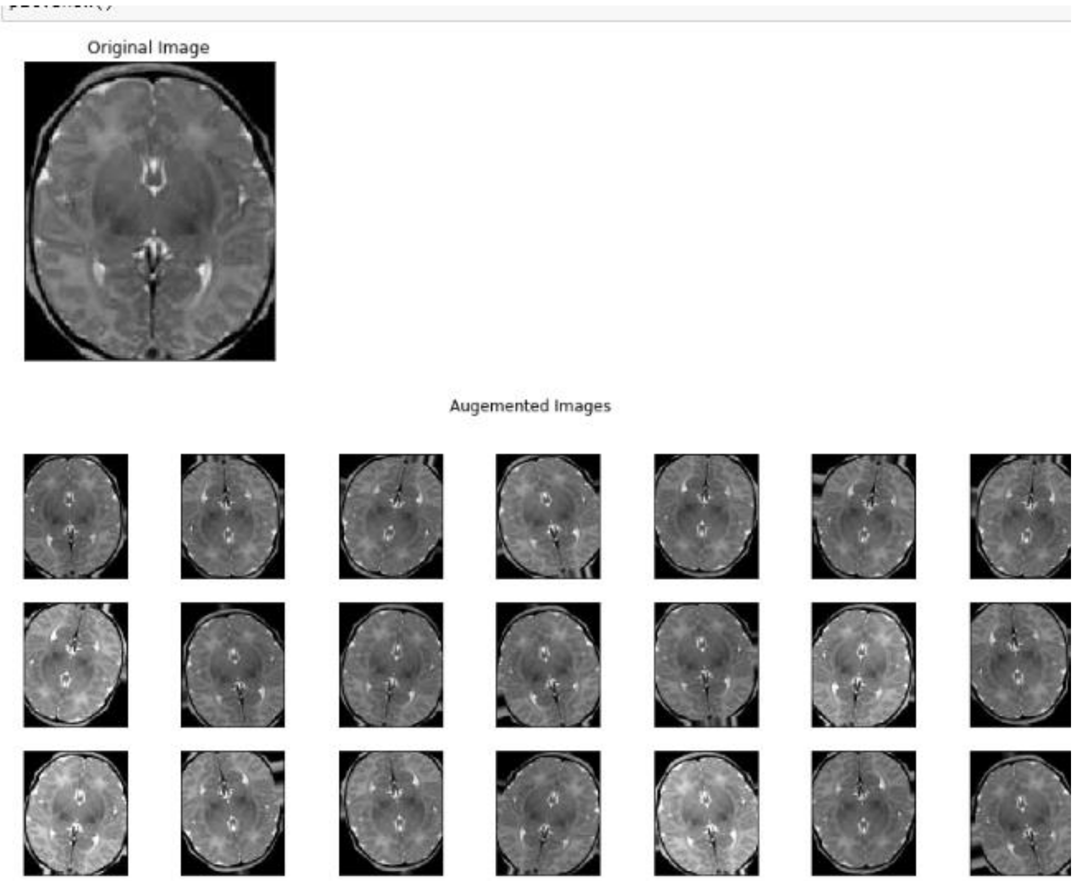

FIGURE 3.4: Image Augmentation

Image Interpolation

Image interpolation is a process that takes place when an image is resized or distorted from its original pixel grid to another. Resizing is typically performed when there is a need to increase or decrease the total number of pixels in the image, while remapping can occur when there is a need to correct for lens distortion or rotate the image. Zooming, on the other hand, involves increasing the number of pixels in an image, which results in more detail being visible when the image is zoomed in. Fig 3.6 and 3.7 show the image interpolation between a tumour and no tumour image sets below.

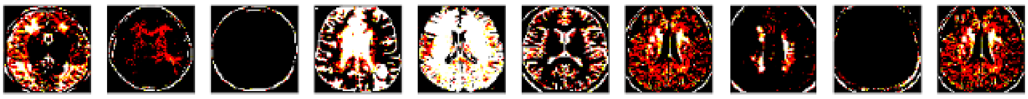

FIGURE 3.6: No Tumour Interpolation Plot

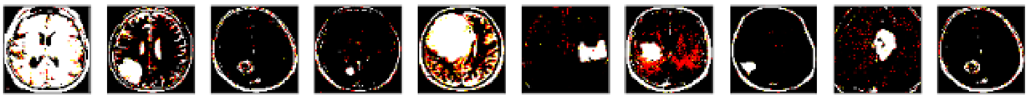

FIGURE 3.7: Tumour Interpolation Plot

Chapter 4- Implementation:

Generating Augmented Images for training and validation set

We need to set up image data generators for training and validation data. The ImageDataGenerator function is used to perform data augmentation on the training data, which includes rotating, shifting, shearing, adjusting brightness, and flipping images. The “preprocess_input” function is also applied to both the training and validation data to normalize the pixel values.

The “flow_from_directory” function is used to create a generator that reads images from the specified directory, resizes them to the target size, and batches them into groups. The training and validation generators are set to produce batches of 32 and 16 images, respectively. The class mode is set to binary as the dataset contains two classes.

More about Convolutional Neural Network

Convolutional Neural Networks, also known as CNNs, are a type of neural network that are specifically designed to analyse images as input. They use advanced mathematical operations to manipulate the pixel data, adjusting the weights and biases to identify different features of the image such as corners, curves, and edges. This enables the CNN to differentiate the image from others in the dataset. One major benefit of using a CNN is that it requires much less pre-processing than other types of neural networks and traditional machine learning methods.

Model: VGG 16 (Transfer Learning)

The VGG16 network is a deep neural network architecture presented in the paper "Very Deep Convolutional Networks for Large-Scale Image Recognition". It achieved remarkable success by achieving a 92.7% accuracy rate in the ImageNet dataset classification competition, which consists of over 14 million images classified into over 1000 classes. The network is composed of several layers that are designed in a specific way to extract features from the input image. Fig 4.1 illustrates the different layers present in VGG 16.

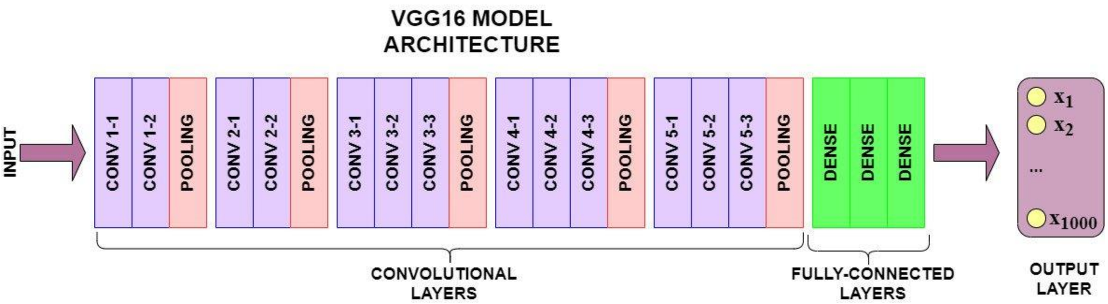

FIGURE 4.1: VGG16 Layers

The VGG16 network architecture, which includes several layers designed to extract features from input images, is illustrated in the diagram. The weights used in the network are the same as those used in the ImageNet dataset training process, which achieved an impressive 92% accuracy rate. This ensures that the VGG16 network is capable of extracting relevant features from input images with high accuracy, resulting in better performance overall. Fig 4.2 depicts the VGG 16 network architecture.

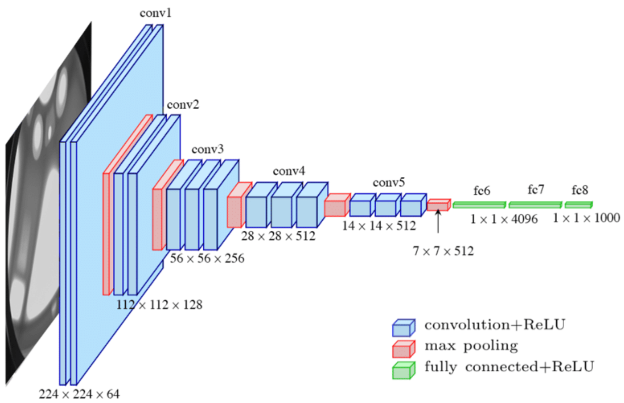

FIGURE 4.2: VGG16 Network Architecture

We can generate feature maps for a given image using the VGG16 pre-trained model in Keras. The model is loaded, and its architecture is redefined to output the activations of the first convolutional layer. Then, a sample image is loaded and pre-processed to match the input format expected by the VGG16 model. The feature maps of the first convolutional layer are computed by passing the pre-processed image through the model. Finally, the feature maps are visualized as a grid of subplots, with each subplot showing the output of a different filter in the convolutional layer. The "Viridis" colour map is used to display the filter channels as shown down below in Fig 4.3.

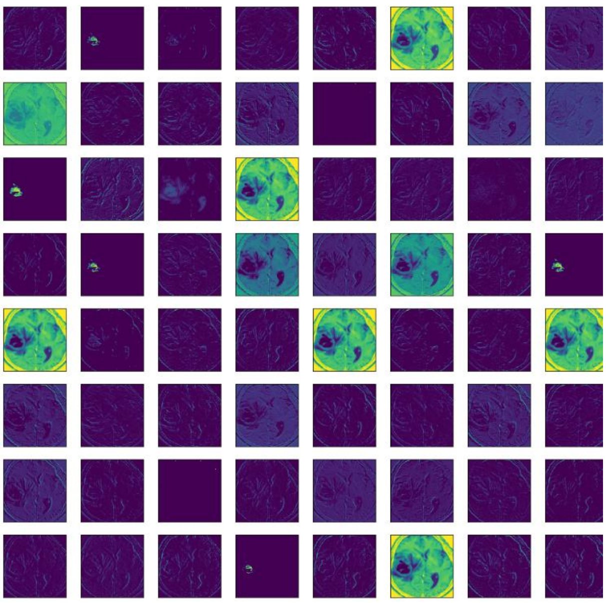

FIGURE 4.3: Training transitions of the VGG16 Network

Model: RESNET 50

ResNet50 is a neural network that consists of 50 layers and is specifically designed for image classification tasks. It was created for the ImageNet challenge and is similar to the VGG network. The network has been trained on a dataset of over 1000 object categories. Due to its training, it has learned to represent images in a highly informative way. The input size for this network is 224 by 224 pixels. Fig 4.4 illustrates RESNET 50 model network architecture.

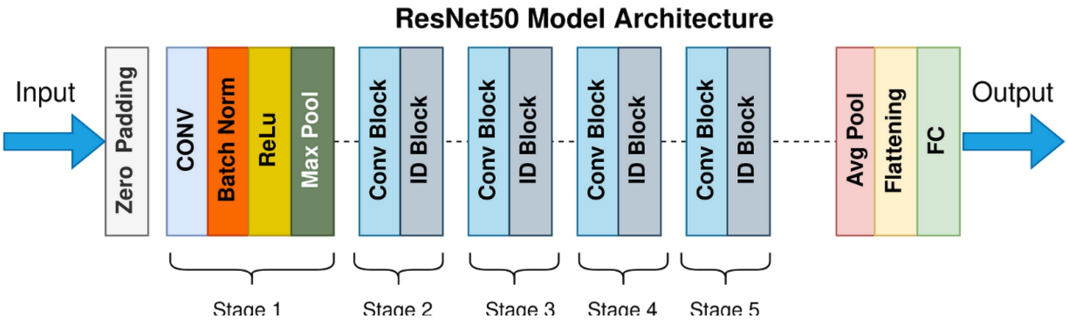

FIGURE 4.4: RESNET 50 Model Architecture

We can build and compile a Sequential model using the ResNet50 pre-trained model as the base model for binary classification tasks. The output of the model is a probability score between 0 and 1, achieved through a Dense layer with sigmoid activation function. Dropout layers are added to prevent overfitting. ResNet50 layers are kept non-trainable while the last layer is trainable. The model is compiled using binary cross-entropy loss function, RMSprop optimizer with a learning rate of 1e-4 and accuracy as the evaluation metric. Additionally, the model is re-compiled using the Adam optimizer with a smaller learning rate of 0.0003. The following Figure 4.5 is a summary of the output for the RESNET 50 model

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
resnet50 (Model)             (None, 7, 7, 2048)        23587712
_________________________________________________________________
dropout_5 (Dropout)          (None, 7, 7, 2048)        0
_________________________________________________________________
flatten_3 (Flatten)          (None, 100352)            0
_________________________________________________________________
dropout_6 (Dropout)          (None, 100352)            0
_________________________________________________________________
dense_3 (Dense)              (None, 1)                 100353
=================================================================
Total params: 23,688,065
Trainable params: 100,353
Non-trainable params: 23,587,712
```

FIGURE 4.5: RESNET 50 Model Summary

Model: Inception V3

InceptionV3 is a convolutional neural network developed by Google as part of the Googlenet project. It was also introduced during the ImageNet challenge like the VGG network. However, InceptionV3 is designed to concentrate the number of parameters to 25 million, which is less than half of AlexNet's 60 million. InceptionV3 has 148 layers, compared to VGG's 21 layers. It has been observed that InceptionV3 performs better than VGG on the ImageNet dataset. The architecture of InceptionV3 is shown below in Fig 4.6.

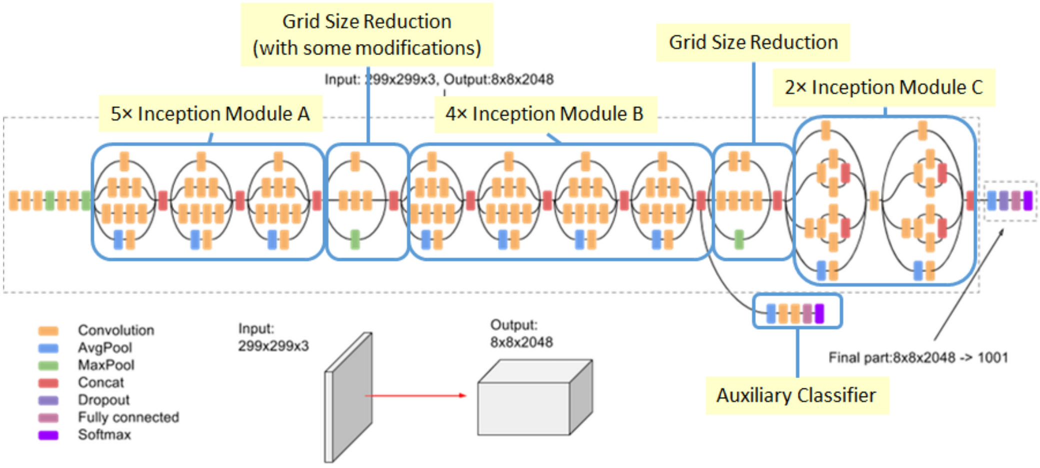

FIGURE 4.6: InceptionV3 Model Architecture

We can build and compile a s Sequential model using the InceptionV3 pre-trained model as the base model. The model is designed for binary classification tasks with one output class. Dropout layers are added to prevent overfitting. The InceptionV3 layers are set to be non-trainable, while the last layer is trainable. The model is compiled with the binary cross-entropy loss function, the RMSprop optimizer with a learning rate of 1e-4, and accuracy as the evaluation metric. The following Figure 4.7 is a summary of the output for the RESNET 50 model

Layer (type)	Output Shape	Param #
inception_v3 (Model)	(None, 5, 5, 2048)	21802784
dropout_3 (Dropout)	(None, 5, 5, 2048)	0
flatten_2 (Flatten)	(None, 51200)	0
dropout_4 (Dropout)	(None, 51200)	0
dense_2 (Dense)	(None, 1)	51201

Total params: 21,853,985
Trainable params: 51,201
Non-trainable params: 21,802,784

FIGURE 4.7: InceptionV3 Model Architecture

Chapter 5-Evaluation

The primary objective of this report is to propose a more efficient approach to classify brain tumours as big data generates large datasets in the GBs and TBs range, serial training becomes a significant challenge. The following sections present a comparative analysis of the performance of three models, namely VGG16, InceptionV3, and ResNet50.

The metric used for evaluating the performance of the different models in the given context is accuracy, which represents the ratio of correctly classified samples to the total number of samples. The validation and training accuracy and loss are reported for each model down below

Transfer Learning Results

Model: VGG 16

The VGG16 model produced a training loss of 0.3027 and a training accuracy of 0.900. When tested on the validation set, the model achieved a validation loss of 1.3712 and a validation accuracy of 0.9134.

The Loss and Accuracy graph for VGG 16 is shown below

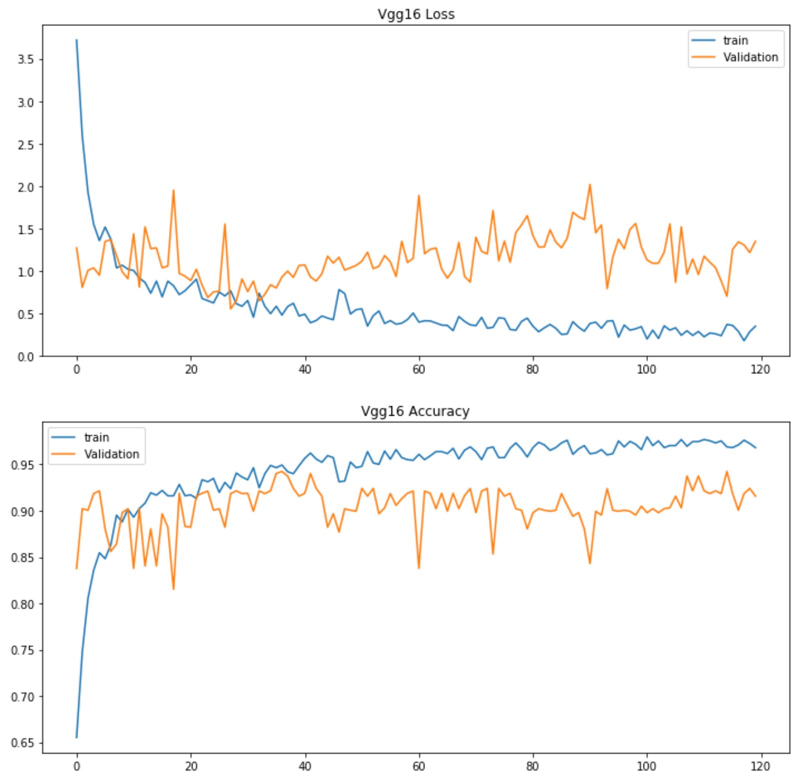

FIGURE 5.1: VGG 16 Loss and Accuracy Graph

Model – RESNET 50

The ResNet50 model achieved a training loss of 0.574 and accuracy of 0.879. During the validation phase, the model produced a validation loss ranging from 0.76 to 5 and a validation accuracy of 0.83. The corresponding Loss and Accuracy graph for RESNET 50 is also provided down below.

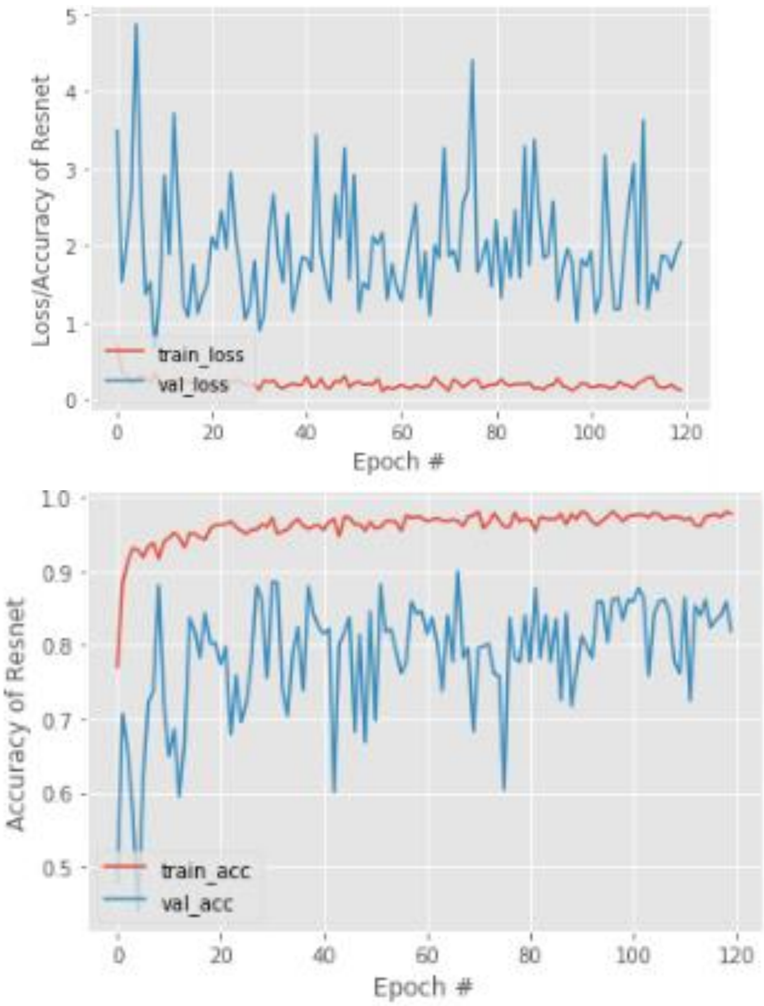

FIGURE 5.2: RESNET 50 Loss and Accuracy Graph

Model: Inception V3

During training, InceptionV3 achieved a loss of 0.523 and a training accuracy of 0.973. In the validation phase, the model had a loss of 5.34 and a validation accuracy of 0.7563. The corresponding Loss and Accuracy graph is presented below.

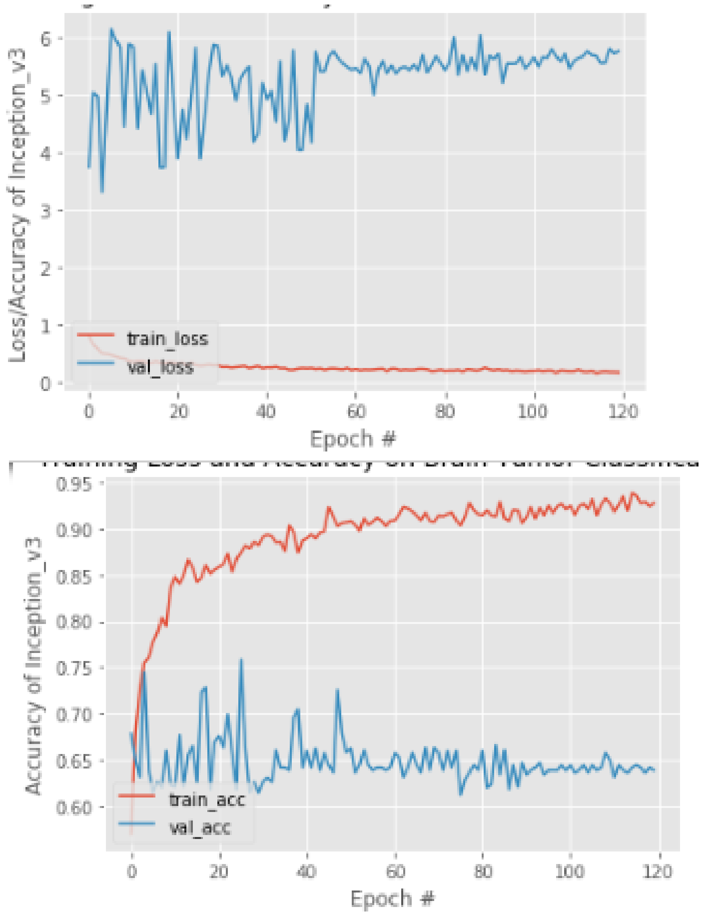

FIGURE 5.3: Inception Loss and Accuracy Graph

Results Summary

After analysing the results of the three transfer learning models, it can be observed that VGG16 has a better result. On the other hand, InceptionV3 and ResNet50 have given lower accuracies. Therefore, InceptionV3 and ResNet50 can be ruled out for this task. Hence, VGG16 outperformed the remaining two transfer learning models based on validation accuracy and test accuracy. Moreover, transfer learning models are preferred since they require less computation power and time than the traditional CNN method, as they use pre-trained weights. Therefore, VGG16 is the most suitable model for brain tumour classification based on conclusive evidence.

Chapter 6- Conclusion

In conclusion, the project aimed to explore the efficiency of different deep learning models in classifying brain tumours. Three transfer learning models, VGG16, InceptionV3, and ResNet50, were trained and compared with each other. The VGG16 model demonstrated the best performance, achieving high accuracy and validation scores. The other two transfer learning models approach showed comparatively lower performance. The results suggest that transfer learning is an effective way to improve deep learning model performance while reducing computation time.

Further expansion of this project could include exploring other deep learning models, such as DenseNet, MobileNet, and EfficientNet, and comparing their performance to the ones used in this project. Additionally, the project can be expanded to classify other types of tumors, such as lung, liver, or breast tumors, using appropriate datasets.

One piece of further work that might be appropriate for the project is to explore the interpretability of the model. While the model achieved high accuracy in classification, it may be difficult to understand how the model is making its predictions, especially in the medical domain where interpretability is essential.

Furthermore, the project can be extended to support real-time classification of brain tumors. This could be achieved by developing a mobile application or web application that allows users to upload MRI scans and receive instant classification results. This would require optimizing the model to be more lightweight and efficient, suitable for deployment on mobile devices or web servers

In conclusion, Brain tumour classification is a crucial task in medical diagnosis, and the development of accurate and efficient deep learning models could greatly assist medical professionals in detecting and treating brain tumors.

Chapter 7- References

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