Goldsmiths, University of London

BSc Computer Science(Machine Learning and Artificial Intelligence)

CM3070 PROJECT

FINAL PROJECT REPORT

Classification of Tumours in the brain using deep learning methods

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Classification of tumours in the brain using deep learning methods

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

GitHub Link : [Classification of Brain Tumours](#)

Abstract

The main objective of this project is to perform a comparative analysis of three different transfer learning models - VGG16, InceptionV3, and ResNet50 - using a comprehensive dataset of Magnetic Resonance Images (MRI) of the human brain using python(Jupyter notebook)

The dataset contains two sets of scans with a total of 3460 and 435 MRI images, each classified into one of two classes tumour and no tumour. Prior to analysis, the dataset has been subjected to exploratory data analysis (EDA) and pre-processing.

The aim of the project is to determine the best neural network model based on the loss and accuracy metrics for the classification of brain MRI images to assist medical professionals to diagnose and treat medical tumours effectively.

A short one-line summary of the following chapters has been provided down below

Introduction: Provides an overview of the project by introducing the relevant concepts which has been used in this project, motivation, and about the dataset

Literature Review: Explores 4 different research papers based on concepts used in this project and provides relevant background information.

Project Design: Outlines the design of the project, including the process of exploratory data analysis and pre-processing steps

Implementation: Describes the implementation of the project, which includes the implementation of the transfer learning models and the respective model summaries

Evaluation: Analyses the effectiveness and performance of the project, and comparing the loss and accuracy metrics of the 3 models

Conclusion: Summarizes the project and its findings, possible extensions, and future work.

Chapter 1 – Introduction

In this chapter, we aim to provide an overview of the different concepts that are relevant to this project. These concepts include deep learning, transfer learning, motivation, and the dataset being used.

Deep learning is a subset of machine learning that involves the use of artificial neural networks to model and solve complex problems.

Transfer learning is a technique used in deep learning that involves the reuse of a pre-trained model for a new task.

Finally, We will discuss the dataset being used in this project and how it relates to our objectives. By understanding these concepts, we can gain a better understanding of the scope and purpose of this project.

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.

Transfer learning

Transfer learning is an emerging technique that is gaining popularity in the deep learning field. The central idea behind transfer learning is to leverage the knowledge learned by a model on one dataset to perform well on a new, previously unseen dataset. Essentially, this means 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 has the potential to significantly reduce the amount of data and computational resources needed to develop effective models, making it an exciting advancement in the field of deep learning.

Motivation

The motivation for exploring transfer learning in the context of brain tumours is driven by the significant health challenge they pose, 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. However, current diagnostic methods can be time-consuming and unreliable, making it necessary to develop more advanced and efficient detection techniques. The use of deep learning algorithms such as Convolutional Neural Networks and Transfer Learning holds promise for addressing this issue.

Dataset

The dataset used for this project contains magnetic resonance images (MRI) of human brains, including both tumourous and non-tumourous images taken from GitHub Website. There are a total of 2065 images in the two folders, consisting of both normal and brain tumor images. A total of 1672 images are used to train and test the model, and the dataset has undergone 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, comparing between three transfer learning models: VGG16, InceptionV3, and ResNet50.

Chapter 2 - Literature Review

In this chapter we will discuss about 4 different papers which are related with the deep learning methods used in this project. A short summary of each of the 4 papers is provided down below.

- "COVID-19 Detection from Chest X-Ray Images using Transfer Learning with Deep Convolutional Neural Networks" by T. Ozturk et al proposes a deep learning approach for detecting COVID-19 using chest X-ray images.

- "Convolutional Neural Networks for Medical Image Analysis: Full Training or Fine-Tuning?" by F. Calimeri et al compares the performance of full training and fine-tuning in medical image analysis using convolutional neural networks.

- "Brain Tumour Detection Using Convolutional Neural Network" by Garg et al presents a deep learning-based approach for detecting brain tumors from MRI images, achieving high accuracy and sensitivity.

- "Breast Cancer Analysis using Deep Learning Methods: A Review" by S. B. Rajput et al provides an overview of recent studies using deep learning methods for breast cancer analysis, including detection, segmentation, and classification.

Paper 1

Introduction

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.

Main Body

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.

Conclusion:

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.

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 authors begin by highlighting the significance of chest X-ray imaging for diagnosing COVID-19 pneumonia, which can detect patterns like ground-glass opacities, consolidation, and bilateral involvement. They also address chest X-ray imaging's limitations, such as false negatives in early-stage infections, but argue that the advantages of chest X-ray imaging outweigh the downsides. The authors then discuss the use of deep learning techniques for the automated diagnosis of COVID-19 from chest X-ray images, pointing out the promise they hold for other medical imaging applications.

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 for both medical image analysis tasks compared to training CNNs from scratch. The optimal number of layers to fine-tune was identified as the last three layers of a pre-trained CNN. This technique may be particularly useful for tasks with limited data available. The authors suggest that fine-tuning pre-trained CNNs is a promising approach for medical image analysis, as it can improve accuracy and reduce the required amount of training data. However, more research is needed in this area.

Conclusion:

Overall, "Convolutional Neural Networks for Medical Image Analysis: Full Training or Fine-Tuning?" presents a comprehensive and insightful review of the debate between full training and fine-tuning for medical image analysis tasks. The study highlights the potential

benefits of fine-tuning pre-trained CNNs for medical image analysis and provides useful recommendations for researchers and practitioners working in this field.

Paper 3

Introduction

In the paper titled "**Brain Tumour Detection Using Convolutional Neural Network" by Garg et al**., a perplexing and ground-breaking method for detecting brain tumours in MRI scans is proposed. The authors acknowledge the importance of early tumour detection, as well as the issues with manual classification, including time-consuming analysis and low diagnostic accuracy. The proposed method is designed to address these challenges and improve the accuracy and efficiency of brain tumour detection through the use of a convolutional neural network (CNN).

Main Body:

The paper begins by providing an overview of the current state of brain tumour detection techniques, highlighting the limitations of manual classification and computer-aided diagnosis. The authors introduce 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 consists of three convolutional layers, followed by two fully connected layers and a SoftMax activation function for classification. Data augmentation techniques, such as flipping and rotating input images, were also applied 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 perplexing metrics, including accuracy, sensitivity, specificity, and the area under the receiver operating characteristic (ROC) curve. The results demonstrated 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 exhibit the impressive 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 difficulties 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 unique approach for brain tumour detection using CNNs, emphasizing the potential of deep learning techniques for improving medical image analysis. The study provides perplexing insights into the design and optimization of CNN architectures for medical image analysis, as well as the perplexing 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

"Breast Cancer Analysis using Deep Learning Methods: A Review" by S. B. Rajput et al.is a comprehensive review of the current state-of-the-art deep learning methods for breast cancer analysis. The authors begin by discussing the importance of early detection of breast cancer and the limitations of traditional diagnostic methods. They note that deep learning methods have shown promising results in improving the accuracy and efficiency of breast cancer analysis.

Main Body:

The authors delve into the complexities of deep learning methods used for breast cancer analysis, including Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and Deep Belief Networks (DBNs). They explain the pros and cons 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 then discuss the challenges and limitations of using deep learning methods for breast cancer analysis. They point out that one of the biggest challenges is the lack of large datasets with annotated images. To overcome this, they suggest that the development of a standardized dataset with annotated images could help 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 useful resource to reference more about the deep learning methods used in image analysis.

Chapter 3 - Project Design

In this project, we will perform an analysis of brain tumour detection using deep learning techniques. For training, 1672 images are used, with 877 being tumor images and 795 being non-tumor images. We will be looking at several important topics related to image analysis and machine learning in this project.

Firstly, we will explore grid plots and how they can be used to visualize image data. We will also discuss the importance of image ratio and imbalance in classification tasks and how to handle them effectively.

Additionally, we will delve into the topic of image pre-processing, including techniques such as normalization.

Furthermore, we will examine the role of data augmentation in increasing the size of the dataset, and how interpolation techniques can be used to improve the quality of augmented images. By addressing these topics, we aim to develop a robust methodology for training a deep learning model for brain tumor classification.

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

For this research, one of the methods employed for the exploratory data analysis is data plotting using grid plots. This was executed by generating grid plots to visualize the data. A display of 10 randomly selected scans from each tumour class and the non-tumour brain scans was plotted on the grid plot. The intention was to get a holistic idea of how the data appeared. The resulting images are presented below.
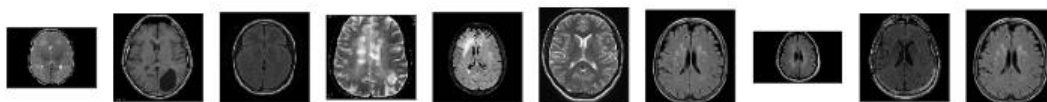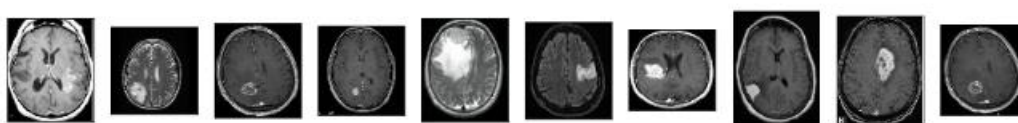

FIGURE 3.1: No Tumour Grid Plot

FIGURE 3.2: Tumour Grid Plot

Image Ratios and Imbalance

As depicted in the above images, the images display a wide range of sizes, indicating the importance of examining the image aspect ratios during the pre-processing phase. This is crucial in machine learning applications, as some deep learning architectures such as VGG-16 may perform better with images having specific aspect ratios.

Image Pre-processing

In the pre-processing phase, the first step was to crop the images and eliminate any extraneous borders to retain only the relevant area. This was achieved by identifying the extreme points of the image and cropping out a rectangular portion. This normalization process was performed to increase the percentage of the image that was relevant. To illustrate this process, a plot showing the four steps involved in the image cropping process is presented below.
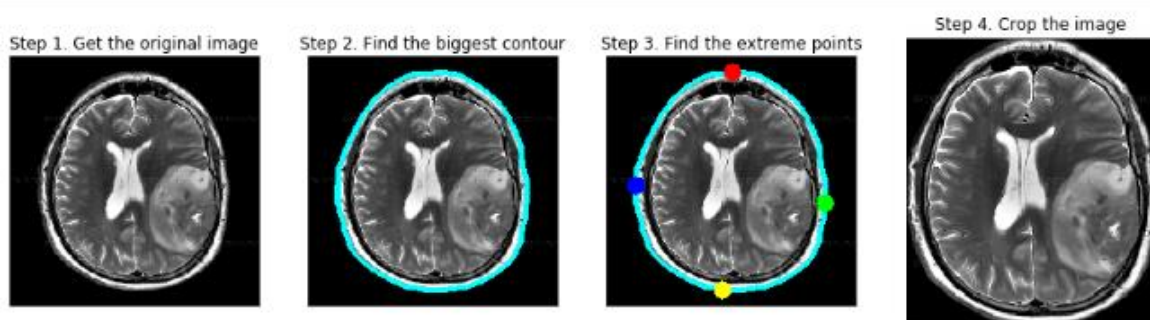

FIGURE 3.3: Image Normalization

Image Augmentation

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.

In order to avoid bias towards any particular image direction or orientation, it is crucial to perform image augmentation by flipping and mirroring the images in all possible ways. This procedure boosts the amount of data available and enhances the diversity of the dataset.

An example of this augmentation process can be seen in the Fig 3.4 , which features a randomly selected image.
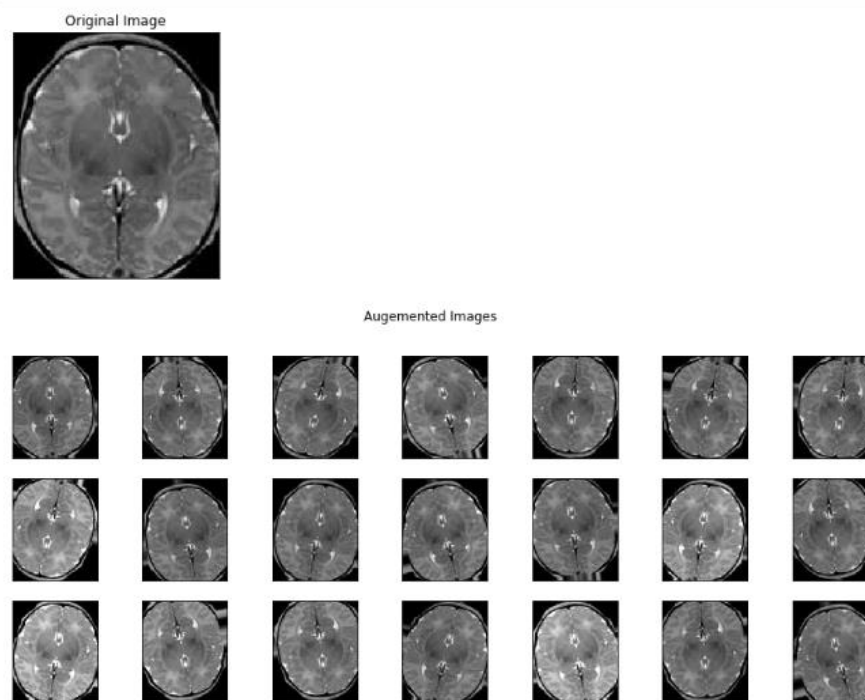

FIGURE 3.4: Image Augmentation

Image Interpolation

Image interpolation is a technical term that refers to the process of resizing or distorting an image from its original pixel grid to another. Typically, resizing takes place when there is a need to increase or decrease the number of pixels in the image, while remapping is used to correct lens distortion or rotate the image. Zooming, on the other hand, involves adding more pixels to an image, resulting in increased detail when the image is zoomed in. Fig 3.5 and 3.6 display the image interpolation between sets of tumour and non-tumour images, which can be seen below.
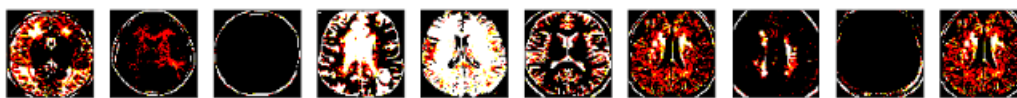

FIGURE 3.5: No Tumour Interpolation Plot

FIGURE 3.6: Tumour Interpolation Plot

Chapter 4- Implementation:

We will now implement three different transfer learning models, namely VGG16, InceptionV3, and Resnet 50, to classify brain tumour MRI images. Transfer learning is a widely used technique in deep learning, which involves taking a pre-trained model and fine-tuning it to perform a specific task. We will generate the respective model summaries to gain insights into the architecture and parameters of each model.

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.
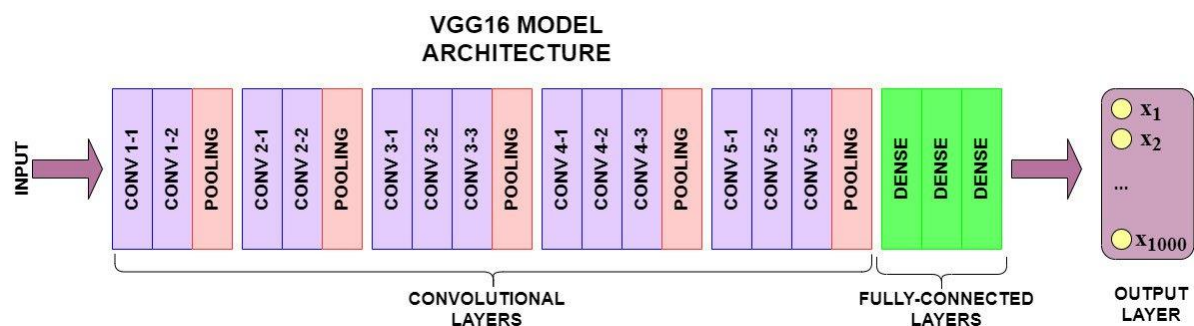

FIGURE 4.1: VGG16 Layers

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.
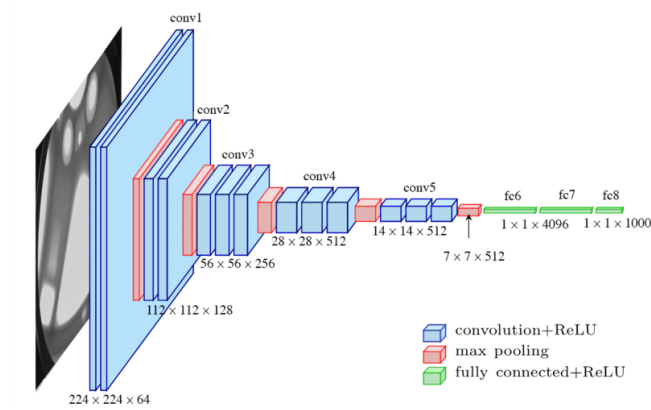
FIGURE 4.2: VGG16 Network Architecture

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.
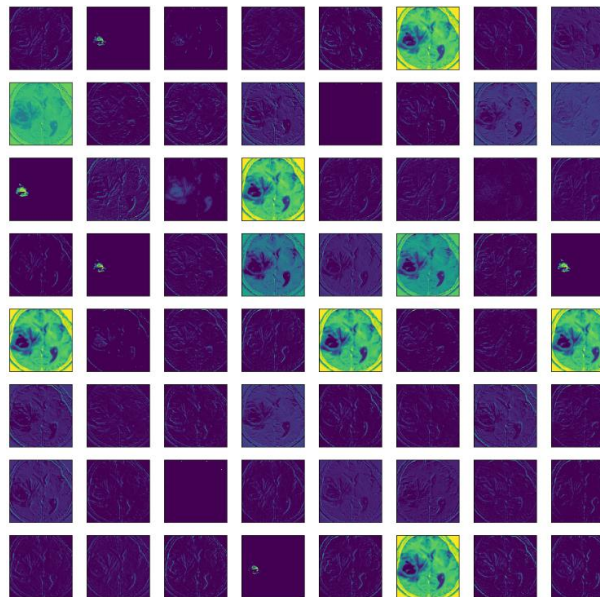

FIGURE 4.3: Training transitions of the VGG16 Network

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.
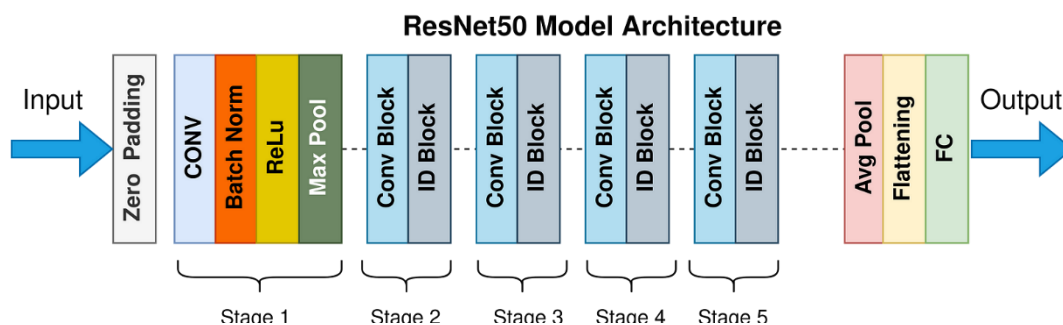
ResNet50 Model Architecture

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.
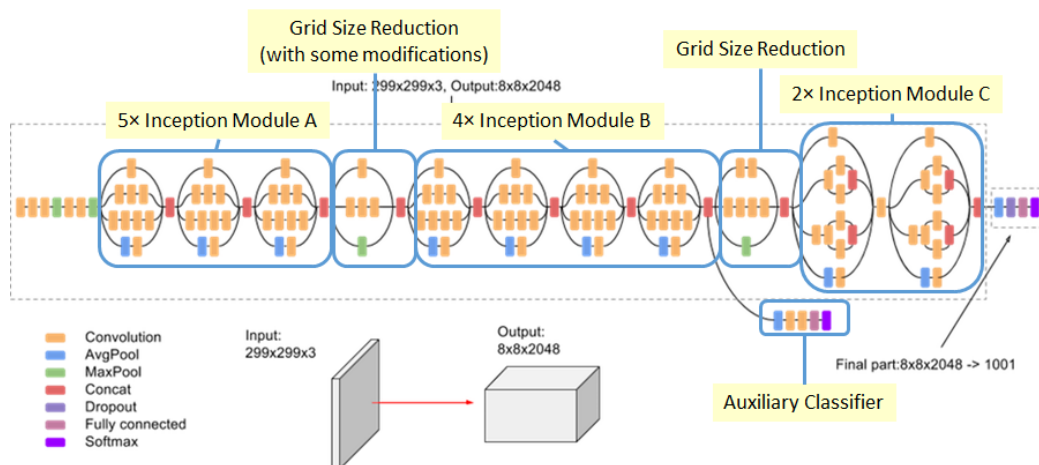
FIGURE 4.6: InceptionV3 Model Architecture

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 Inception V3 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

In this chapter, we will be evaluating the performance of three different transfer learning models, namely VGG16, InceptionV3, and ResNet50, based on the loss and accuracy metric. As the size of the data becomes larger, training the model using serial training becomes a significant challenge, and thus the objective of this report is to propose a more efficient approach to classify brain tumours. The metric used for evaluating the performance of the different models is accuracy, which represents the ratio of correctly classified samples to the total number of samples. The validation and training accuracy and loss will be reported for each model.

Transfer Learning Models and 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.

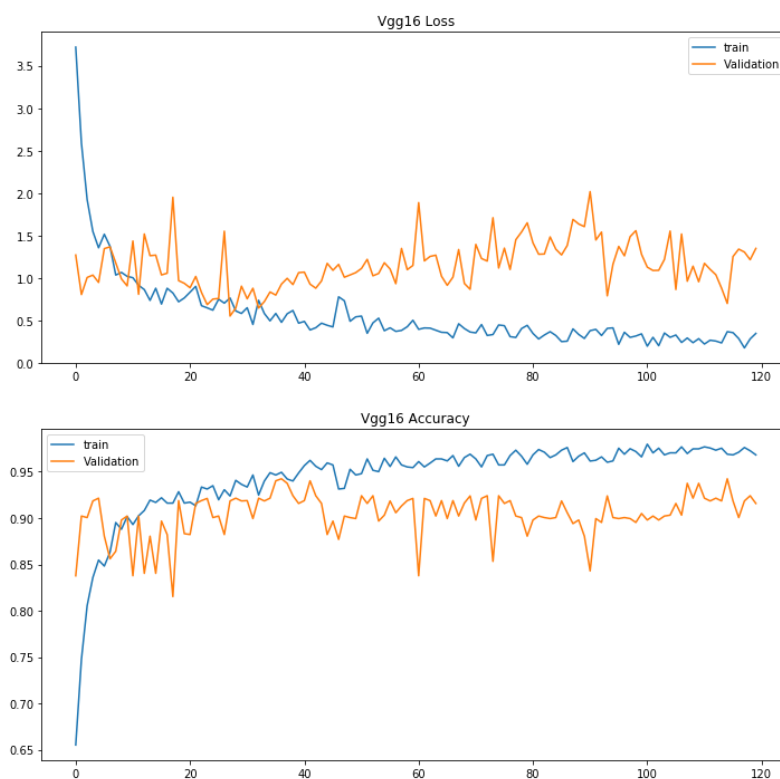The Loss and Accuracy graph for VGG 16 is shown below

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.
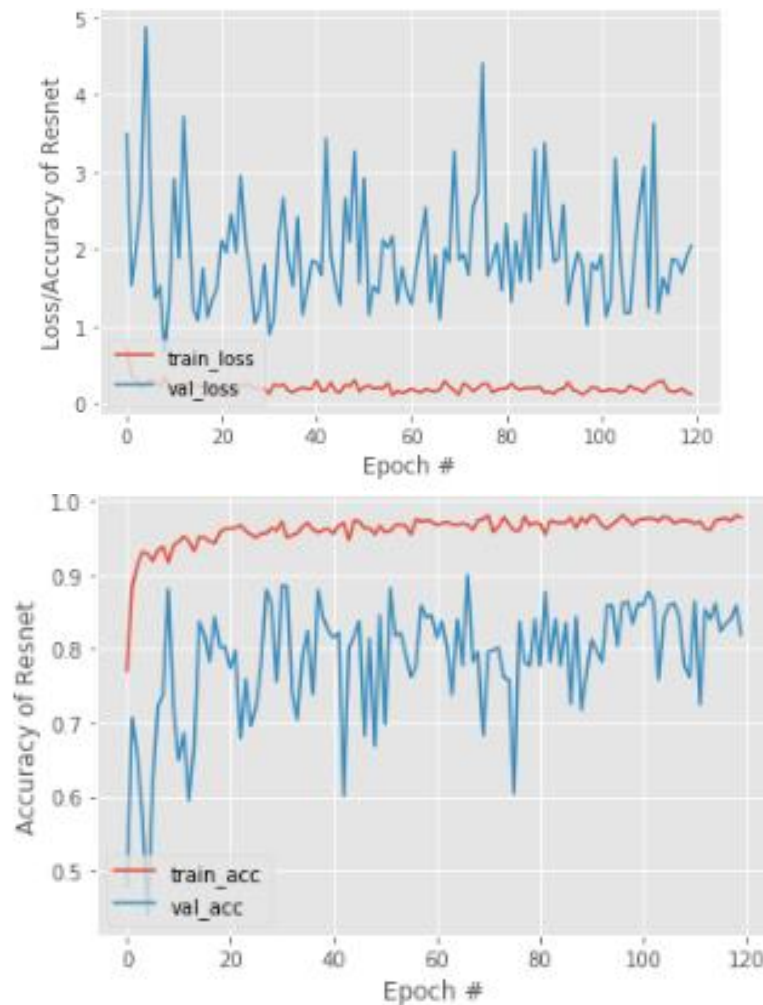

FIGURE 5.2: RESNET 50 Loss and Accuracy Graph

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.
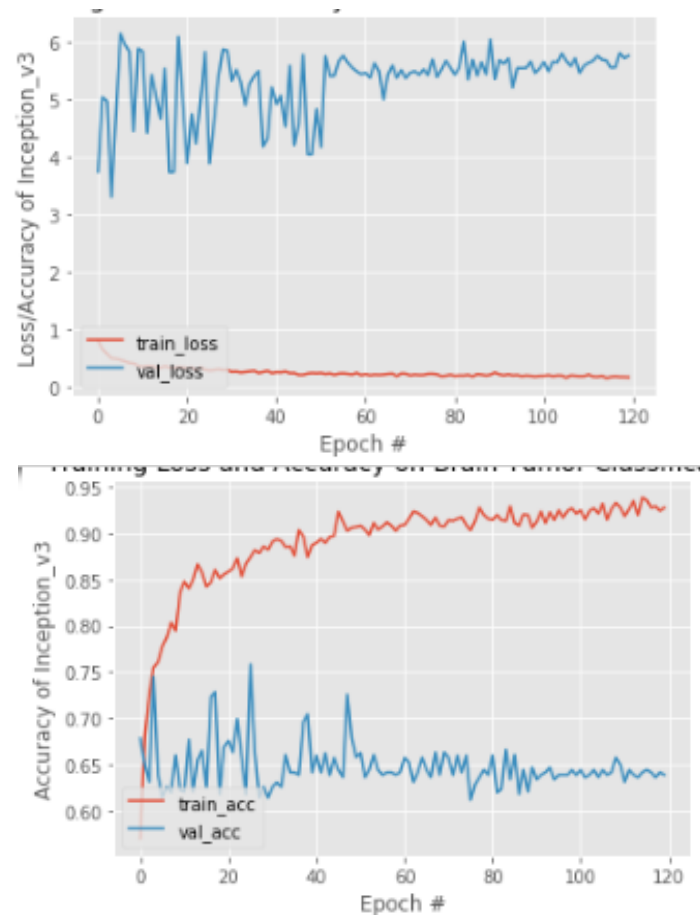

FIGURE 5.3: Inception Loss and Accuracy Graph

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 if given more time 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 tumours, such as lung, liver, or breast tumours, 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 tumours. 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 tumours.

Chapter 7- References

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