Brain Tumor Detection using Deep Learning Models

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Ms Data Analytics

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Brain Tumor Detection using Deep Learning Models

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Abstract

Brain tumors are made up of abnormal brain cells. Brain cancer is classified into benign and malignant tumors. Most tumors are diagnosed using magnetic resonance imaging (MRI). The early detection of a brain tumor is crucial, since it is a fatal condition. This study, therefore, employs Inception V3, VGG-16, and ResNet50 models, which are deep learning and transfer learning models, respectively. In this study, data augmentation is proposed to minimize overfitting since limited MRI data were used in the project. The study will use hyper-parameter tuning in order to provide field workers with a more accurate model. Critically evaluated metrics such as accuracy, precision and recall are used.In this study, VGG16, InceptionV3 and ResNet50 gives accuracy of 75%,67% and 94%. With the ResNet50 giving better accuracy, it can efficetively detect brain tumor hence healthcare workers can provide better treatment.

1 Introduction

It is critical in medical image processing to detect brain tumours for MR images. In order to increase a patient's treatment options and likelihood of survival, brain tumours must be detected in their early stages. Detection by hand is highly subjective, differs from doctor to doctor, and takes a long time to complete. On the other hand, accurate detection enables doctors to make better decisions by allowing them to replicate findings and store records electronically, enhancing assessment and treatment planning. In the last few decades, neural networks (NN) and support vector machines (SVM) have become increasingly popular for brain tumour diagnosis. The application of deep learning to brain tumour detection automation, however, has recently gained attention because of its ability to represent complicated structures, self-learn, and rapidly process large volumes of MRI data.
This study analyzes brain tumours using a three-step deep network technique.

1. The early stages of model creation utilize multiple pre-processing approaches, including the augmentation of data and normalization of MRI image data, to minimize over-fitting.

2. Transfer learning models like VGG-16, InceptionV3, and ResNet50, are utilised to build classification models. Hyperparameter tuning is performed during the model building process and this helps in fine tuning the base models.

3. A better model is picked based on the evaluation and comparison of the performance measures

With this three-stage procedure, clinical problems can be diagnosed using an MRI quickly and accurately.

1.1 Background and Motivation

Different types of cells make up the human body, each with its own function. It is necessary for bodies to remain healthy for cells to divide and expand in a controlled manner. In the absence of proper cell division, cells multiply uncontrollably, resulting in the formation of tumours. tumours in the brain are lumps of tissue containing abnormal cells.It is important to diagnose tumours early, even if they are not malignant, so that treatment can beginRaut et al. (2020).
To determine the location, size, behavior, and growth status of a suspected brain tumour, a radiological investigation is necessary. It is simple to determine the correct treatment for a patient based on this information, such as radiation, chemotherapy, optimum therapy, and surgery. It is also important that the chances of survival of an infected patient may increase with early detection of a brain tumour. Many types of new imaging technology are transforming the medical industry. Most commonly used imaging techniques include magnetic resonance imaging (MRI), computed tomography (CT), positron emission tomography (PET), single photon emission computed tomography (SPECT), ultrasound, and X-ray *Brain tumor detection in MR image using superpixels, principal component analysis and template based K-means clustering algorithm* (2021). MRI is the most common non-invasive method for identifying changes in tissue composition. Due to its ability to produce the highest contrast pictures of the brain and cancerous tissues, it is preferred over other medical imaging techniques. MRI provides abundant information on clinically suspected illness, as well as highly detailed images of the human body. Medical and biological research also greatly benefit from MRI.Liu et al. (2014)
Cancer detection may be enabled by using models such as ResNet50, InceptionV3 and VGG16, which are deep learning approaches. With these models, one can recognize faces, analyze images, categorize, comprehend the weather conditions, and many more.
Deep learning, as a more specific and unusual technique, has sparked intense interest across the board, including among the medical profession, for image analysis, with predictions that deep learning will control roughly $300 million of medical imaging market by 2021, Sharma and Miglani (2020). A significant portion of the funding would go to medical research, and the accuracy and outcomes would be improved for complicated projects.
The process of transfer learning in deep learning is where patterns previously learned from solving one problem are used to solve another instead of starting from scratch. By using pre-trained models that were already trained on large benchmark datasets, transfer learning can be achieved. The study applies the data augmentation technique to classify brain tumours using MRI images as cancerous or non-cancerous through our study using Brain MRI Image and also transfer learning models, such as Inception V3 and VGG-16, are used. The data augmentation techniques are applied to the MRI slices for generalization of results, increasing the dataset samples and reducing the chance of over-fitting. Two stages define the purpose of this study:

1. Using deep learning and transfer learning, the study can identify brain tumours.

2. Doctors and healthcare experts will be able to diagnose brain tumours as soon as possible using this approach.

1.2 Research Objectives

Research question of the study is defined and explained below

How accurately deep learning models using transfer learning can detect brain tumour?

The given Table 1 states all the research objectives defined in the study and meant to solve research question. The main objective of this study is to detect a brain tumour as early as possible so that the health-workers can provide better treatment hence, improving medical facilities. To achieve this objective various other objectives such as building a strong deep learning model by identifying gap between deep learning and machine learning is been defined.

Table 1 states all the objectives in detail with evaluation matrix.

Research Objectives	Description	Evaluation Metrics
First Objective	The evaluation in study helps to recognize gaps of previous study	-
Second Objective	Visualization and augmentation of data using pre-processing techniques	-
Third Objective	Modeling and evaluating VGG16	Accuracy, precision recall
Fourth Objective	Modeling and evaluating ResNet50	Accuracy, precision recall
Fifth Objective	Modeling and evaluating InceptionV3	Accuracy, precision recall
Sixth Objective	Analyzing all the models based on evaluation metrics	Accuracy, precision recall

Table 1- Research Objective of this research

2 Related Work

2.1 Papers related to Brain tumour Detection using Machine Learning Algorithms.

Machine learning algorithms are used to detect brain tumours in this study Sharma et al. (2014) . Texture-based information (GLCM) is retrieved using Gray Level Cooccurrence Matrix. In this suggested study, energy, contrast, correlation, and homogeneity are all textural characteristics of the picture. 212 brain MR images were analyzed using the Multi-Layer Perceptron and Nave Bayes machine learning algorithms, with the best sensitivity being 98.6% and 91.6 %. It is almost certainly possible to improve this accuracy by analyzing a large set of data and extracting both intensity-based characteristics and texture-based characteristics.

The authors, Mudgal et al. (2017) propose an efficient and precise model which requires MRI images to be handled using a modified K-Means Clustering algorithm so that detection is reduced later on, and then using Mean Shift Detection to maximize the efficiency of images entering the processing stage and to increase MRI contrast and intensity. Comparing XGBoost models with other comparable machines, as well as hybrid models that employ these extreme models, on a large dataset presents a wealth of research opportunities. Feature selection can be improved using PCA, LDA, or GA, as well as eXtreme

boosted machines. A number of alternatives have been presented for watershed management, and the existing system can be improved.
In order to increase segmentation accuracy, a variety of strategies have been used in this study Abbas et al. (2019). These included noise reduction and image enhancement. In this data set, some of the samples had poor MR image quality, so these pictures have been enhanced. This project now includes LIPC. Another way of reducing requirements is by using LDA. Further, the work can be complicated and time-consuming due to the addition of underlying or textural attributes. Based on the division result, our LIPC-based system provides more and more appropriate precision compared to other methodologies. In this investigation, the dice score was 0.95. Future research will apply Deep Learning models like CNN. In order to detect photos automatically, CNN is the best model.

2.2 Papers related to Deep Learning Models

In this study Bhanothu et al. (2020), a deep learning system was used to identify and categorize brain tumours from MR images. Using the Faster R-CNN method, tumour locations were identified and categorized into three categories: gliomas, meningiomas, and pituitary tumours. Faster R-CNN was implemented using a deep convolutional network architecture known as VGG-16. With the test dataset, a higher mAP was achieved for identifying brain tumours. The proportion of the tumour's area relative to the brain may also be determined using this technique. In addition to skin lesion segmentation and classification, this technology has applications in other medical fields.
Researchers, Grampurohit et al. (2020) are using deep-learning techniques such as the Convolutional Neural Network (CNN) model and the VGG-16 architecture (created from scratch) to determine where tumours are located in scanned brain images. Brain MRI scans of 253 individuals were analyzed, 155 of which were tumourous and 98 of which were not. The results of this research are compared with those of the CNN and VGG-16 models.
The characteristics of current pre-trained models are often derived from layers that are different from natural or medical images. Taking this issue into account, this study Noreen et al. (2020) suggests a concatenation and multi-level feature extraction method for the early detection of brain tumours. As it uses Inception-v3 and DensNet201, this model makes sense since these deep learning models are pre-trained. Two alternative scenarios were examined using these two models for detecting and classifying brain tumours. A pre-trained Inception-v3 model was used to combine the characteristics from several Inception modules for brain tumour classification. These features were then used to classify the brain tumour using the softmax classifier. A pre-trained DensNet201 was used to extract features from multiple DensNet blocks.
Using CNN, the researchers Choudhury et al. (2020) are able to discriminate tumourous MRI images from non-tumourous ones. It achieved 96.08 percent accuracy with a f-score of 97.3. It consists of just three layers of a CNN and several preprocessing steps to produce results in 35 epochs. In this study, we aim to emphasize the relevance of diagnostic and therapy prediction applications based on machine learning. Scientists plan to use Convolutional Neural Networks to identify brain tumours using neutrosophical principles in the future.
Brain tumours are caused by uncontrolled cell proliferation. MRI can be used to identify this type of tumour, which helps to segment the tumour territory into different ways for surgical and medical planning. The manual identification method is cumbersome and sub-

ject to errors. Several deep learning algorithms are used by researchers Sangeetha et al. (2020) to identify the tumour site automatically. Millions of photos are trained and fine-tuned within a short time. As an additional benefit, this work provides multi-iteration classification algorithms based on CNNs such as GoogleNet, VggNet, and ResNet 50. In terms of speed and accuracy, ResNet 50 is demonstrated to be superior to VggNet and GoogleNet.
In this publication Raut et al. (2020), a CNN model is proposed for detecting brain tumours. The first step is to enhance brain MRI scans so that there is enough data for deep learning. Pre-processing of the photos follows, enabling them to be processed for the next stage. It is based on MRI brain images that have already been processed to use training characteristics to identify newly input images as tumours or not. A back propagation technique reduces error during training and produces more accurate results. A picture is constructed by removing extraneous information with autoencoders and segmenting the tumour region using K-Means, which is an unsupervised learning algorithm.
The authors of this publication Nalepa et al. (2019), examined in detail several brain tumour detection strategies. In addition to this, a deep-learning technique based on CNN has been developed to detect and classify multiple forms of brain tumours. The limited size of the medical imaging dataset is being improved using a data augmentation strategy. As a data augmentation strategy for medical imaging, rotating at 90 degrees was found to be more effective. The proposed model was also assessed against AlexNet and VGG-16 models from the point of view of sensitivity, precision, specificity, f1, and accuracy using MATLAB scripts. Alternative networks did not perform as well as the suggested model, which achieved an accuracy of 96.05 percent.
Convolutional neural networks are presented as a method of identifying tumours in brain scans in this paper Seetha and Raja (2018). Input brain pictures are then used to train the CNN model, and features are extracted. A fully connected layer followed by softmax activation is used to categorize the pictures based on the retrieved characteristics. Harvard Medical School's database of MR brain images is used to evaluate the strategy. For both classification and training, CNN models like VGG16, ResNet, and Inception are used. The experimented database offers 100 percent accuracy. Data augmentation is used to improve segmentation accuracy. A learning rate that prevents overfitting the model is chosen. MR brain images will be categorized in the future based on tumour grade, allowing for better analytics and treatment planning.
In deep learning optical representation analysis Saxena et al. (2021) , convolutional neural networks are often used. There are currently techniques available for detecting brain cancers, but they require large datasets and image processing techniques. Three of the main components of the proposed system (CNN) are image enhancement, preprocessing images, and the use of convolutional neural networks. A deep learning algorithm and a large dataset are used to create a system. In this study, the CNN outperformed all other state-of-the-art training techniques with an accuracy of 87.42 percent and minimum difficulty.
Expertise and understanding of doctors are crucial in treating brain tumours. As a result, an automated system for detecting brain tumours is critical for radiologists and clinicians. This research focuses on the use of convolutional neural networks (CNNs) for predicting brain malignancies and accurately interpreting magnetic resonance imaging (MRI) data. An example of a method is the use of picture pre-processing algorithms that identify extreme shapes and trim away black borders from images. The photos are then scaled to the appropriate size. An Adaptive Moment Estimation (Adam) Optimizer was imple-

mented in our network in order to speed up the training process.In order to evaluate F1 score, the researchers used MRI dataset which was developed by their entire team. on Kaggle to train and evaluate the best model.

This research Zhang et al. (2021) uses a novel cross-modality deep feature learning approach to detect brain cancers in multi-modality MRI data. Rather than rely on small data sets, the focus is on mining patterns across multi-modal data sets. The cross-modality feature transitions (CMFTs) and cross-modality feature fusions (CMFFs), both of which essentially aim at learning rich feature representations by merging and transiting knowledge obtained from different modes of data. A cross-modality deep feature learning framework based on cross-modality deep learning is found to improve brain tumour segmentation performance compared to baseline approaches and state-of-the-art methods as demonstrated in extensive trials on the BraTS benchmarks.

3 Methodology

Specifically, the research was aimed at the development of a device to aid doctors in diagnosing and improving life expectancy. An automated method could potentially replace the time-consuming and ineffective process of physically detecting brain tumours. In a related study, deep learning proved to be a very effective method for detecting brain tumours. It has been found that reviewing a variety of data sources for decision-making can increase profitability and originality. The study follows CRISP-DM methodology to detect if there's a tumour present or not. Figure 1

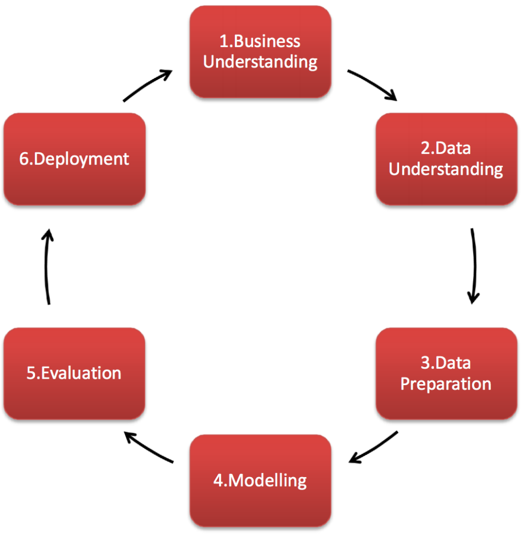

Figure 1: CRISP-DM Methodology

3.1 Data Collection

It is easier to identify anomalies of tissue composition using MRI, which is a non-invasive method. Because it produces a clear picture of the brain and cancer tissues better than other imaging techniques, it is preferred over other methods. An MRI provides excellent

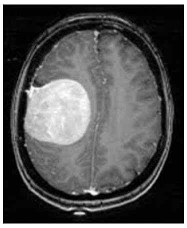

Figure 2: Tumor Present

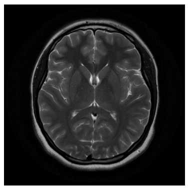

Figure 3: Tumor Not present

anatomical picture structures and abundant information for diagnosing clinically suspected illnesses. Additionally, it contributes to medical and biological research. One of the most obvious benefits of MR imaging is the high spatial resolution with cross-section pictures. The study uses Brain MR images to detect tumourous or non-tumourous images. The given dataset has two folders namely yes which represent tumourous images as shown in first image whereas the second folder represents non tumourous images as shown in the second image. The dataset contains a total of 253 tumourous and non tumourous images.

3.2 Data Preparation

Once MR images are gathered, it is necessary to prepare these MR images before training so that the models are efficient. Firstly dataset is divided into three folders namely 'Test', 'Train', 'Val' and sub-folders namely 'yes' and 'no' are created. In the next step image normalization is performed, the process of normalizing alters the range of pixel intensity values. The primary goal of this session is to identify extreme points in the image and crop the edges. Noise is removed from the image by performing series of erosions and dilations . Finding contours in the threshold image and then extreme points in MR image is retrieved.

Figure 6 shows the cropping of image which is then applied to the dataset. In this session,

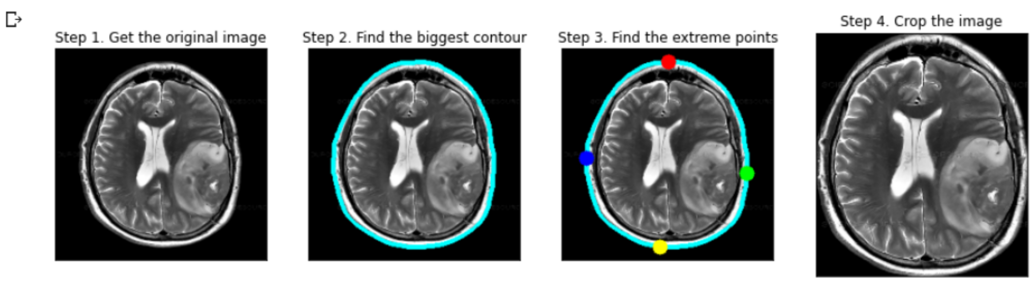

Figure 4: Image Cropping

data augmentation is also performed. Deep neural networks' ability to generalize is improved by data augmentation, also known as implicit regularization. Such information is of critical importance when there is a shortage of high-quality data and gathering additional samples is both costly and time-consuming. Medical picture analysis typically presents this problem, particularly in the context of tumour delineationNalepa et al. (2019). 5

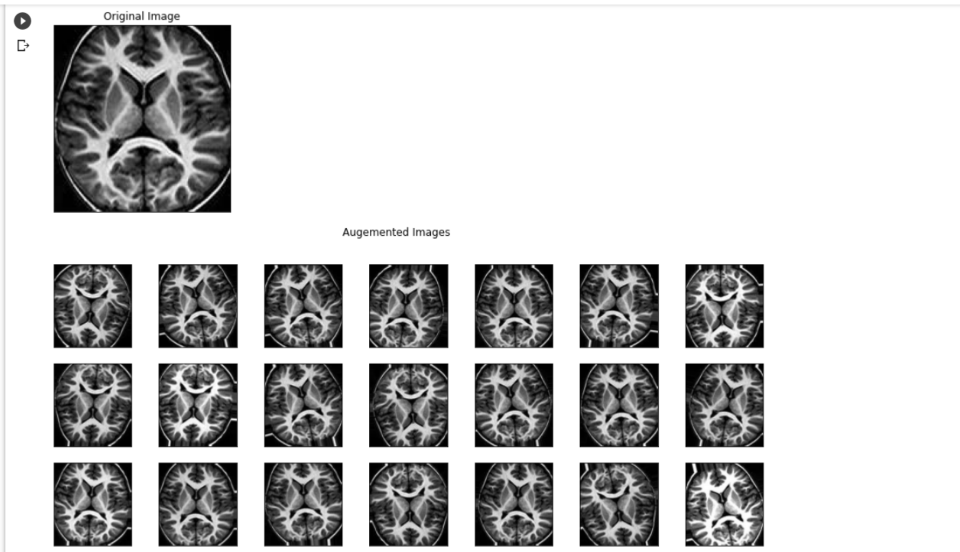

Figure 5: Data Augmentation Technique Applied

3.3 Modeling Techniques

3.3.1 VGG-16

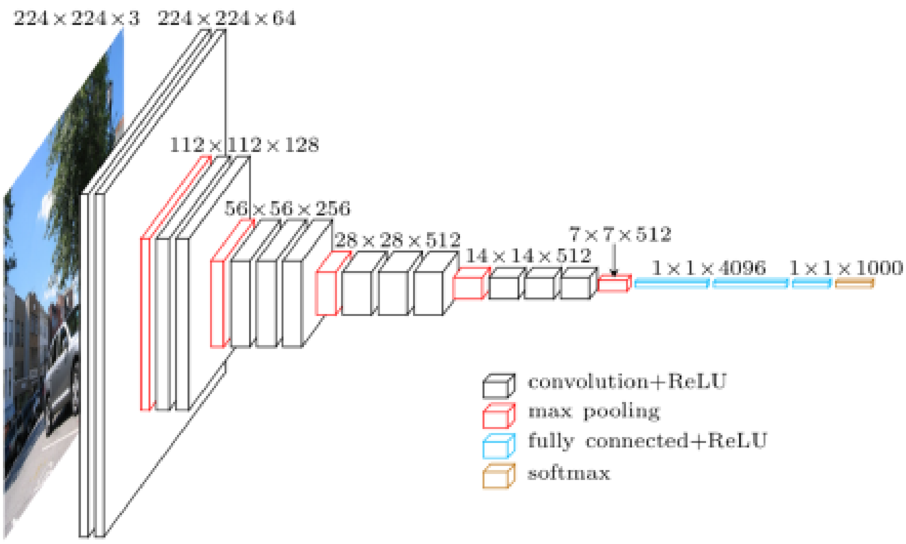

Figure 6: VGG16 Architecture

The Visual Geometry group is abbreviated as VGG. The weights and convolutions are divided evenly into 16 layers, and the output layer is completely linked to the other layers. In the study, VGG-16 downloads the Imagenet weights with an input picture size of (224,224,3); therefore, the first step is to obtain the weights from Imagenet.Figure 6 Wickrama Arachchilage and Izquierdo (2020) shows the architecture of VGG16. As implied by the name, the VGG-16 model does not require any retraining.

```
Model: "sequential_1"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 vgg16 (Functional)          (None, 7, 7, 512)         14714688

 flatten_1 (Flatten)         (None, 25088)             0

 dropout_1 (Dropout)         (None, 25088)             0

 dense_1 (Dense)             (None, 1)                 25089

=================================================================
Total params: 14,739,777
Trainable params: 25,089
Non-trainable params: 14,714,688
_________________________________________________________________
```

Figure 7: Model Summary of VGG16

3.3.2 InceptionV3

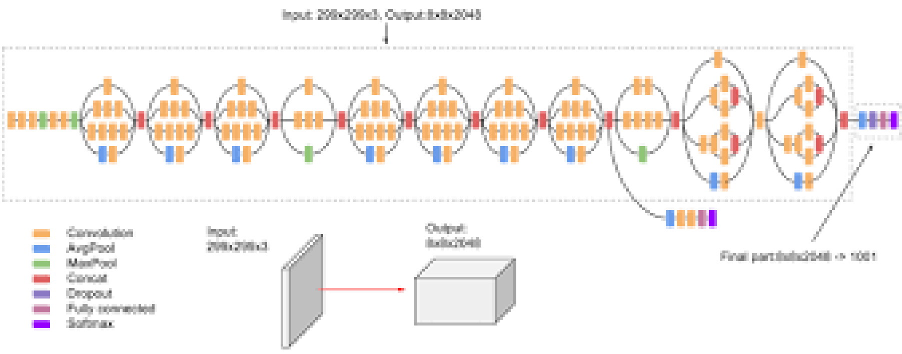

Figure 8: Inception Architecture

Figure 8 Wickrama Arachchilage and Izquierdo (2020) shows the architecture of InceptionV3. The Inception-v3 convolutional neural network is based on the ImageNet database and trained by the Google Brain Team. The system divides photos into 1000 categories depending on how many layers there are in the deep neural network. This model is capable of learning rich representations of various photographs. Each input image needs to be 224x224 pixels. With Inception-v3, the number of parameters is dramatically reduced by batch normalization, picture distortion, RMSprop, and several tiny convolutions Sharma and Miglani (2020). The InceptionV3 model does not need to be retrained as, as its name suggests, it has been trained on a huge data set and has been used to classify a variety of classes. InceptionV3 will then be set to 'FALSE' for the output layer. Other than the output layer, all of the layers have been disabled. The final step will be to introduce a layer of new classification to train the data set photographs. As a result of the research, the layer will be flattened and the 'ReLu' activation function will be used to create a 1024-layer connected layer. A dropout layer of 0.1 is added to eliminate overlapping. In the dense output layer is a function known as 'Softmax' that activates the output.

```
[182] inception_model.add(Dense(1,activation='sigmoid'))
```

```
[183] inception_model.summary()
```

```
Model: "sequential_9"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 inception_v3 (Functional)   (None, 5, 5, 2048)        21802784

 dropout_23 (Dropout)        (None, 5, 5, 2048)        0

 flatten_9 (Flatten)         (None, 51200)             0

 batch_normalization_200 (Ba  (None, 51200)            204800
 tchNormalization)

 dense_19 (Dense)            (None, 1024)              52429824

 batch_normalization_201 (Ba  (None, 1024)             4096
 tchNormalization)

 activation_196 (Activation)  (None, 1024)             0

 dropout_24 (Dropout)        (None, 1024)              0

 dense_20 (Dense)            (None, 1024)              1049600

 batch_normalization_202 (Ba  (None, 1024)             4096
 tchNormalization)

 activation_197 (Activation)  (None, 1024)             0

 dropout_25 (Dropout)        (None, 1024)              0

 dense_21 (Dense)            (None, 1)                 1025

=================================================================
```

Figure 9: Inception Model

3.3.3 ResNet50

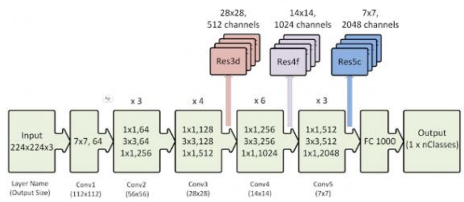

Figure 10: ResNet50 Architecture

Resnet-50 is a residual network consisting of 50 layers and Figure 10 Wickrama Arachchilage and Izquierdo (2020) shows an architecture of ResNet5 . Remaining features are called residues. As a result of the layer's learning, residue corresponds to its characteristics. The training of these networks is much easier than that of traditional deep convolutional neural networks. Moreover, they are also less prone to accuracy degradation.The ResNet50 model does not need to be retrained as, as its name suggests, it has been trained on a large number of images and has been used to classify a variety of classes. Resnet50 will then be set to 'FALSE' for the output layer. Other than the output layer, all of the layers have been disabled. As a result of the research, the layer will be flattened and the 'ReLu' activation function will be used to create a 1024-layer connected layer. A dropout layer of 0.1 is added to eliminate overlapping. In the dense output layer is a function known as 'Softmax' that activates the output.

```
[196] resnet_model.summary()

Model: "sequential_10"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 resnet50 (Functional)       (None, 7, 7, 2048)        23587712

 dropout_26 (Dropout)        (None, 7, 7, 2048)        0

 flatten_10 (Flatten)        (None, 100352)            0

 batch_normalization_203 (Ba  (None, 100352)           401408
 tchNormalization)

 dense_22 (Dense)            (None, 1024)              102761472

 batch_normalization_204 (Ba  (None, 1024)             4096
 tchNormalization)

 activation_198 (Activation)  (None, 1024)             0

 dropout_27 (Dropout)        (None, 1024)              0

 dense_23 (Dense)            (None, 1024)              1049600

 batch_normalization_205 (Ba  (None, 1024)             4096
 tchNormalization)

 activation_199 (Activation)  (None, 1024)             0

 dropout_28 (Dropout)        (None, 1024)              0

 dense_24 (Dense)            (None, 1)                 1025

=================================================================
Total params: 127,809,409
Trainable params: 127,551,489
Non-trainable params: 257,920
```

Figure 11: ResNet50 Model Summary

4 Design Specification

The design architecture specified in the study is used to complete the project. The architecture includes a Data Layer, a Business Layer, and a Client Layer.

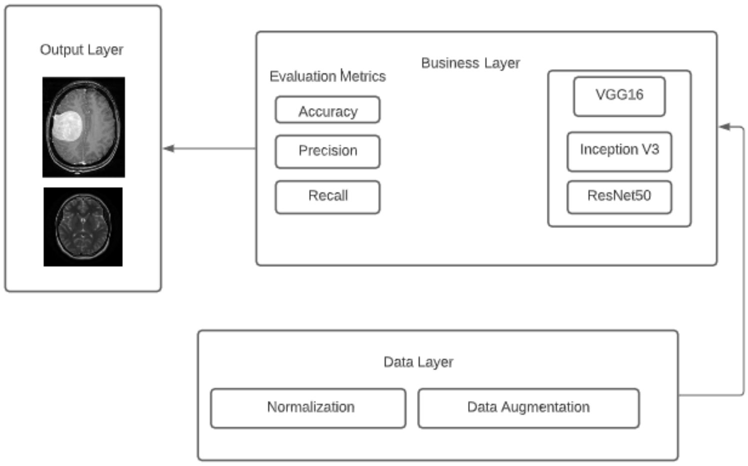

Figure 12: Proposed System Designed

1. **Data Layer:** In this layer, different steps such as collection of data, image processing and data augmentation techniques are implemented. Initial dataset contains 253 MRI images of brain which states whether a patient is having a brain tumour or not. The MRI image set includes overall of 155 pictures that depicts a tumour in a brain and rest representing tumour not present. Once the dataset is gathered, normalization technique is performed. In normalization technique, firstly a series of erosions and dilations are performed to remove noise present in the images. In the next step, finding contours in the threshold image and then extreme points in MR image is retrieved. Finally, the images are cropped according to the extreme points. Once image is pre-processed, Data augmentation is performed to scale, rotate and to solve overfitting problem in a dataset.

2. **Business Layer:** Once data is pre-processed, it is ready to train the models. In this layer various transfer learning models such as VGG-16, InceptionV3 and ResNet50 are trained to achieve results. All these models have been built using python language. In this section, various evaluation metrics are critically evaluated to achieve the research objectives and also help health practioners to provide better treatment by detect a brain tumour as early as possible.

3. **Output Layer:** After critically evaluating results, outputs are provided to health practitioners to provide better and effective treatment. By studying classification reports and graphs it will be easy to detect a tumour present in a brain or not. The underlying architecture and accompanying requirements of the implementation are presented in this section.

5 Implementation

5.1 Setup

The study uses Google Collaboratory with 13.6 GB RAM, this test is performed. Because big image data necessitates additional layers, all models run slower. GPUs are used to accelerate the processing of transfer learning models in real time. TensorFlow and Keras are used to implement these models. Google Collaboratory Notebook uses Python 3. The information is stored in Google Drive. Numpy and Keras are used for image normalization, argumentation, and cropping.

5.2 Data Handling

In the beginning, image data set is mounted from Google Drive to Google Colbartory. The given data set includes two sub folders namely 'yes' and 'no'. The dataset contains a total of 253 images. In sub folder 'yes', it contains a total of 155 images whereas, sub folder 'no' contains a total of 98 images. Data obtained from the API and data source is excellent, and both of them are reliable. Python programming language is used to perform image pre-processing techniques such as cropping. Te given image dataset is divided into three parts namely test, train and val. Normalization technique is performed. The Image Augmentation, Keras, and Tenserflow libraries are utilized to establish a uniform dimension for all inputs, making the model more general and specific. In the training set, 70% of the data is placed, while the remaining 30% goes to the testing set. Studying parameters that affect post-processing throughput, which all affect the extraction of function patches, is crucial for this study. Finally, all parameters are recorded for the uncommon method after the components are removed for further inspection. This can be achieved through Transfer Learning.

5.3 Transfer Learning

A trained model is used to learn a new collection of data by transferring the information from one problem to another. In this study, a transfer learning environment was employed. The pre-trained CNN designs include VGG16, ResNet-50,Inception-v3. Human accuracy is being tested using the best available findings. A picture is input into the networks, and they output the picture's object name as well as the probability of its category.Figure 13 explains workflow of ResNet50.

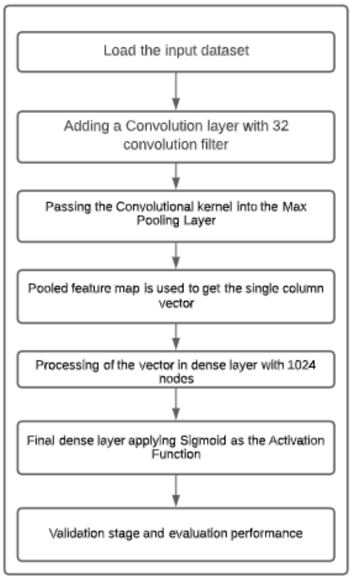

Figure 13: WorkFlow of ResNet50

6 Evaluation

Under this section, the results various transfer learning models such as VGG16, InceptionV3 and ResNet50 are evaluated. Various evaluation metrics such as confusion matrix, accuracy, recall and model performance plots are critically evaluated. The accuracy and loss of each process are calculated for each epoch while evaluating models. Accuracy and loss charts are presented in this section. Based on the prediction and test results, the test accuracy is calculated.

6.1 VGG16 Evaluation

```
[171] #classification report of the model
      from sklearn.metrics import classification_report
      print('Model: VGG16', '\n', classification_report(y_test, predictions, target_names = ['Yes', 'No']))

      Model: VGG16
                    precision    recall  f1-score   support

               Yes       0.88      0.58      0.70        60
                No       0.69      0.92      0.79        60

          accuracy                           0.75       120
         macro avg       0.78      0.75      0.74       120
      weighted avg       0.78      0.75      0.74       120
```

Figure 14: Classification Report of VGG16 Model

From Figure 14, There were different epoch values tested and epoch=5 provided the best accuracy. This model employs a batch size of 32. The number of accurately classified predictions is known as precision,for labels ‘yes’ which is tumour positive and ’No’ which is tumour negative the correct classification percentages are 88% and 69%. This recall which is actually correct classification in this case is 58%, 92% for a brain tumour and non-tumorous images. F1 is simply the sum of recall and precision

6.2 InceptionV3 Evaluation

```
[190] #classification report of the model

from sklearn.metrics import classification_report

print('Model: InceptionV3 model', '\n', classification_report(y_test, predictions, target_names = ['Yes', 'No']))

Model: InceptionV3 model
              precision    recall  f1-score   support

         Yes       0.73      0.53      0.62        60
          No       0.63      0.80      0.71        60

    accuracy                           0.67       120
   macro avg       0.68      0.67      0.66       120
weighted avg       0.68      0.67      0.66       120
```

Figure 15: Classification Report of Inception Model

With Inception-v3, the number of parameters is dramatically reduced by batch normalization, picture distortion, RMSprop, and several tiny convolutions.
For brain tumor detection, InceptionV3 model provides accuracy values of 67 percent with precision value of 73% for tumorous images and 63% for non-tumorous images. For brain tumour and non-tumours images, the recall, i.e. actual values of true positives, is 53% and 80% respectively, from Figure 15 .
In order to achieve a better learning rate, the RMSprop optimizer is used, because the output is multi-class classification categorical cross-entropy. Using the hyperparameters adjusted, the epoch value for this model is 10. This model has a batch size of 32 and an epoch value of 10.

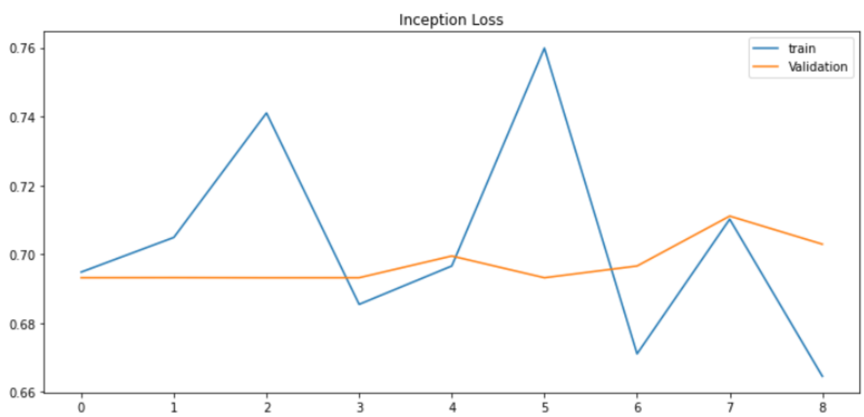

Figure 16: InceptionV3 Model Loss Plot

The given Figure 16 illustrates Inception Model loss throughout the epoch process. It is seen that the training losses fluctuated throughout the epoch process and at last went down. Whereas, model loss of validation data was stable till epoch 3 and then was fluctuating a bit till the end.

The given Figure 17 explains accuracy of training and validation tests through the epochs. It is seen that for validation set the accuracy was stable at 50% and there was no changes noticed while the accuracy of training model was 58% approx. initially then there was a pattern of up and down and at last the final accuracy was more than 60%.

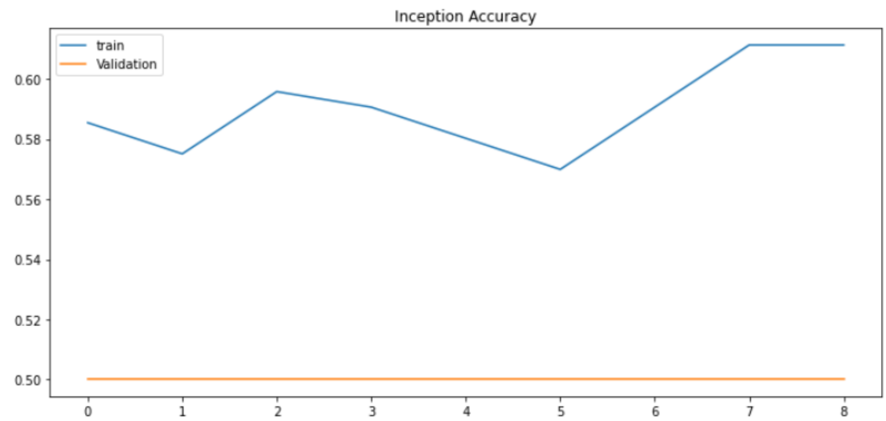

Figure 17: InceptionV3 Model Accuracy Plot

6.3 ResNet50 Evaluation

From the Figure 18, the classification report of ResNet50 shows that the model has achieved better accuracy of 94% which is highest than the other models. The implemented model can correctly identify 98% of images with tumour and 90% of images with no tumour. The ResNet50 model gives better recall than other models as recall plays a crucial role in medical field.The precision value is the number of correctly classified predictions, so in this case for labels 'yes' which is tumour positive and 'No' which is tumour negative the correct classification percentages are 88% and 69%.
In order to achieve a better learning rate, the RMSprop optimizer is used, because the output is multi-class classification categorical cross-entropy. Using the hyperparameters adjusted, the epoch value for this model is the same as the previous one. This model has a batch size of 32 and an epoch value of 10. The given figure illustrates ResNet50 Model loss throughout the epoch process.

```
from sklearn.metrics import classification_report

print('Model: Resnet model', '\n', classification_report(y_test, predictions2, target_names = ['Yes', 'No']))
```

```
Model: Resnet model
              precision    recall  f1-score   support

         Yes       0.91      0.98      0.94        60
          No       0.98      0.90      0.94        60

    accuracy                           0.94       120
   macro avg       0.94      0.94      0.94       120
weighted avg       0.94      0.94      0.94       120
```

Figure 18: ResNet50 Classification Report

The model losses of ResNet50 through all the epochs have been getting low in Figure 19. For validation set, there was a significant drop of model loss from 3.5 to 2 at step 1 epoch. The model loss of validation set was decreasing gradually through out the epoch process. The initial accuracy of training set was approx. 68% which was fluctuating in an up-

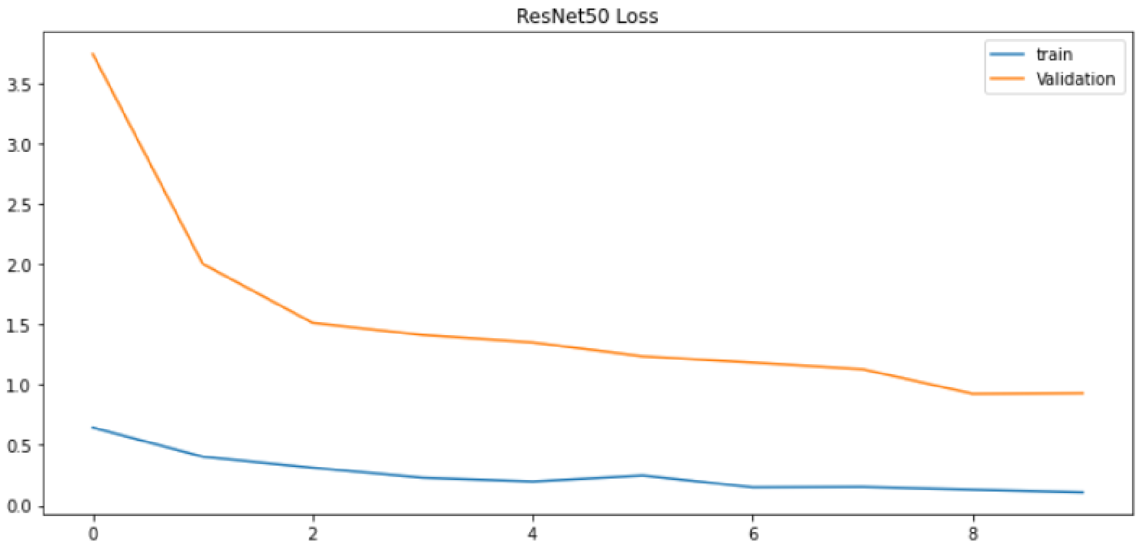

Figure 19: ResNet50 Model Loss Plot

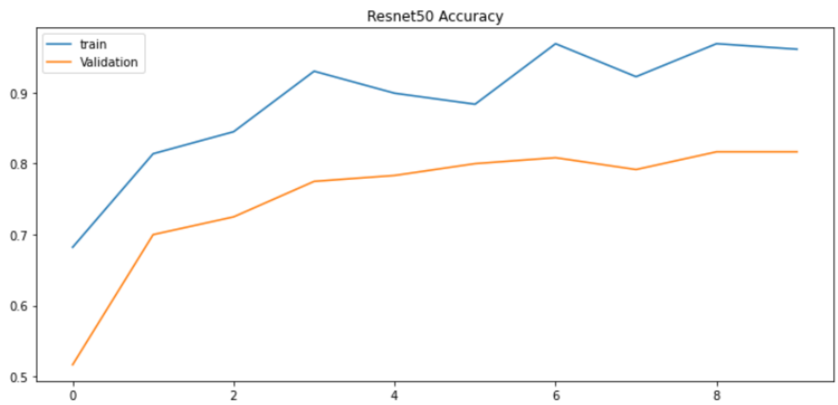

Figure 20: ResNet50 Model Accuracy Plot

ward way and at final epoch stage it was more than 90% for training data in Figure 20. Whereas, accuracy of validation set was less than 80% but showed an upward trend .

6.4 Discussion

Model Name	Accuracy	Precision (Tumour Present)	Precision (Tumour Not Present)	Recall (Tumour Present)	Recall (Tumour Not Present)
VGG16	75%	0.88	0.69	0.58	0.92
InceptionV3	67%	0.73	0.63	0.53	0.80
ResNet50	94%	0.91	0.98	0.98	0.90

Figure 21: Comparing all three models

This study aims to improve the precision and accuracy of brain tumor identification. It shortens the processing time and increases precision by using Google Colab.Three transfer learning models such as VGG16, InceptionV3 and ResNet50 were built to detect a tumor present in a brain or not. In evaluation method, all the models were critically evaluated individually and explained model performance with the help of different plots. In this section, Figure 21 gives overview of all the models evaluated in terms of accuracy, recall and precision. VGG16 gives a total accuracy of 75% which is higher than InceptionV3 Model and also VGG16 model's precision and recall are better than InceptionV3. ResNet50 gives the best accuracy of 94% which is better than other two models. Also precision that is correctly classified tumour and non-tumour images are 91% and 98% respectively. ResNet50 correctly identifies 98% of tumour presented images and 90% of tumour not presented images, interpreted by recall parameter of ResNet50. Hence, ResNet50 model can detect a tumour present in a brain or not more efficiently and accurately.

Figure 22 illustrates the accuracy level of all three models. From the Figure 22 it is clearly seen that ResNet50 gives better accuracy whereas VGG16 produces less accuracy as compared.

7 Conclusion and Future Work

This study employed VGG16,InceptionV3 and ResNet50 to identify brain cancers using magnetic resonance images (MRI). The suggested method enhances the accuracy by over 90% while also reducing runtime. The study uses multiple techniques such as normalization to enhance the quality of image, data augmentation and transfer learning models such InceptionV3, VGG16 and ResNet50 on brain tumour MR images data set. Compared to earlier transfer learning algorithms, this model has exceptional accuracy and consistency. This strategy enables the model for fast learning images which will give better performance. Thus the study can efficiently and accurately detect tumor in a brain which helps the health worker to provide better treatment as early as possible.

Patients with brain tumors may benefit from the proposed approach for identifying tumors.Future research might use the proposed approach to address categorical classifica-

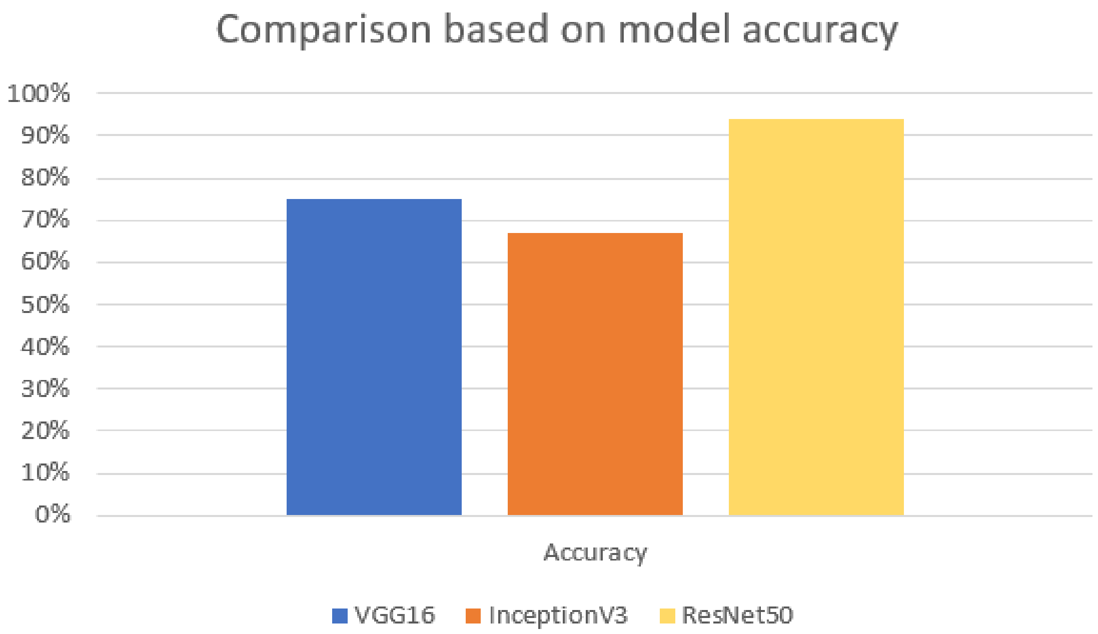

Figure 22: Comparison of Accuracy

tion problems, like distinguishing between Gliomas, Meningiomas, and Pituitary tumors, or identify other brain disorders. A proposed system may also provide early detection in other clinical domains involving medical imaging, such as lung cancer and breast cancer, both of which are highly fatal diseases worldwide.

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