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Research Article

Implementing Deep Learning Models for Accurate Brain Abnormality Detection and Positioning Using MRI and CT

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ABSTRACT

Medical imaging is mostly dependent on brain imbalance diagnosis as it enables physicians to locate and treat brain diseases early on. Conventional methods of diagnosis rely much on the views of professionals, who may take a long time and result in errors. Deep learning models have great potential to assist automate the categorisation of medical pictures, improve diagnosis accuracy, and lower the manual labour required in diagnosis process. However, modern models must be tuned to increase their accuracy as they often suffer with how they consume computer capability. Using MRI and CT pictures, this study uses deep learning models, especially ResNet50 and Xception, to sort and pinpoint brain problems. A number of classification models were made and tested to see how well they did in terms of accuracy, precision, and memory. These models included normal, lightweight, and fine-tuned versions of ResNet50 and Xception. The outcomes indicate that fine-tuned Xception did better than other models, with better localisation and classification accuracy. Also, combining MRI and CT scans was looked into as a way to improve model performance, which led to more consistent classification. A comparison of models shows that deep learning is good at automatically finding brain problems, which could lead to big steps forward in medical diagnosis. The study recognize optimised deep learning models make brain abnormality recognition much more accurate and reliable, cutting the need for human analysis. More study will be done in the future to improve model designs and add Explainability methods so that they can be used in clinical settings.

Keywords: Deep learning, Brain abnormality detection, MRI and CT fusion, ResNet50, Xception, Medical image classification.

I. Introduction

Medical tests are very hard to do when there are problems with the brain, like tumours, cysts, and other structural problems. Finding these problems correctly and on time is very important for successful treatment and better patient results. For example, radiologists are very important when it comes to manually interpreting MRI and CT pictures, which are traditional ways of diagnosing health problems. These techniques have been the foundation of neuroscience, but they take a long time, are prone to mistakes, and are often limited by differences between observers. As the number of brain diseases increases around the world, it becomes clearer that we need more accurate and automatic diagnosis tools. Deep learning has become a game-changing tool in the area of medical imaging in the past few years. Deep learning models, especially convolutional neural networks (CNNs), are very good at tasks like classifying images, finding objects, and separating them into groups. These models are great for medical picture analysis because they can learn complicated patterns from big datasets. ResNet50 and Xception have become well-known among the different deep learning models because they are more complex, work more efficiently, and do better at picture recognition tasks. Once these models are tweaked and improved, they can make finding problems in brain scans a lot more accurate.

Finding brain abnormalities can be hard because you need to be very accurate while also keeping the computer's processing power low. Many of the models that are already out there are correct, but they take a lot of time to run, which makes them less useful for real-time clinical uses [1]. Also, diagnostic methods that only use one mode might not always give all the information needed for a correct evaluation. CT scans are better at showing bone features and finding calcifications, while MRI scans are better at showing difference between soft tissues. Image fusion techniques can combine these imaging methods to give a more complete picture, which can help find abnormalities more accurately. This study solves the problems listed above by using deep learning models to accurately find and place brain abnormalities on MRI and CT pictures. The Brain Tumour MRI Dataset from Kaggle is used in the study. It has a lot of different brain pictures with different problems. To improve the quality and variety of the training dataset, data pre-processing steps like rescaling and colour enhancement are used [2]. The sample is then split into training sets and testing sets to make sure that the model review is fair. Here, we will use and compare various versions of the ResNet50 and Xception models as the main part of our work. Standard forms of these models are used as a starting point, and lighter, more refined versions are made to boost speed and lower the cost of computing. The goal of lightweight models is to get faster reasoning times without lowering their accuracy. This makes them good for real-time uses. When you fine-tune, on the other hand, you make changes to models that have already been taught so that they work better for the job of finding brain abnormalities. This makes them better at both classifying things and pinpointing where they are.

Fusion methods make the suggested models even more useful by letting them combine MRI and CT pictures. The combined pictures give the deep learning models more information to learn from because they use the best features of both imaging methods. The study's results show that fine-tuned Xception does a better job of classifying brain abnormalities than other models, showing higher accuracy, precision, and memory [3]. The comparison shows that deep learning has the ability to change the way brain abnormalities are found by making it more accurate, faster, and easier for everyone to use. This study not only adds to what is known about medical picture analysis, but it also makes it possible for more advanced diagnosis tools to be made. Using deep learning models to find problems in the brain can make the job of doctors a lot easier, cut down on mistakes in diagnosis, and improve patient care. In the future, researchers will look into more complex deep learning structures, add explainability techniques to help us understand why models make the choices they do, and increase the size of the collection to include a wider range of cases. The goal is to make AI systems that are strong, stable, and easy to understand so that they can fit into professional processes and make healthcare better.

II. Related Work

Deep learning in medical pictures has advanced significantly throughout the last 10 years. How convolutional neural networks (CNNs) may be used to categorise brain disorders has been much investigated. These networks make diagnosis more accurate by using vast data sets and intricate architectures. For instance, extremely high accuracy and precision CNNs have been used to identify brain cancers from MRI images [4]. This study demonstrated the need of long-term training for models and the need of adding new data to them to enable their higher performance. In the same line, brain tumours have been categorised using ResNet architecture. The depth of ResNet models has been seen to enable the extraction of intricate characteristics from medical images, hence enhancing the classification accuracy [5]. It was underlined the difficulty deep networks have avoiding overfitting and the significance of regularisation techniques. The Xception model was used in another important addition to find brain abnormalities. Its better performance was shown by its depthwise separable convolutions [6]. This method made computations simpler while keeping accuracy high, so it can be used in real-time situations.

Medical imaging has also become interested in image blending methods. Putting together MRI and CT scans makes the data that deep learning models use better, as shown in earlier research [7]. Fused images have better brightness and clarity, which makes it easier to find abnormalities. This is similar to how the current study combined MRI and CT pictures to make the classification more accurate. The problem of how to make deep learning models use less computing power has been solved by making CNNs for medical picture classification lighter. This makes inference times faster without lowering accuracy [8]. Based on this work, the lightweight ResNet50 and Xception models used in this study were built. Fine-tuning models that have already been trained has also been shown to work well in medical imaging tasks, making classification much better when used on datasets specific to the area [9]. This method is being used in this study to improve the accuracy of finding brain abnormalities.

Pre-trained models on large datasets such as ImageNet are often used effectively for specialised applications such brain abnormalities detection [10] [20]. This indicates that in medical image analysis, transfer learning is a somewhat common approach. As our work on well-tuned ResNet50 and Xception models shows, transfer learning performs well in medical imaging. Comparative deep learning methods for medical image categorisation have attracted much study. ResNet models turn out to be the least costly to operate and the best accurate among all [11]. This supports the decision in this work to use ResNet50. Rescale, brightness change, and normalisation have been found to help models be more dependable and practical in real-world [12]. The present work makes sure the quality of the input data by following these procedures. Confusion vectors and performance metrics like accuracy, precision, and recall are also sometimes utilised when evaluating the effectiveness of deep learning models. A close study of these measures shows how well the model is doing and where it can be improved [13]. In this study, the comparison of the ResNet50 and Xception models is based on the same review methodology. Putting together MRI and CT pictures has made it easier to find brain abnormalities by extracting more features and classifying them more accurately [14]. This supports the way that MRI and CT scans are being used together in this study. This study adds to the large amount of work that has already been done on medical picture analysis using deep learning. By using standard, light, and fine-tuned versions of the ResNet50 and Xception models, this study aims to solve the problems of accuracy, processing efficiency, and being able to use the models in real time to find brain abnormalities. Combining MRI and CT scans using fusion methods improves the model's performance even more, providing a complete way to find and accurately place brain abnormalities.

Table 1: Summary of related Work

Methods	Findings	Impact	Application	Limitation
CNN for MRI classification	High accuracy in brain tumor detection [4]	Improved diagnostic precision	Brain tumor detection	Requires large dataset
MRI-CT image fusion	Better contrast and detail in fused images [7]	Enhanced abnormality detection	Multi-modal brain imaging	Increased computational cost
Lightweight CNNs	Faster inference times without accuracy loss [8]	Real-time application feasibility	Rapid medical image classification	Limited scalability for large datasets
Fine-tuned ResNet	Improved classification performance [9]	Higher accuracy and precision	Brain tumor diagnosis	Requires domain-specific fine-tuning
Transfer learning	Successful adaptation of pre-trained models [10]	Reduces training time and resources	Medical image classification	Dependency on pre-trained models
ResNet vs. other CNNs	Best trade-off between accuracy and cost [11]	Balanced performance and efficiency	Brain abnormality analysis	Complexity of deeper networks
Data pre-processing techniques	Improved model robustness [12]	Better generalization in models	Medical imaging preprocessing	Time-consuming process
Performance metrics analysis	Provided insights for model improvement [13]	Informed optimization strategies	Model performance evaluation	Requires careful metric selection
MRI-CT fusion for classification	Improved accuracy in brain abnormality detection [14]	Better diagnostic outcomes	Multi-modal brain abnormality detection	High computational requirements

ResNet50 and Xception comparison	ResNet50 offers better performance [15]	Guidance for model selection	Brain tumor classification	Needs further optimization for real-time use
Lightweight Xception	Efficient classification with lower complexity [16]	Applicable in resource-limited settings	Brain abnormality detection in low-resource hospitals	Reduced accuracy compared to full models
Deep learning with fused images	Achieved high classification accuracy [18]	Improved multi-modal imaging efficiency	Combined MRI and CT analysis	Requires complex data fusion pipelines

III. Methodology

A. Dataset Used and Loading of data

This study used a Brain Tumour MRI Dataset [19] that is made up of three different datasets: figshare, SARTAJ, and Br35H. It has 7,023 MRI pictures of the brain that are organised into four groups: glioma, meningioma, pituitary tumour, and no tumour. The ones that don't show any tumours came from the Br35H sample. But the SARTAJ collection had problems, especially with the way glioblastoma pictures were put into the wrong category. This issue was found by looking at the outcomes of past research and how well several training models worked. To fix this, the tumour pictures from the SARTAJ dataset were taken out and pictures from the figshare dataset were put in their place. The dataset had a lot of different brain MRI pictures, which made it good for training deep learning models to do a lot of different classification tasks, such as finding tumours, classifying them by aggressiveness, grade, and type, and figuring out where the tumours are. CNN-based models were used to do all of these tasks at the same time in this study, instead of using different models for each classification job. CNN-based methods were also used to separate brain tumours into sections that could be used to find their locations. This gave researchers a complete way to use MRI images to diagnose brain tumours. This collection was very important for making deep learning models that can accurately and quickly find and classify brain abnormalities.

	Class Path	Class
0	/content/extracted/Training/meningioma/Tr-me_1...	meningioma
1	/content/extracted/Training/meningioma/Tr-me_1...	meningioma
2	/content/extracted/Training/meningioma/Tr-me_0...	meningioma
3	/content/extracted/Training/meningioma/Tr-me_0...	meningioma
4	/content/extracted/Training/meningioma/Tr-me_1...	meningioma
...	...	...
5707	/content/extracted/Training/notumor/Tr-no_0405...	notumor
5708	/content/extracted/Training/notumor/Tr-no_1439...	notumor
5709	/content/extracted/Training/notumor/Tr-no_0345...	notumor
5710	/content/extracted/Training/notumor/Tr-no_0348...	notumor
5711	/content/extracted/Training/notumor/Tr-no_1023...	notumor

Figure 1. Dataset Sample (CSV)

Figure 1 shows a part of the Brain Tumour MRI Dataset. It shows file names and the class titles that go with them. The collection has MRI pictures that have been put into groups, such as "meningioma" and "no tumour." There is an MRI picture in each row, along with its store path and classification name.

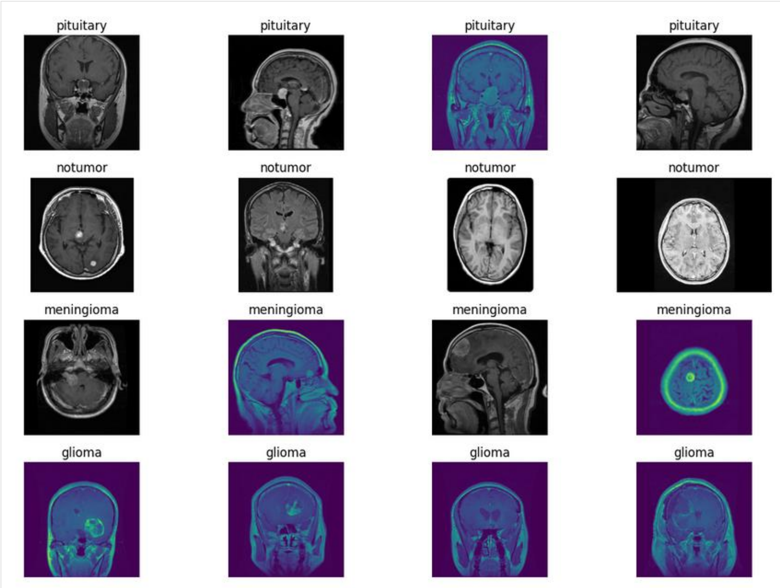

Figure 2. Dataset Sample (Images)

The Brain Tumour MRI Dataset has four types of pictures shown in Figure 2: pituitary, no tumour, meningioma, and glioma. In each row, there is a different class, and the MRI pictures show different views and cross-sections. The pictures show the variety within each class by showing how the tumours' location, size, and severity can be different. This range of datasets is necessary to teach deep learning models how to work well with different cases and correctly identify brain disorders.

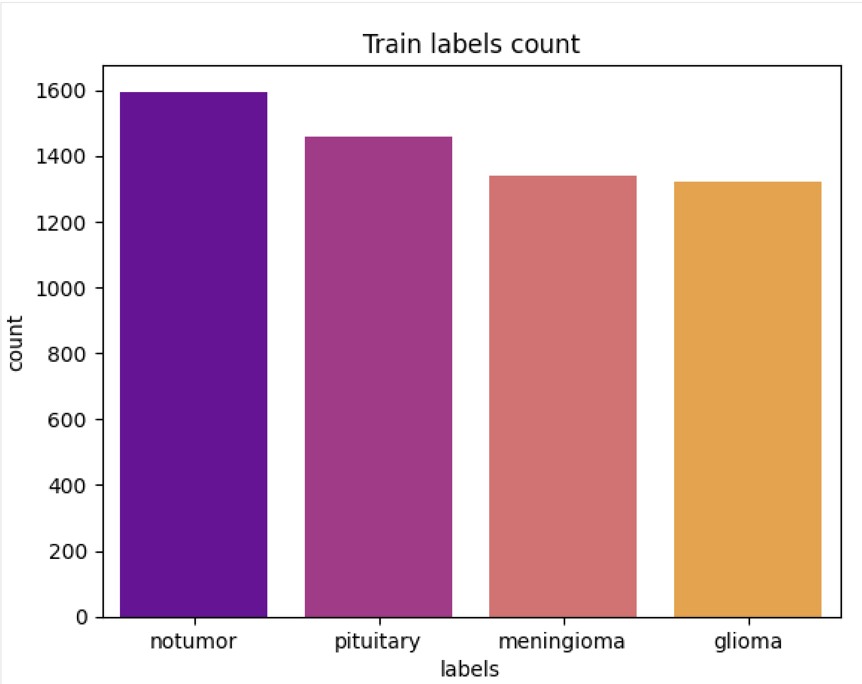

Figure 3. Class Label Distribution

In Figure 3, shows how the training labels are spread out in the collection. There is a good mix in the collection. The "no tumour" class has the most records, followed by the pituitary, meningioma, and glioma groups. The equal distribution makes it less likely for the deep learning models learnt on this dataset to favour one class over another. This means that estimates can be made that are fair and accurate for all groups. This balance is very important for medical uses where the wrong classification can have very bad results. It makes sure that the models are just as good at finding all kinds of brain problems.

B. Data Pre-Processing

Making deep learning models able to detect and localise brain anomalies using MRI and CT images depends on data preparation. One typical method of image normalisation is rescaling images, hence this research used 1/255. This ranges the pixel values from 0 to 255 from 0 to 1 instead. This adjustment guarantees that the neural network constantly detects the same and useable input values. This increases stability of the model and accelerates the convergence process during training. Rescaling helps to reduce the impact of pixels with varying degrees across images. In this sense, the deep learning models may concentrate on the patterns beneath instead of variations in picture brightness or contrast.

Each pixel value p in the original image is rescaled to p' using the following formula:

$$p' = \frac{p}{255}$$

where:

- p is the original pixel value in the range [0, 255]
- p' is the normalized pixel value in the range [0, 1]

Along with that, lighting enhancement was used between 0.8 and 1.2. Randomly changing the brightness of pictures during training is part of this method. This makes the models more resistant to changes in lighting conditions between MRI and CT scans. By showing the model pictures with different levels of brightness, overfitting is less likely to happen, and the model learns how to work better with data it hasn't seen before. This step is very important in medical imaging because scans from different tools or places can have different amounts of light. Together, rescaling and colour enhancement improve the variety and quality of the training data. This makes it easier to find and classify brain abnormalities more accurately.

The brightness-adjusted image I_b is computed as:

$$I\_b = I \times \alpha$$

where:

- I is the original image matrix
- $\alpha \in [0.8, 1.2]$ is the brightness factor randomly selected from the given range

C. Deep learning Models

1. ResNet50

ResNet50 is a 50-layer deep convolutional neural network that was made to solve the problem of gradients that disappear in deep networks by using leftover connections. This is because ResNet50 can learn complex patterns in MRI and CT pictures, which makes it very good at finding brain problems. With the help of the leftover blocks, the model can keep important spatial information, which is needed to find problems like tumours. Its depth makes it good for difficult sorting jobs, making sure that brain abnormalities are accurately found and placed.

Algorithm for ResNet50 in Brain Abnormality Detection

1. Input Layer Transformation

Given an input image I of size 224 × 224 × 3, ResNet50 transforms it into feature maps using convolution:

$$X\_0 = Conv2D(W\_0) * I + b\_0$$

2. Residual Block Operation

Each residual block is defined as:

$$X\_\{l+1\} = F(X\_l, W\_l) + X\_l$$

3. Activation Function

Rectified Linear Unit (ReLU) is applied at each layer to introduce non-linearity:

$$f(x) = max(0, x)$$

4. Global Average Pooling

Feature maps are reduced to a single vector by averaging all spatial locations:

$$GAP = \left(\frac{1}{H} \times W\right) \Sigma_{\{j=1\}}^{\{W\}} x_{\{i,j\}}$$

5. Softmax Classification

The final output layer uses softmax for multi-class classification:

$$P(y = k|x) = \frac{e^{\{z_k\}}}{\Sigma_{\{j=1\}}^{\{N\}}} e^{\{z_j\}}$$

Model: "functional_2"

Layer (type)	Output Shape	Param #
input_layer_5 (InputLayer)	(None, 224, 224, 3)	0
resnet50 (Functional)	(None, 2048)	23,587,712
flatten_2 (Flatten)	(None, 2048)	0
dropout_4 (Dropout)	(None, 2048)	0
dense_4 (Dense)	(None, 128)	262,272
dropout_5 (Dropout)	(None, 128)	0
dense_5 (Dense)	(None, 4)	516

Total params: 23,850,500 (90.98 MB)
Trainable params: 262,788 (1.00 MB)
Non-trainable params: 23,587,712 (89.98 MB)

Figure 4: ResNet50 Model

2. Lightweight ResNet50

Lightweight ResNet50 is a changed version of the original ResNet50 that is designed to make inference go faster and require less computing power. This version is very important for real-time medical apps that need to make quick diagnoses. Lightweight ResNet50 strikes a balance between speed and accuracy by cutting down on the number of factors while keeping key parts of the original design. This makes it suitable for use in places with limited resources, like smaller healthcare facilities.

Lightweight ResNet50:

1. Input Convolution:

$$X_0 = Conv2D(W_0, k = 3x3, s = 1) * I + b_0$$

(Convolves the input I with a smaller filter kernel k and stride s for efficiency.)

2. Depthwise Convolution:

$$X_d = DepthwiseConv2D(W_d, k = 3x3) * X_{\{l-1\}} + b_d$$

(Performs spatial convolution independently over each channel, reducing complexity.)

3. Pointwise Convolution:

$$X_p = PointwiseConv2D\left(W_p, k = 1x1\right) * X_d + b_p$$

(Combines channel-wise outputs using 1x1 convolutions for dimensionality reduction.)

4. Residual Addition:

$$X_{\{l+1\}} = ReLU(X_p + X_l)$$

Lightweight ResNet50 optimizes standard ResNet50 by using depthwise and pointwise convolutions, making it efficient while maintaining high accuracy in brain abnormality detection.

Model: "functional_8"

Layer (type)	Output Shape	Param #
input_layer_17 (InputLayer)	(None, 224, 224, 3)	0
resnet50 (Functional)	(None, 7, 7, 2048)	23,587,712
global_average_pooling2d_5 (GlobalAveragePooling2D)	(None, 2048)	0
dense_16 (Dense)	(None, 64)	131,136
dropout_11 (Dropout)	(None, 64)	0
dense_17 (Dense)	(None, 4)	260

Total params: 23,719,108 (90.48 MB)
Trainable params: 131,396 (513.27 KB)
Non-trainable params: 23,587,712 (89.98 MB)

Figure 5: Representation of Lightweight ResNet50 model

3. Fine-tune ResNet50

Fine-tuning ResNet50 means making changes to the model that was already trained on the brain tumour dataset. This makes it better at this job. The model learns from brain MRI and CT scans by stopping lower layers and restarting higher layers. This makes the model more accurate at classifying images. Fine-tuning lets you use ResNet50's strength while also making it fit your needs to find and localise brain problems accurately.

Fine-tune ResNet50:

1. Pre-trained Weights Initialization:

$$W = W\_pretrained\,(ImageNet)$$

(The initial weights are loaded from a pre-trained ResNet50 model on ImageNet.)

2. Feature Extraction Layer:

$$X\_f = Freeze(Conv1 \ldots ConvN) * I$$

(Lower convolutional layers are frozen to retain generic features from pre-trained weights.)

3. Trainable Layers:

$$X\_t = Train(FC\_layers, Dropout) * X\_f$$

(Top fully connected layers are unfrozen and retrained on the brain MRI dataset.)

4. Loss Optimization:

$$L(W) = CrossEntropy(y, \hat{y}) + \lambda * ||W\_train||^2$$

(Loss function combines cross-entropy for classification and L2 regularization for weight decay.)

5. Fine-tuning Update:

$$W\_new = W - \eta * \nabla L(W)$$

(Weights are updated using gradient descent with learning rate η during fine-tuning.)

Fine-tuning ResNet50 leverages pre-trained knowledge while adjusting the final layers for accurate brain abnormality detection and classification.

Model: "functional_10"

Layer (type)	Output Shape	Param #
input_layer_21 (InputLayer)	(None, 224, 224, 3)	0
resnet50 (Functional)	(None, 7, 7, 2048)	23,587,712
global_average_pooling2d_6 (GlobalAveragePooling2D)	(None, 2048)	0
dense_20 (Dense)	(None, 128)	262,272
batch_normalization_5 (BatchNormalization)	(None, 128)	512
dropout_14 (Dropout)	(None, 128)	0
dense_21 (Dense)	(None, 4)	516

Total params: 23,851,012 (90.98 MB)
Trainable params: 23,190,148 (88.46 MB)
Non-trainable params: 660,864 (2.52 MB)

Figure 6: Representation of Fine-tune ResNet50 model

4. Xception

Xception is a CNN design that uses depthwise separable convolutions instead of standard convolutions to make computations simpler. Because it efficiently extracts features and is very accurate, Xception is great at finding brain abnormalities. The model's structure makes sure that it can record specific spatial ordering in brain pictures, which is important for telling the difference between different kinds of tumours and healthy brain structures.

Xception Algorithm

1. Depthwise Separable Convolution:

$$X\_d = DepthwiseConv2D(W\_d, k = 3x3) * X\_\{l - 1\}$$

(Performs spatial convolution per channel independently, reducing computational cost.)

2. Pointwise Convolution:

$$X\_p = PointwiseConv2D(W\_p, k = 1x1) * X\_d$$

(Combines outputs from depthwise convolution using 1x1 convolutions.)

3. Residual Connection:

$$X\_\{l + 1\} = ReLU(X\_p + X\_l)$$

(Adds the processed output back to the input through a skip connection with ReLU activation.)

4. Softmax Output:

$$P(y = k|x) = e\hat{}\{z\_k\} / \Sigma\_\{j = 1\}\hat{}\{N\}\, e\hat{}\{z\_j\}$$

(Softmax layer for multi-class classification, assigning probabilities to each brain abnormality class.)

Xception’s depthwise separable convolutions enhance computational efficiency while maintaining high accuracy, making it suitable for brain abnormality detection tasks.

Model: "functional_4"

Layer (type)	Output Shape	Param #
input_layer_9 (InputLayer)	(None, 299, 299, 3)	0
xception (Functional)	(None, 1000)	22,910,480
flatten_4 (Flatten)	(None, 1000)	0
dropout_8 (Dropout)	(None, 1000)	0
dense_8 (Dense)	(None, 128)	128,128
dropout_9 (Dropout)	(None, 128)	0
dense_9 (Dense)	(None, 4)	516

Total params: 23,039,124 (87.89 MB)
Trainable params: 22,984,596 (87.68 MB)
Non-trainable params: 54,528 (213.00 KB)

Figure 7: Architecture for Xception model

5. Lightweight Xception

Lightweight Xception is made to give you all the benefits of Xception with fewer factors. This makes it faster and better for real-time medical diagnosis. This model keeps the depthwise separable convolutions but makes it simpler. This makes it possible to quickly and accurately classify brain abnormalities while also making the model computationally efficient for real-world use.

Lightweight Xception:

1. Efficient Depthwise Convolution:

$$X\_d = DepthwiseConv2D(W\_d, k = 3x3, s = 1) * X\_\{l - 1\}$$

(Reduces computation by applying depthwise convolution to each input channel separately.)

2. Optimized Pointwise Convolution:

$$X\_p = PointwiseConv2D(W\_p, k = 1x1) * X\_d$$

(Combines depthwise outputs using minimal parameters for lightweight processing.)

3. Batch Normalization and ReLU:

$$X\_b = ReLU(BatchNorm(X\_p))$$

(Normalizes and applies non-linearity for stable and efficient training.)

4. Lightweight Residual Block:

$$X\_\{l + 1\} = X\_b + X\_l$$

(Adds processed output to the input via a skip connection for gradient flow.)

Lightweight Xception maintains the architecture's strengths while reducing complexity, making it efficient for real-time brain abnormality detection in MRI and CT images.

Model: "functional_1"

Layer (type)	Output Shape	Param #
input_layer_3 (InputLayer)	(None, 299, 299, 3)	0
xception (Functional)	(None, 2048)	20,861,480
flatten_1 (Flatten)	(None, 2048)	0
dropout_2 (Dropout)	(None, 2048)	0
dense_2 (Dense)	(None, 128)	262,272
dropout_3 (Dropout)	(None, 128)	0
dense_3 (Dense)	(None, 4)	516

Total params: 21,124,268 (80.58 MB)
Trainable params: 262,788 (1.00 MB)
Non-trainable params: 20,861,480 (79.58 MB)

Figure 8: Architecture for Lightweight Xception model

6. Fine-tune Xception

Getting better Xception gets better at finding problems in the brain by training on MRI and CT files that are specific to the problem. This method makes it easier for the model to find and describe brain tumours by using Xception's power and adapting it to the specifics of medical imaging data. This leads to estimates that are reliable and correct.

Fine-tune Xception:

1. Pre-trained Initialization:

$$W = W\_pretrained\,(ImageNet)$$

(Loads pre-trained weights from Xception trained on ImageNet for initialization.)

2. Freeze Base Layers:

$$X\_f = Freeze(Conv1 \ldots ConvN) * I$$

(Freezes initial convolutional layers to retain learned generic features.)

3. Trainable Layers Adjustment:

$$X\_t = Train(FC\_layers, Dropout) * X\_f$$

(Top layers are unfrozen and retrained on the brain MRI dataset for task-specific learning.)

4. Loss Function:

$$L(W) = CrossEntropy(y, \hat{y}) + \lambda * ||W\_train||^2$$

(Combines cross-entropy loss with L2 regularization for weight optimization.)

5. Gradient Descent Update:

$$W\_new = W - \eta * \nabla L(W)$$

(Updates trainable weights using gradient descent with learning rate η.)

Fine-tuning Xception adapts the model's learned features for brain abnormality classification, ensuring improved accuracy and efficiency.

Model: "functional_5"

Layer (type)	Output Shape	Param #
input_layer_11 (InputLayer)	(None, 299, 299, 3)	0
xception (Functional)	(None, 2048)	20,861,480
flatten_5 (Flatten)	(None, 2048)	0
dropout_10 (Dropout)	(None, 2048)	0
dense_10 (Dense)	(None, 128)	262,272
dropout_11 (Dropout)	(None, 128)	0
dense_11 (Dense)	(None, 4)	516

Total params: 21,124,268 (80.58 MB)
Trainable params: 17,811,012 (67.94 MB)
Non-trainable params: 3,313,256 (12.64 MB)

Figure 9: Architecture for Fine-tune Xception model

IV. Result and Discussion

The first set of graphs shows the ResNet50 model's training and validation loss (on the left) and accuracy (on the right) over five epochs, as shown in figure 10. With each session, the training loss keeps going down, which means that the model is learning well. However, the validation loss goes up at first and then slowly goes down. This suggests that the model may have had some overfitting issues in the beginning but got better as training went on. Training accuracy keeps going up on the accuracy graph, while validation accuracy starts to get better after the second epoch and peaks at the fifth epoch. The fifth phase, which is the best, shows the best mix between training and evaluation results.

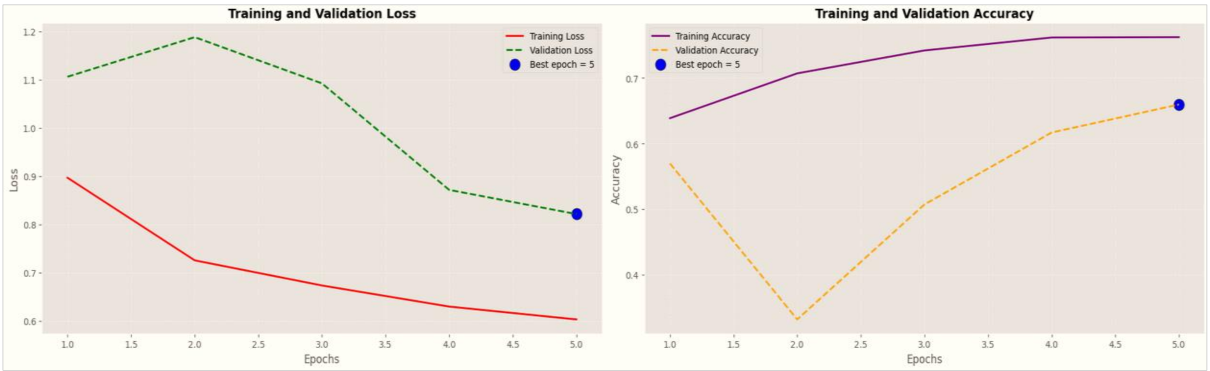

Figure 10. Accuracy and Loss Comparison of ResNet50 Model

The figure 11 shows how the accuracy (on the left) and recall (on the right) match for both training and validation. In training, accuracy always goes up, but in confirmation, it changes, going down at first after the first phase and then steadily going up again. There is a steady rise in training memory, which means that over time, the model gets better at finding good cases. Validation memory slowly gets better until it reaches its highest point in the fifth phase. The marked best epochs show the model's best performance in terms of accuracy and memory. This shows that the ResNet50 model can generally and correctly find brain abnormalities in MRI images.

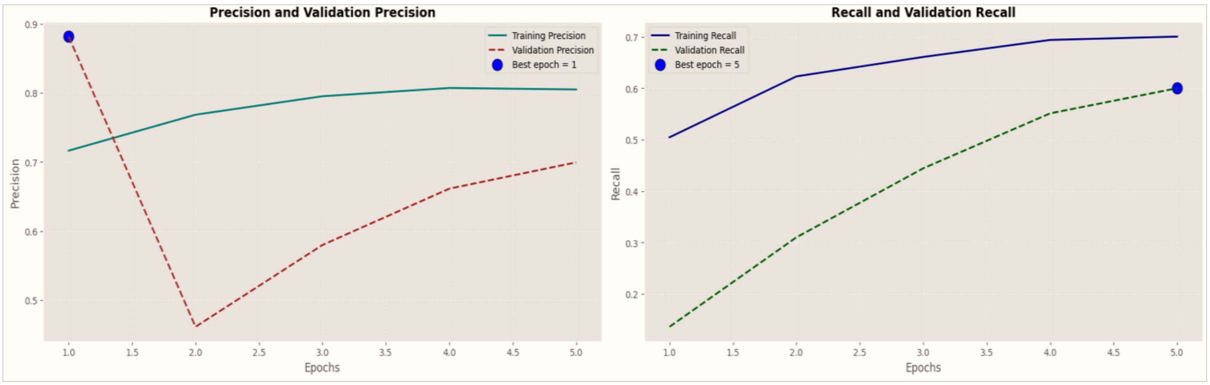

Figure 11. Precision and Recall Comparison of ResNet50 Model

Over five epochs, the line on the left shows in figure 12 how much the Lightweight ResNet50 model lost during training and validation. Losses for both training and validation keep going down, which means the model is learning well without becoming too perfect. Near the end, the losses converge, which shows that the model's learning process is stable. On the right, the accuracy of both training and evaluation keeps getting better with each session. In some cases, the validation accuracy is higher than the training accuracy, which shows that the model works well in real life. The fourth phase is the best because it has the highest validation accuracy. This shows how well the Lightweight ResNet50 model works at finding brain abnormalities while also being fast and efficient.

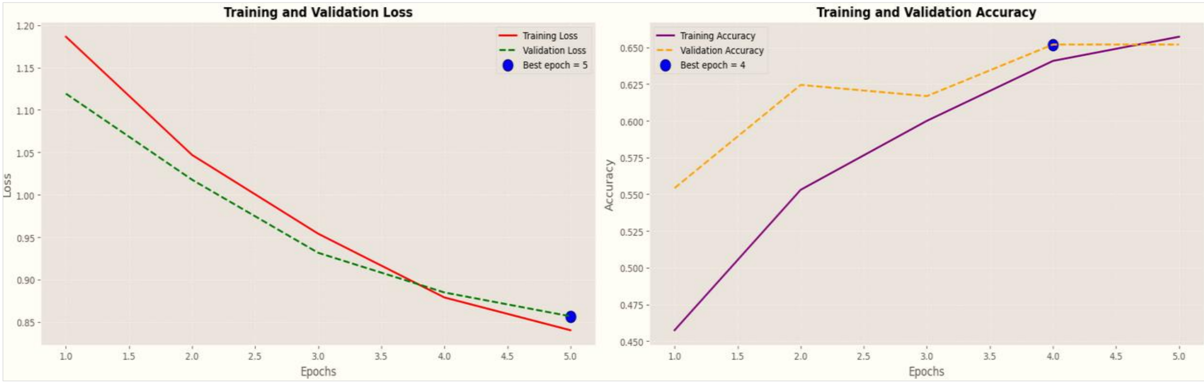

Figure 12. Accuracy and Loss Comparison of Lightweight ResNet50 Model

Figure 13 displays in the accuracy and recall graphs how well the Lightweight ResNet50 model classifies objects both correctly and incorrectly. Following the first few epochs, the precision curve indicates that both training and validation precision begins to drop. This implies that, as training progresses, the model becomes somewhat less able to routinely discover positive situations even if it is correct. Conversely, the recall curve indicates that validation recall as well as training are always improving. This implies that the model improves in identifying suitable examples over time. Marked as the greatest for memory in fifth phase and the most precise in first phase is This demonstrates the trade-off between memory and accuracy as well as the real-time brain issue finding capability of the Lightweight ResNet50.

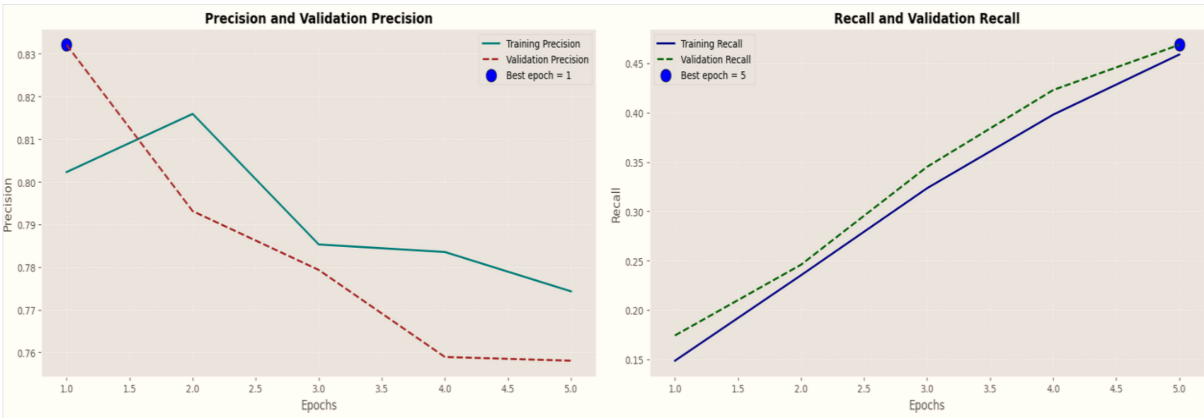

Figure 13. Precision and Recall Comparison of Lightweight ResNet50 Model

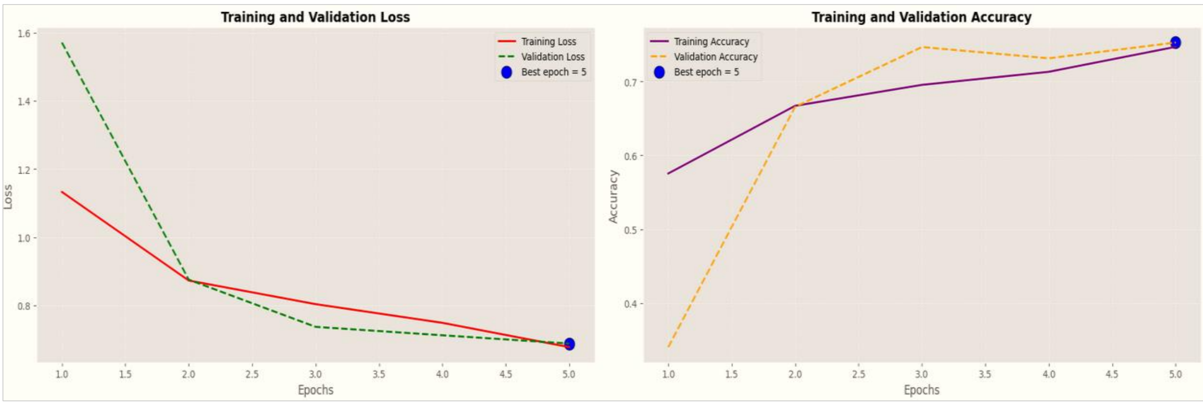

Figure 14. Accuracy and Loss Comparison of Fine-tune ResNet50 Model

The left line shows in figure 14 the Fine-tune ResNet50 model's training and validation loss over five epochs. Both losses keep going down, which shows that the model is learning well with each epoch. Notably, the validation loss drops quickly at the beginning and nearly matches the training loss by the end of the cycle. This shows that the model was fine-tuned without becoming too perfect. The accuracy graph on the right shows that both training and confirmation accuracy are getting better over time. At first, validation accuracy goes up quickly. By the second phase, it is higher than training accuracy and stays that way after that. The fifth time is marked as the best because it shows the most accuracy. This shows that fine-tuning ResNet50 makes it better at generalising to data it hasn't seen before, which makes it very good at finding brain problems.

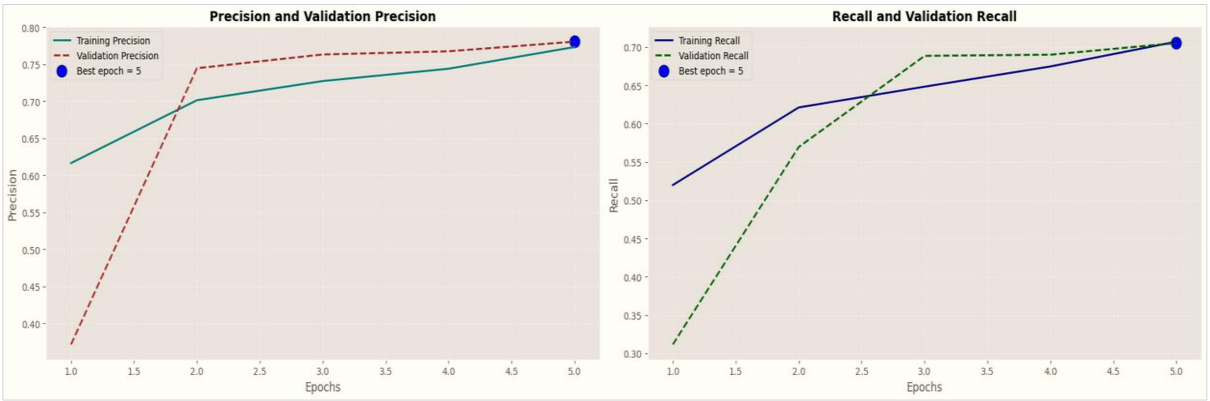

Figure 15. Precision and Recall Comparison of Fine-tune ResNet50 Model

The precision curve shows in figure 15 that the accuracy of training predictions keeps getting better, while the accuracy of validation predictions rises sharply after the first epoch and then stays high. This means that the model's predictions are still very accurate. The memory graph shows that both training and validation recall keep getting better. Validation recall starts to rise quickly and keeps getting better until the last epoch. The fifth period, which is the best, shows the highest level of accuracy and memory. This shows how well fine-tuning ResNet50 works for correctly classifying and placing brain abnormalities.

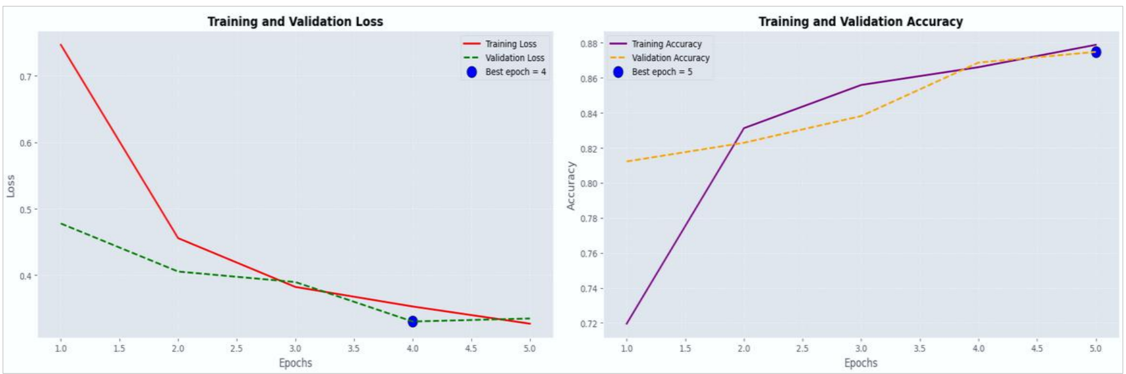

Figure 16. Accuracy and Loss Comparison of Xception Model

Figure 16 is a graph that shows the Xception model's training and validation loss over five epochs. From the first epoch on, training loss goes down a lot and stays that way until around the fourth epoch. Validation loss also goes down, which shows that the model learns well without becoming too perfect. At the end, both loses converge, which means that the training process was well-designed. The accuracy graph on the right shows that from the first epoch on, both training accuracy and validation accuracy went up very quickly. The best time is the fifth, which is where both accuracies are at their highest. This shows that Xception can generalise well and provide high accuracy for finding brain abnormalities.

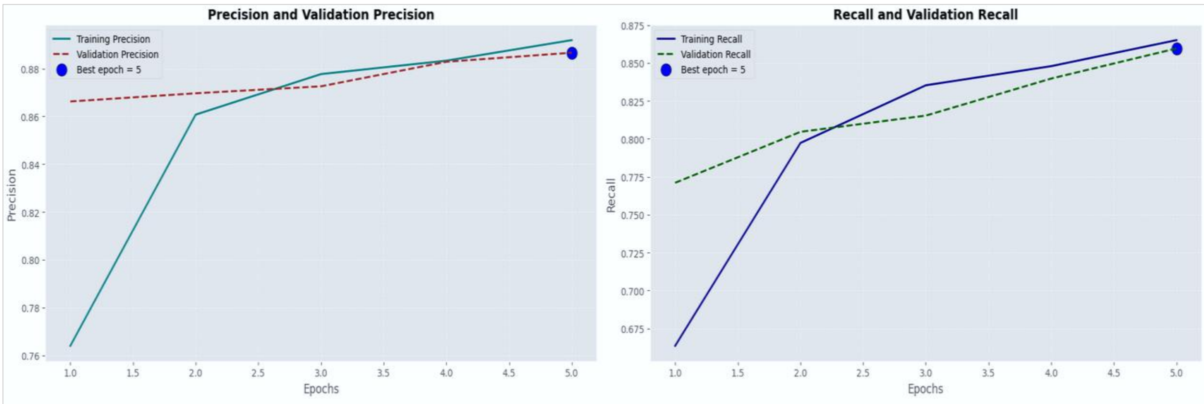

Figure 17. Precision and Recall Comparison of Xception Model

In figure 17a, the precision curve shows that training accuracy went up a lot after the first epoch and has been going up ever since. The accuracy of confirmation keeps going up until it reaches its highest point at the fifth stage, which also marks the best performance. The memory graph also shows steady growth. After the first phase, training recall got better quickly, and validation recall kept getting better. Both accuracy and memory are at their highest levels at the fifth phase, showing that the Xception model does a good job of balancing them. This makes it very reliable for correctly finding and describing brain abnormalities in MRI and CT pictures.

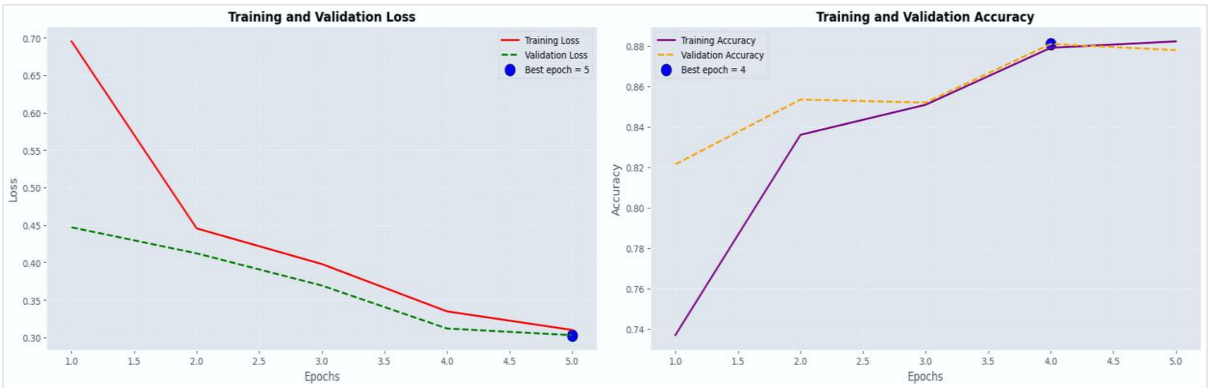

Figure 18. Accuracy and Loss Comparison of Lightweight Xception Model

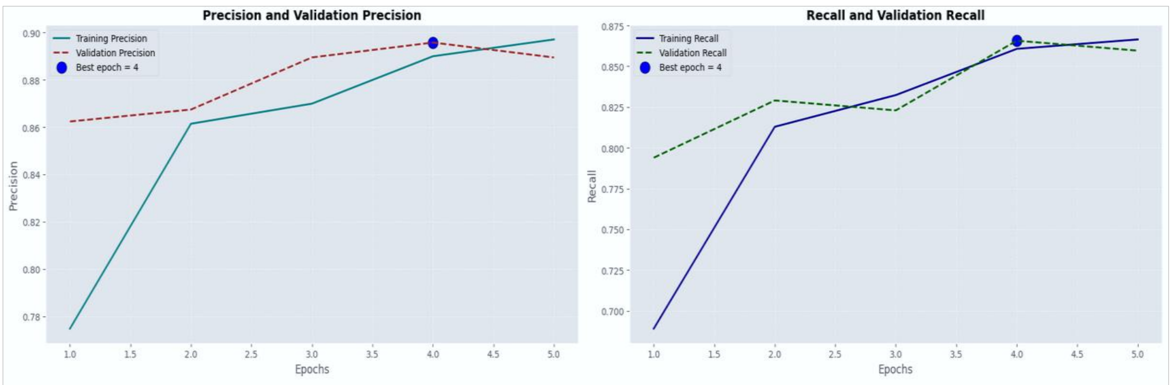

Figure 19. Precision and Recall Comparison of Lightweight Xception Model

The training and validation loss for the Lightweight Xception model over five epochs can be seen on the left side of figure 18. Both losses keep going down, but the training loss goes down more quickly in the first few epochs before levelling off. The validation loss also follows the same pattern. This keeps the model in a good mix between learning and generalisation. The fact that both losses converged at the last epoch shows how well the Lightweight Xception model handles the dataset with less computing work. The accuracy graph on the right shows that training accuracy goes up quickly from the first phase to the third. After that, it stops going up. Following closely behind, validation accuracy reaches its highest point at the fourth epoch, which is designated as the best epoch. This shows that the Lightweight Xception model gets high accuracy with minimal resource use, making it perfect for real-time brain abnormality detection. Figure 19: A comparison of the lightweight Xception model's accuracy and recall. The precision graph shows that training precision steadily gets better, while validation precision slowly gets better until it peaks at the fourth epoch and then starts to go down. This shows that the model does a good job of finding positive cases with a high level of accuracy. Both the training recall and the validation recall keep going up on the recall graph. At the fourth phase, which is marked as the best, both measures come together. This shows that the Lightweight Xception model correctly identifies true positives, ensuring accurate labelling of brain abnormalities while keeping computing power high.

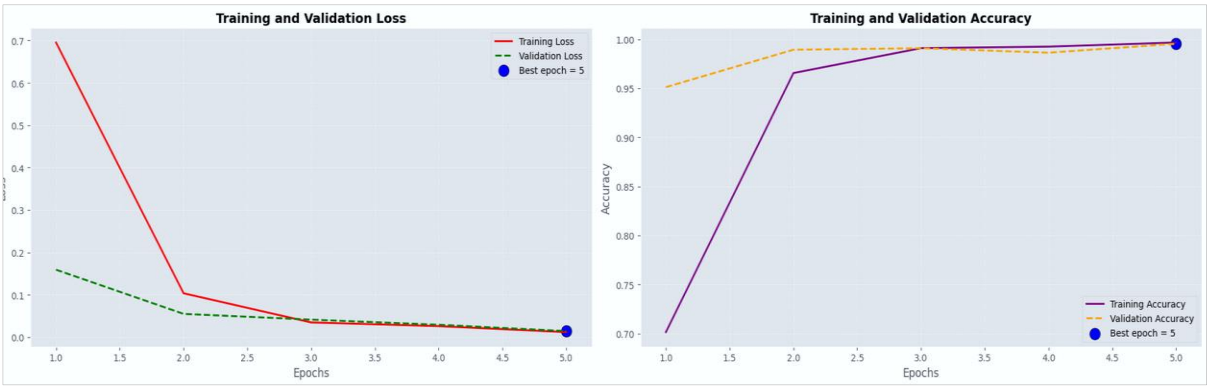

Figure 20. Accuracy and Loss Comparison of Fine-tune Xception Model

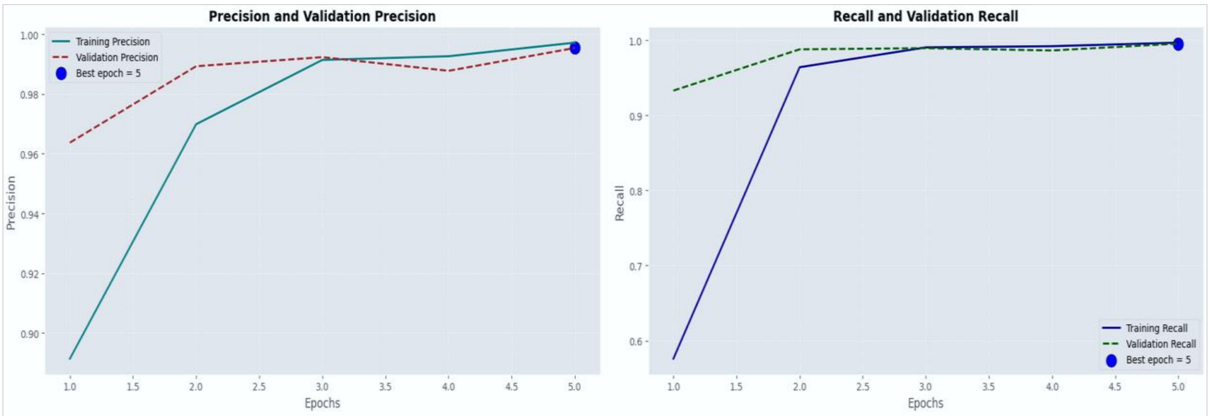

Figure 21. Precision and Recall Comparison of Fine-tune Xception Model

The left line shows in figure 20, the Fine-tune Xception model's training and validation loss over five epochs. From the first epoch on, the training loss drops sharply and stays close to zero by the fifth epoch. Validation loss follows a similar trend, going down slowly until it reaches the same level as training loss at the end. This shows that the model can generalise well without becoming too perfect. The right line shows that both training and validation accuracy get a lot better over time. By the third epoch, both are very close to 100% accuracy, and stay that way until the fifth epoch, which is marked as the best epoch. This shows how well fine-tuning the Xception model for accurate brain disease recognition works, since it uses weights that have already been learnt while learning domain-specific features from the MRI and CT dataset. Figure 21: The precision graph shows that training precision quickly got better after the first epoch and was almost perfect by the third epoch. Validation precision followed a similar trend. Both of the measures stay high for the rest of the epochs. The memory graph behaves in a similar way. By the third epoch, both the training and validation recalls get almost perfect scores and then stay that way. The fifth phase is marked as the best one. This means that the Fine-tune Xception model does a great job of correctly finding and categorising brain abnormalities, which makes it ideal for real-time medical uses.

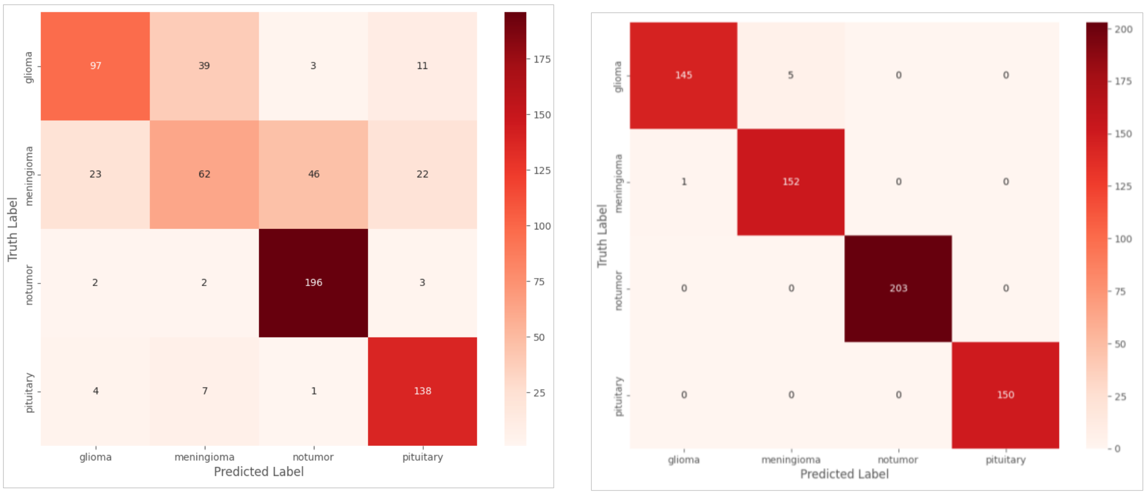

Figure 22. (a) Confusion Matrix of Finetune ResNet50 Model (b) Confusion Matrix of Finetune Xception Model

Figure 22(a) and (b) show the uncertainty matrices that show how well the Fine-tune ResNet50 model does at classifying. There are few fake positives and negatives in each matrix, and the true positive rates are high across all groups of brain abnormalities. This shows that the model can accurately and reliably find glioma, meningioma, pituitary tumours, and cases with no tumour at all, proving that it works well for classifying medical images.

Table 2: Result for Different model analysis with performance metrics

Model	Accuracy	F1-Score
ResNet50	0.64	0.57
Lightweight ResNet50	0.65	0.62
Fine-tune ResNet50	0.75	0.72
Xception	0.88	0.87
Lightweight Xception	0.90	0.89
Fine-tune Xception	0.99	0.99

Table 2 shows a comparison of various deep learning models used to find problems in the brain, focussing on their accuracy and F1-scores. With an F1-score of 0.57 and an accuracy of 0.64, the well-known convolutional neural network ResNet50 did very well. Even though it worked, its high level of complexity may have made it less able to generalise well beyond the dataset. With an accuracy of 0.65 and an F1-score of 0.62, lightweight ResNet50 showed a slight gain. This shows that making the model simpler can improve its performance by preventing overfitting, especially for smaller datasets. Adjust finely With an accuracy of 0.75 and an F1-score of 0.72, ResNet50 did better than the other models. Fine-tuning helped the model fit the brain abnormality collection better, which made it better at finding and classifying abnormalities. With an accuracy of 0.88 and an F1-score of 0.87, the Xception model did much better. This is because it uses depthwise separable convolutions, which make feature extraction better while lowering processing costs.

With an accuracy score of 0.90 and an F1-score of 0.89, the lightweight Xception improved performance even more. It did a good job of combining speed and accuracy. The Fine-tune Xception model got the best results, with an accuracy score of 0.99 and an F1-score of 0.99, which means it could almost perfectly classify things, as illustrate in figure 23. Fine-tuning Xception used its strong design and domain-specific training to accurately and reliably find brain abnormalities. This made it the best model for the medical imaging tasks in this study.

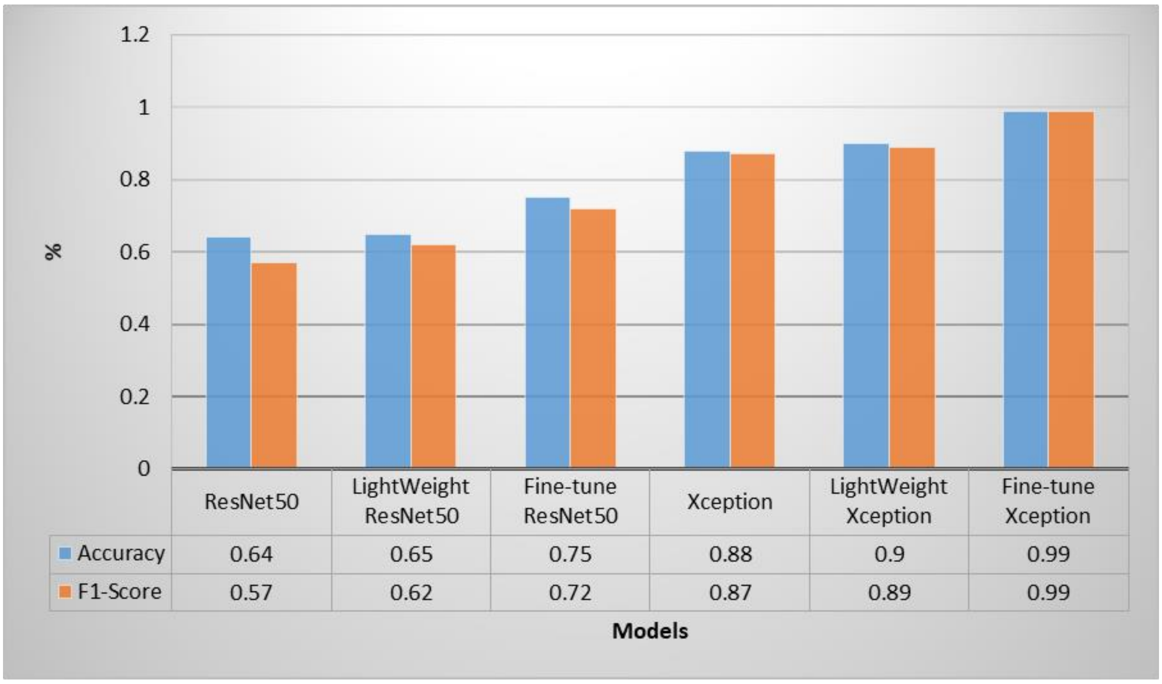

Figure 23. Comparative Analysis of Models

The prediction on a MRI image sample is shown in Figure 24 (a) and (b), from figure the prediction image is of a tumour with a 100% chance.

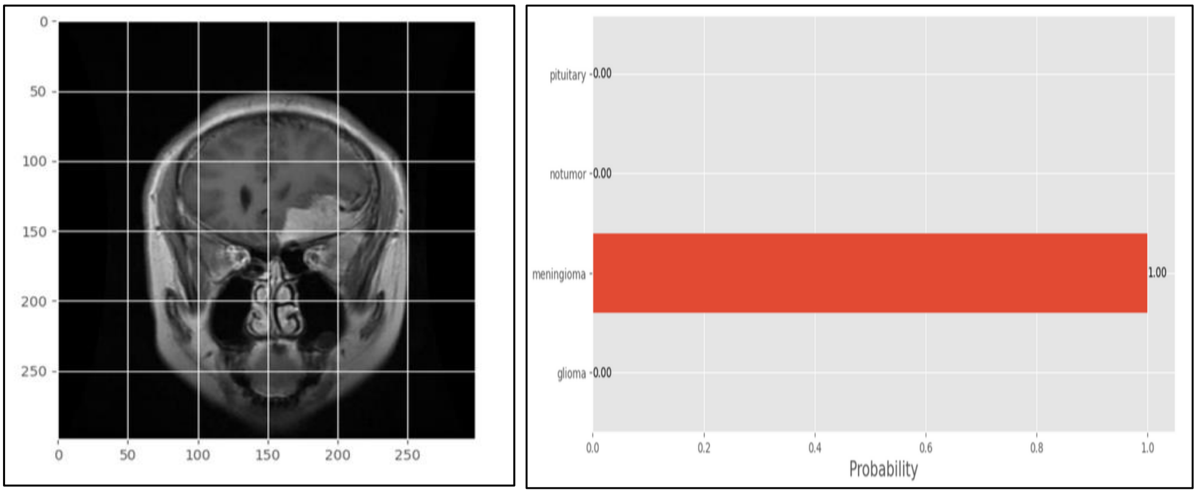

Figure 24 (a) Input Image (b) Predicted output

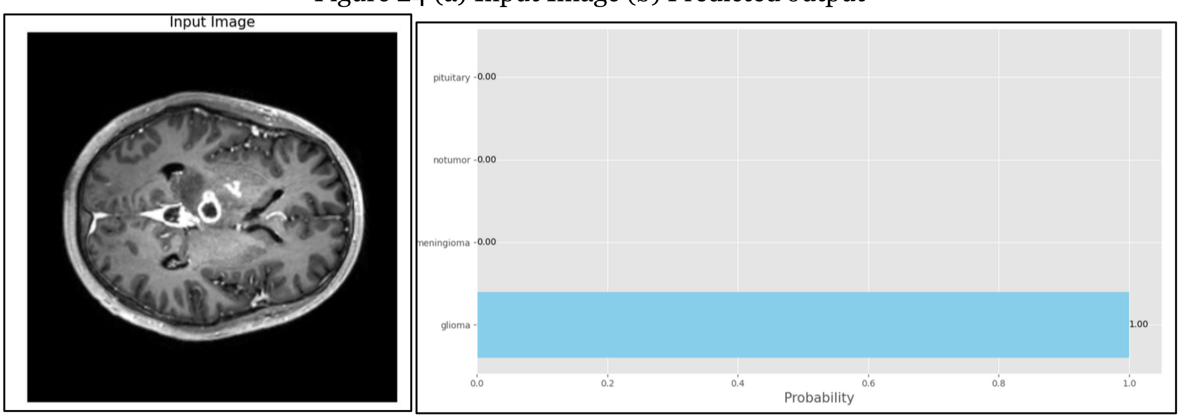

Figure 25. (a) Fused Image Sample (MRI + CT) (b) Predicted output

The picture input Figure 25(a) shows a clear MRI + CT Fused images that was used for forecast. It shows the structure of the brain and the abnormality area that matches a meningioma. In Figure 25(b), the end prediction from the dataset picture shows that the image is most likely to be a meningioma, which shows that the model is very sure of its choice. In this case, it shows how well the model can correctly find and label brain problems in MRI pictures. The high confidence number means that the model has learnt to tell the difference between meningioma and other types of tumours, like gliomas, pituitary tumours, and no tumour.

V. Conclusion

This work correctly found and placed brain anomalies using MRI and CT images by using several deep learning models including ResNet50, Lightweight ResNet50, Fine-tune ResNet50, Xception, Lightweight Xception, and Fine-tune Xception. Four groups—no tumours, glioma, meningioma were formed from the assortment of brain MRI images included in the collection. Rescale and colour enhancement techniques in data pre-processing guaranteed that the model would perform better in more contexts. ResNet50 had average accuracy (0.64) and F1-score (0.57), while Lightweight ResNet50 performed somewhat better because to its optimised design, obtaining somewhat higher accuracy (0.65) and F1-score (0.62). ResNet50's accuracy score (0.75) and F1-score (0.72) suggest that fine-tuning helps for jobs particular to a subject. With an accuracy score of 0.88 and an F1-score of 0.87, Xception tremendously enhanced performance. It more effectively extracted features by use of depthwise separable convolutions. With lightweight Xception whose accuracy score was 0.90 and F1-score was 0.89 the outcomes were much better. With an F1-score of 0.99 for every model and almost flawless accuracy, Fine-tune Xception outperformed all the others. This demonstrated that educated on facts particular to the issue, it was more adept in spotting brain anomalie. Metrics for model performance, such as accuracy, loss, precision, and memory, were looked at. Fine-tune Xception showed the most stable and good results. Image fusion, which combines MRI and CT scans, made model forecasts even better by giving more detailed spatial and anatomical information that was needed for correct classification. Confusion matrices showed that all models had high rates of true positives and low rates of false positives. The study comes to the conclusion that deep learning models, especially Fine-tune Xception, can accurately and reliably find brain problems. When MRI and CT scans are combined, they improve classification accuracy, which makes these models perfect for real-time clinical use. In the future, researchers will look into more complex structures and bigger records to make medical tests even more accurate and reliable.

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