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# Optimized Transfer Learning Approach for Brain Tumour Classification

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**Abstract**
A brain tumour can form in the brain cells, or it can begin elsewhere and spread to the brain. There are 3 most common tumour types: Pituitary, Glioma and Meningioma. As the tumour grows, it creates pressure on and changes the function of surrounding brain tissue, which causes signs and symptoms such as headaches, nausea, and balance problems. If neglected, it might be a potent life destroyer. The paper demonstrates an optimised Transfer Learning approach with DenseNet121. By adjusting the hyper-parameters of the network, the Convolution layers in the DenseNet121 design have been optimised, improving the tumour identification capabilities. The suggested method is tested on 6854 MRI brain tumour pictures from three key kinds of tumors—gliomas, meningiomas, and pituitary tumors—that are included in publicly accessible medical datasets. In comparison to cutting-edge image classification architectures like VGG19, VGG16, MobileNet, ResNet50, and EfficientNet, DenseNet121 provides superior classification ability and accuracy with a significantly fewer number of trainable parameters. The classification accuracy of CNN's top dense layers is improved by 2.314% for the DenseNet121 architecture through hyper-parameter tuning. The proposed method outperforms the previously mentioned methods with a 99.15% accuracy rate.

**Keywords:** DenseNet121, VGG19, VGG16, EfficientNet, MobileNet, ResNet50

## 1. Introduction

A brain tumour is a grouped area of abnormal cell proliferation or mass in the brain. There are numerous varieties of brain tumours. Both benign (noncancerous) and malignant (cancerous) brain tumours can occur (malignant). Brain tumours can start as primary brain tumours inside the brain or as metastatic (secondary) brain tumours when malignant cells from other parts of the body move to the brain. A brain tumour's rate of growth can change depending on a variety of circumstances and possibilities. How a brain tumour will impact the nervous system's activities depends on both its rate of growth and its location. Given that there are many types of brain tumours that can occur, some of the most occurring and active cases of brain tumours are - glioma, meningioma and pituitary.

*Glioma* is a tumour in the central nervous system (brain or spinal cord) and peripheral nervous system that form out of various types of glial cells (neuroglia). Glial cells are referred to as "supportive cells" because they surround, insulate, feed, repair, and protect neurons which transmit electrical signals and information throughout the nervous system. They do not directly influence synaptic transmission and electrical signals but rather provide supportive functions for neurons and the transmission of information.

A tumour that develops in the meninges called ***Meningioma*** (the membranes that which surround the spinal cord and the brain). It is included even though it isn't a typical brain tumour because it typically compresses and affects the nearby brain, nerves, and blood vessels. Most meningiomas develop very slowly, likely over many years without showing any symptoms. However, sometimes the damage done to surrounding brain structures, nerves, or blood vessels might result in severe disability.

Tumours that grow abnormally in the pituitary gland are known as ***Pituitary tumours***. The overall number of hormones that control crucial bodily processes can increase in some pituitary tumours. On the other hand, some pituitary tumours decrease the overall production and release of hormones. Pituitary tumours are often benign growths (non-cancerous). They don't spread

to other bodily areas and remain in the tissues of the pituitary gland or its surroundings.

## 2. Literature Review

The first study to use CNN for the multi-classification of brain tumour MRI images did so because nearly all of CNN's hyper-parameters are chosen automatically by the grid search optimizer. For the chosen CNN model, the best CNN architecture and hyper-parameters can be chosen using the grid search optimization algorithm [1]. Later was the CDLLC method for brain tumour MR image classification proposed. The CDLLC (Convolutional Dictionary Learning with Local Constraint) was introduced to overcome the issues in CNN structure as it was utilized to seek sparse representation in the nonlinear space which led to the discriminative approximation of the coding vectors on different classes in the dataset.

The manifold structure of the codes is preserved by the suggested approach CDLLC, which makes use of the locality constraint of atoms. In the architecture of deep learning, CDLLC automatically extracts useful CNN features as opposed to standard dictionary learning, which is based on manual feature extraction. Meningiomas, gliomas, and pituitary tumour types were classified on the Cheng dataset, and AST, OLI, and GBM types on the REMBRANDT dataset, with high performance in terms of accuracy, recall, precision, F1-score, and balance loss [2]. Later, using three different brain datasets—uncropped, cropped, and segmented region of interest—a novel CNN architecture was created for the classification of a brain tumour (ROI). In all dataset situations of uncropped, cropped, and segmented, the design was successful in classifying the brain tumour into three groups with high performance in accuracy and sensitivity. Using T1 weight contrast-enhanced brain MR images, the method was able to considerably grade the tumour into three tiers, including meningioma, glioma, and pituitary tumour [3]. Based on a CNN architecture that was intended for multiscale processing, a fully automatic segmentation and classification system for brain tumours was put into place. A dataset of T1-weighted, contrast-enhanced MRI images was used to assess performance. To extend the training dataset and avoid overfitting, data augmentation and elastic transformation were used.

The obtained performance metrics fell among the top 10 techniques from the BRATS 2013 benchmark [4]. A new methodology was implemented which internally used ConvNet architecture for

grading the tumours that arose in the brain non-invasively. The two existing ConvNet models were tuned finely for conversion of brain MRI to HGG and LGG. Visualizations of the intermediate layer feature maps showed that filters in the convolution layers learned automatically to detect different tumour features that resembled closely of tumour grading criteria. ConvNets that were trained on natural images performed satisfactorily by performing fine-tuning the final convolution layer on the MRI dataset [5].

### 3. Densely Connected Convolutional Networks (DenseNet)

*Convolutional Neural Networks* (CNNs) are primarily used in the field of pattern recognition within images. It allows encoded image-specific features into the architecture, making the network more suited for image-focused tasks - whilst further reducing the parameters required to set up the model. A ***DenseNet*** is a type of CNN that utilizes dense connections between layers, through Dense Blocks, which connects all layers directly with each other.

This dense connection design has the somewhat counterintuitive effect of requiring fewer parameters than conventional convolutional networks since redundant feature-maps do not need to be relearned. Traditional feed-forward architectures can be thought of as state-containing algorithms that are transferred from layer to layer. Each layer writes to the following layer after reading the state from the layer before it. It alters the situation while simultaneously transmitting important information. The DenseNet architecture clearly distinguishes between information that is maintained and information that is introduced to the network.

DenseNet layers are tightly constrained, adding just a limited number of feature-maps to the network's total body of knowledge while maintaining the integrity of the other feature-maps. Based on all feature-maps in the network, the final classifier at the end of the network determines a classification. In addition to having superior parameter efficiency, DenseNets also have enhanced information flow and gradients throughout the network, making them simple to train. Additionally, the regularising impact of dense connections minimises overfitting on tasks with smaller training set sizes.

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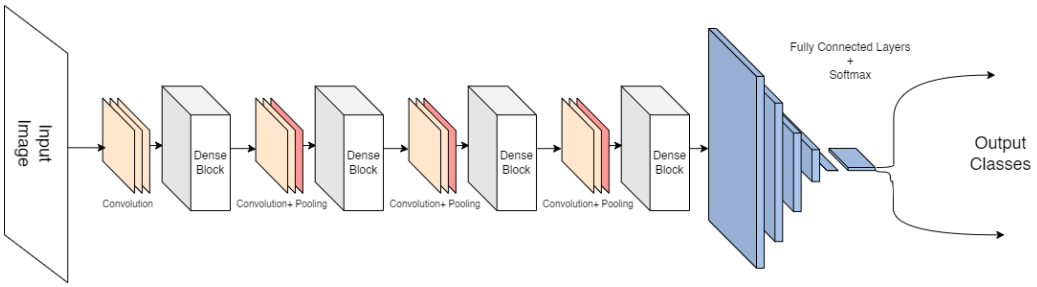


**Figure 1**: DenseNet Overview

## 4. Transfer Learning Approach

***Transfer learning*** is a potent machine learning technique that allows an inferior model to master new related tasks by receiving knowledge from a superior model. Pre-trained models that have already been trained on a large database of photos are used and fine-tuned to categorise new data. As a result, starting from scratch is not required, and computational complexity is significantly decreased. The dataset's input MRI brain images are divided into training and test data. There will be a considerable variance in estimations of the model parameters if there are fewer training data. Performance indicators will vary widely if there is a lack of testing data. Therefore, it is important to choose an ideal value. The train-test ratio is set at 80:20 since it is thought to be the optimum option for big data sets. The initial step in pre-processing is always to normalise the input photos.

Once again, one of the conventional normalising procedures is applied, this time "Min-max normalisation," which scales the intensity value in the range of [0 1].

Deep CNNs must be trained from scratch using random weight initialization, which takes time and does not produce promising results with little training data.

The weights of the DenseNet121 pretrained on Chest X-ray data set are utilised as a starting point in the job of classifying brain tumours in the proposed method, which uses transfer learning using DenseNet121 pre-trained on CheXNet weights. With the exception of the top dense layers, a sequential model is built using the DenseNet121 network as its foundation. The model is then given a flatten layer, followed by dense layers, and dropout layers.

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The optimiser and loss function are set during model compilation. The network receives the training images and labels, and the model is trained. The model is trained using input images while the hyper-parameters, including the number of units in the dense layer, the kind of activation function, the dropout rate, and the learning rate of the optimiser, are adjusted using a random search tuner. The test images are categorised using the trained model with adjusted hyper-parameters. The batch size is set to 32, the number of epochs is set to 20, and the input images are 224 × 224 × 3. Adam, an optimizer with a very low learning rate of 0.0001, is employed. In order to maintain the original pre-trained weights without distortion because they have previously been changed, a very slow learning rate was adopted. The loss function utilised, categorical cross entropy, calculates the difference between the SoftMax classifier's projected output and the actual output.

DenseNet121's convolution and pooling layers extract features, and the FCL with softmax activation function is utilised to classify data. Dropout is carried out at a rate between 0.2 and 0.4 to prevent overfitting training. The dropout rate and learning rate are controlled in hyper-parameter tuning.

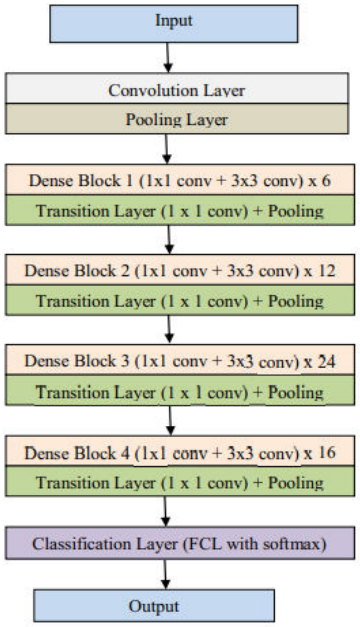


**Figure 2:** Architecture of Finetuned DenseNet121

The pre-trained model's top dense layers are deleted, and new dense layers are added. To optimise the network, the number of units and activation function of the additional dense layers, as well as the learning rate and dropout rate, are tweaked. Using a network with fine-tuned hyper-parameters increases classification accuracy.

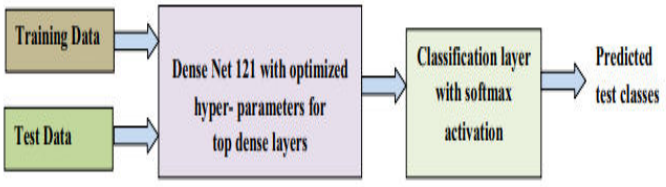


**Figure 3:** Model Pipeline

**Results & Plots**

Various state-of-the-art models have been evaluated against the MR Images data. Every model differs the rest in terms of activation functions, functional layers, number of functional layers and their connections and acceptable input shape of images. Each model has been trained and tested using same optimizers, same learning rate, same loss function and same number of epochs and the results are demonstrated below.

**Tabular Results**

**Training:**

**Optimizer:** *Adam*, **Learning rate:** *0.1*, **Loss:** *Sparse Categorical Crossentropy*

| Model | DenseNet121 | Resnet50 | VGG16 | VGG19 | EfficientNet |
|---|---|---|---|---|---|
| TTP | 8.0 M | 25.6 M | 138.3 M | 143.6 M | 9.1 M |
| Accuracy | 0.9915 | 0.9817 | 0.9012 | 0.8751 | 0.9834 |

**Key word**: TTP (Total Trainable Params)

**Table 1**: *Training Results on MR Images*

**Testing:**

**Optimizer:** *Adam*, **Learning rate:** *0.1*, **Loss:** *Sparse Categorical Crossentropy*

| Model | DenseNet121 | Resnet50 | VGG16 | VGG19 | EfficientNet |
|---|---|---|---|---|---|
| TTP | 8.0 M | 25.6 M | 138.3 M | 143.6 M | 9.1 M |
| Accuracy | 0.9429 | 0.9214 | 0.8342 | 0.8423 | 0.9321 |

**Plots**

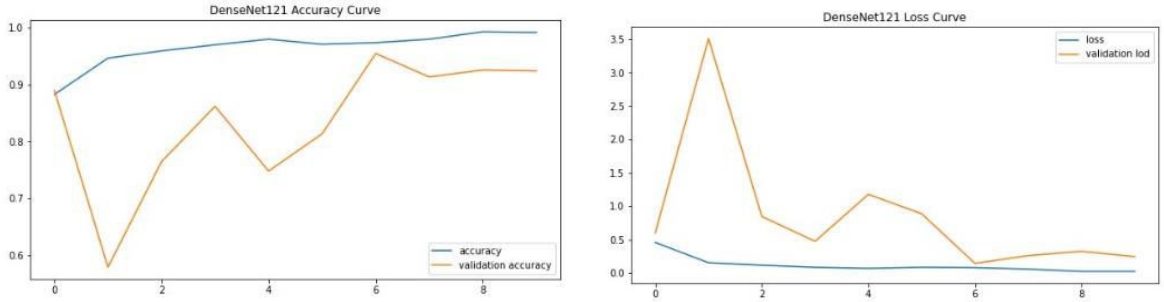


**Figure 4:** Accuracy & Loss curves of *DenseNet121*

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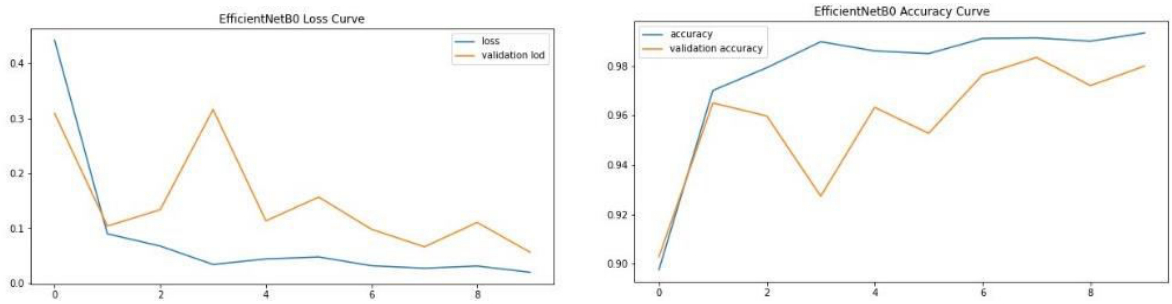


**Figure 5:** Accuracy & Loss curves of *EfficientNet*

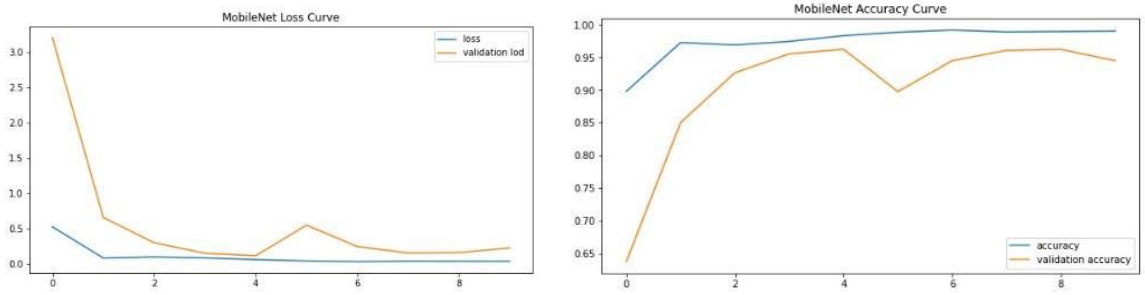


**Figure 6:** Accuracy & Loss curves of *MobileNet*

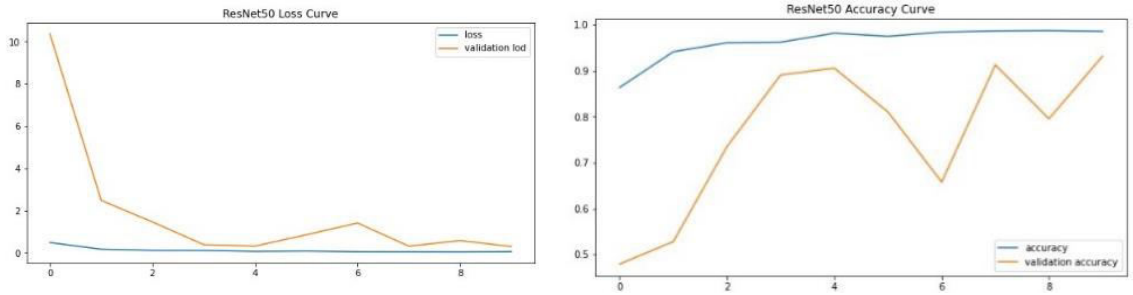


**Figure 7:** Accuracy & Loss curves of *ResNet50*

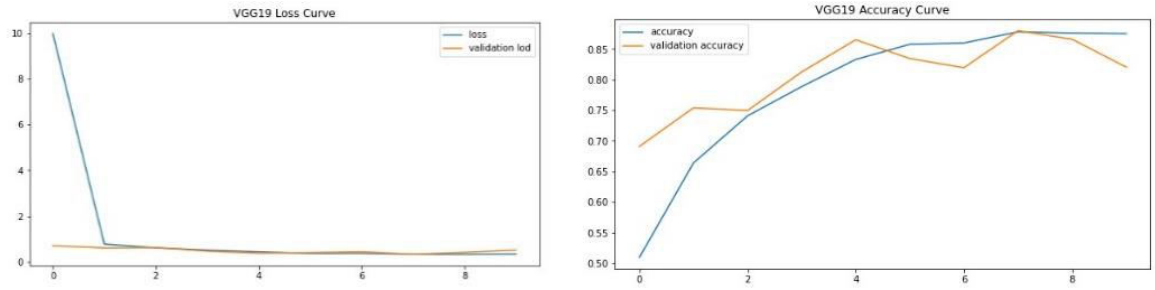


**Figure 8:** Accuracy & Loss curves of *VGG19*

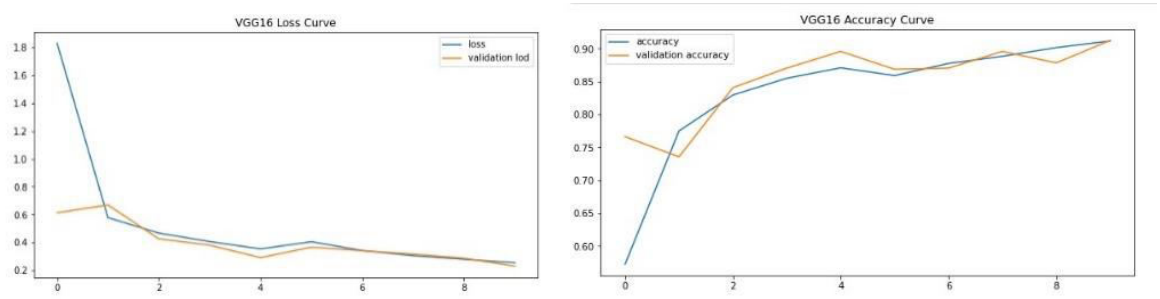


**Figure 9:** Accuracy & Loss curves of *VGG16*

## Conclusions

In this research, we developed an optimized approach for brain tumour classification using transfer learning techniques. Here are some of the inferences:

1. TTP (Total Trainable Params) is a key indicator to the computational complexity. The higher it is, the more it becomes computationally expensive and vice versa.
2. Though ***VGG16*** and ***VGG19*** produced good training and testing accuracy, they have extremely high TTPs of 138 M (million) and 146 M (million), which makes them least usable. [*Table 1 & 2*]
3. ***Resnet50*** provides good results and less computationally expensive compared to ***VGG16*** and ***VGG19***, but more expensive than ***DenseNet121*** and ***EfficientNet***. [*Table 1 & 2*]
4. ***DenseNet121*** and ***EfficientNet*** have near-similar TTPs, but ***DenseNet121*** outshines ***EfficientNet*** in training and testing inspite of having 1M less trainable params. [*Table 1 & 2*]

It is very clear that DenseNet121 outperforms all other models in all possible ways with the least computational expenditure. From the results, it can be confirmed that with finetuning an existing DenseNet121 with additional parameters and layers, the model produces greater results to that of the state-of-the-art models with less params to compute, which makes it robust, agile, spontaneous and reliable for brain tumour classification.

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