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A Transfer Learning Based DCNN Framework for Brain Tumour Multi-Classification

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Abstract:

One of the most frequent diagnoses in neuroradiology is brain tumours. The brain tumours are the most frequent and most aggressive diseases and their greatest quality of life is quite short. Thus, the planning of treatments is a vital step in improving patients' quality of life. Improved technology and machine learning can enhance tumour diagnosis by radiologists without intrusive methods. Nowadays, Convolutional Neural Networks (CNN) is the most often used algorithm for visual learning and image recognition. This research seeks to multi-classify brain tumours for early detection by using CNN. Two distinct CNN models are presented for two classification tasks. The first model of CNN is used to identify brain tumours with 97.60% accuracy. The other model can classify the brain tumour with an accuracy of 98% into four tumour kinds such as glioma, normal, meningioma and pituitary. In addition, the performance of our CNN model was evaluated using 5-fold cross validation technique and compared with other state-of-the-art models of CNN.

Keywords: *convolutional neural network; brain tumour classification; magnetic resonance imaging; neural networks*; *image processing; transfer learning*

1. Introduction

Image processing is a way for carrying out certain operations on an image to obtain an improved image or to extract some relevant data from it. The photographs utilised are in digital format in today's environment. Recently, the advent of IT and e-health systems in the medical area allow clinical specialists to take care of their patients in better way. The World Health Organization (WHO) reports that cancer is the second major cause of mortality worldwide [1]. It is not always feasible to detect the cancer in early stage to prevent death. Over the last two decades, research has clarified the genetic reasons of carcinogenesis in both common and uncommon brain tumours, suggesting the hope that a better knowledge might lead to better categorization [1]. During image diagnostics, physicians are sometimes confused between tumour-causing illnesses and infection-caused illnesses. A tumour doesn't need to be a malignancy. When cells change and become uncontrolled in the brain, a brain tumour begins. As they expand further, a clump of cells is formed, which becomes a tumour.

The brain tumour may be identified based on its growth level and also because of its parent cell similarities. On the basis of the tumour growth, a brain tumour may be categorised into benign or malignant. The benign brain tumour is structurally consistent and does not include active (cancer) cells, while malignant brain tumours have heterogeneous structure and active cells. The most prevalent grading system employs Grade I through Grade IV to distinguish benign and malignant forms of tumours according to WHO and the American Brain Tumours Association [2]. Grade I tumours develop slowly and probably do not spread. Often, they can be healed with operations. Grade II tumours will not grow and spread, but will return following therapy. Grade III tumours tend to divide the cells faster than dead cells. It may grow fast. In Grade IV, cells in the tumour aggressively split. Furthermore, the tumour has a growth of both the blood vessel and dead tissue regions. The tumours can rapidly develop and spread. In the brain, tumours can be discovered in neurons, arteries, skull, lymph tissue, the hypophysis and the pineal gland. At all ages, the brain tumour can influence people. The effects may not be the same on every person. Because of such a complex human brain anatomy, it is a challenge to diagnose tumour region in the brain.

Detecting, identifying and classifying such brain tumours at an early stage is thus a severe problem in medical scientific practise. By improving the novel imaging methods, physicians are able to monitor the incidence and progress in tumour-affected locations at various stages so that these pictures may be properly diagnosed. The major problem was the early diagnosis of the brain tumour, to enable adequate treatment. The tumour visibility depends on the features of the surrounding tissues. The physical or metabolic features are helped to visualize the tumour if they differ from the tumour. The physical or metabolic features are helped to visualize the tumour if they differ from the normal cells. The margin of the tumour is separate or unclear, otherwise. With the aid of its matrix a tumour may be distinguished from the normal tissue. The matrix is homogenous dependent on the tumour kind, and can be structured. The tumour boundaries can be visualised very much depending on the tissues around them.

In this paper, multiple sequence images of Magnetic Resonance Imaging (MRI) are used for diagnostic purposes, such as T1 weighted MRI, T2 weighted MRI, and FLAIR-weighted MRI. Once clinically suspected, the brain tumour is radiologically evaluated to assess the situation, size and

influence of the tumour on its surroundings. This information can be used to determine the most appropriate therapy, radiation, surgical treatment or chemotherapy. It is so obvious that a tumour-infected patient's chances of survival might be greatly boosted when the tumour is appropriately discovered early [3]. In consequence, the investigation of brain tumours utilising imaging methods in the radiology department has become more important.

The rest of the paper is organized as follows: Section 2 presents the related works, Section 3 presents the materials and methods with the steps used in the proposed technique, Section 4 presents the results and discussion, Section 5 presents the comparative analysis, and finally Section 6 contains the conclusions and future work.

2. Related Works

Magnetic Resonance Imaging (MRI) is the most prevalent approach for tumour type diagnosis. The early diagnosis of brain-tumours depends largely on the radiologist's experience. It is vital to build a technology for diagnosing tumours and classifying them using MRI images to ensure accurate diagnosis and to prevent surgery and subjectivity [4]. New technological developments, in particular Artificial Intelligence (AI) and Machine Learning (ML), have had substantial implications for the medical industry and are a vital support tool to several medical sectors, including image processing. MRI image processing uses several machine-learning techniques to segment an image and to classify it to provide radiologists a second point of view.

A highly crucial step for determining correct therapy on the proper moment is to divide the images of brain tumours from Magnetic Resonance Images (MRI) or other medical imaging methods. A number of techniques were suggested for the classification of brain tumours in MR images, which includes the Fuzzy Clustering Means (FCM), Artificial Neural Network (ANN), Support Vector Machines (SVM), knowledge-based technologies and Expectation-Maximisation (EM) algorithm. Here are an overview and conclusions of some of the most recent and leading studies. The neural network methodology for brain tumour identification and classification had been introduced by Damodharan and the Raghavan [5]. The quality rate is individually calculated for White Matter (WM), Gray Matter (GM) and CerebroSpinal Fluid (CSF) The cerebral white matter is an intricate network of myelinated fibers that connect gray matter regions and support brain function. Cerebrospinal fluid (CSF) is a clear fluid that surrounds the brain and spinal cord. It cushions the brain and spinal cord from injury and also serves as a nutrient delivery and waste removal system for the brain. and achieved the accuracy of 83% by applying neural network-based classifier.

A technology for the automated categorization of brain tumours from MR images utilising an SVM based classification was reported by Alfonse and Salem [6]. In this study, the features are retrieved with the help of Fast Fourier Transform (FFT) and the reduction of features are handled by Minimal- Redundancy-Maximal-Relevance (MRMR) technique to enhance the accuracy of the classifier. The accuracy of this approach is 98.9%. For extracting the brain tumour, the brain MR images need to be separated into two sections [7]. The brain tumour cells are located in one place, while the normal brain cells are included in another [8]. In [9], Mohsen et al. were able to categorise a data set of 66 MRI images into four classes using the Deep Neural Networks, one of the Deep Learning architectures and obtained the accuracy of 96.97%. Various modifications have been done to pre-trained networks that are used for image analysis, segmentation and classification. Various techniques to the MR images of brain tumour, as well as tumours from different sections of the human body have been evaluated in various medical databases [10-11].

The 22-layered CNN architecture for the brain tumour classification has been constructed by Badza and Barjaktarovic [12] utilising 3064 T1-weighted contrast enhanced MRI data. Their suggested model has resulted in a 96.56 percent accuracy classification of the brain tumour as meningioma, glioma and pituitary. A profound 3D CNN multi-scale brain tumour gradation model using 3D MRI images was reported by Mzoughi et al. [13] in another study. In identifying the brain tumour images as low grade and high-grade Glioma, the suggested technique obtained 96.49 per cent accuracy. CNN-based, computer-aided diagnostics system (CAD) has been suggested by Ayadi et al. [14]. Trials on 3 distinct datasets employing 18-weighted layered CNN models obtained accuracy of the 94.74 percent brain tumour classification and accuracy of the 90.35 percent in tumour grading.

Abiwinanda et al. [15] has designed the simplest architecture feasible for CNN to identify the three most prevalent forms of brain tumour, that is, glioma, meningioma, and the pituitary. In combination with Discrete Transform Wavelet (DWT) and Principal Component Analysis (PCA), Mohsen et al. [16] have employed the Deep Neural Network (DNN) technique for classifying brain MRI images into four groups. It was observed that the accuracy was 96.97%. Khan et al. [17] suggested a profound learning approach in which tumours in brains may be classified as carcinogenic or non-cancerous using 253 actual brain MRI with augmented data. Before extracting the features via a basic CNN model, they employed boundary detection to locate a region of interest for the MRI image. They achieved the accuracy rate of 89%. In [18], Kabir Anaraki et al. proposed an ensemble CNN architecture with Genetic Algorithm (GA) to classify various grades of glioma using MRI. In one case study, they have achieved an accuracy of 90.9% and in another case study, the accuracy is 94.2%.

For multi-grade tumour classification, a deep CNN with more data was designed by Sajjad et al. [19]. The pre-trained CNN model is perfectly adapted for categorization. Likewise, Swati et al. [20] developed a CNN model by fine tuning of transfer learning to classify the brain tumours. Deepak and Ameer [21] suggested a three-class classification by using the combination of transfer learning and support vector machine. Authors have used GoogleNetfs to extract brain MR imaging characteristics. After that the SVM classification was applied and 97% precision was attained.

In the categorization of brain tumours, it is a hard challenge to improve classification precision. We have attempted to develop an efficient model with improved accuracy for two types of classification. For four-class classification, a deep CNN was designed based on transfer learning approach. In order to achieve high performance, the suggested model uses four dense layers. In addition, the drop-out approach was employed to prevent overfitting of the model.

3. Proposed Methodology

3.1 Dataset

In this study, two distinct datasets are used which can be obtained from publicly available databases. For first classification, we have taken the brain MRI dataset from Kaggle, which is an online repository for data scientists and machine learning researchers. In this dataset, a total of 253 images of MRI are available. 155 of them are labelled as "yes," showing there is a tumour and 98 are labelled with a "no" indicating that no tumour exists. Now we face a new challenge called imbalance of data. Data imbalance means that no equally distributed number of observations per class. To solve this problem, we did the data augmentation to increase the size of dataset. For second classification, we have taken the brain MRI dataset comprises of T1-weighted images. We took 2656 slices from 233 individuals, which included 374 meningiomas, 926 gliomas, 431 normal and 925 pituitary tumours [22-23]. Figure 1 illustrates certain samples of brain MRI images from data-store.

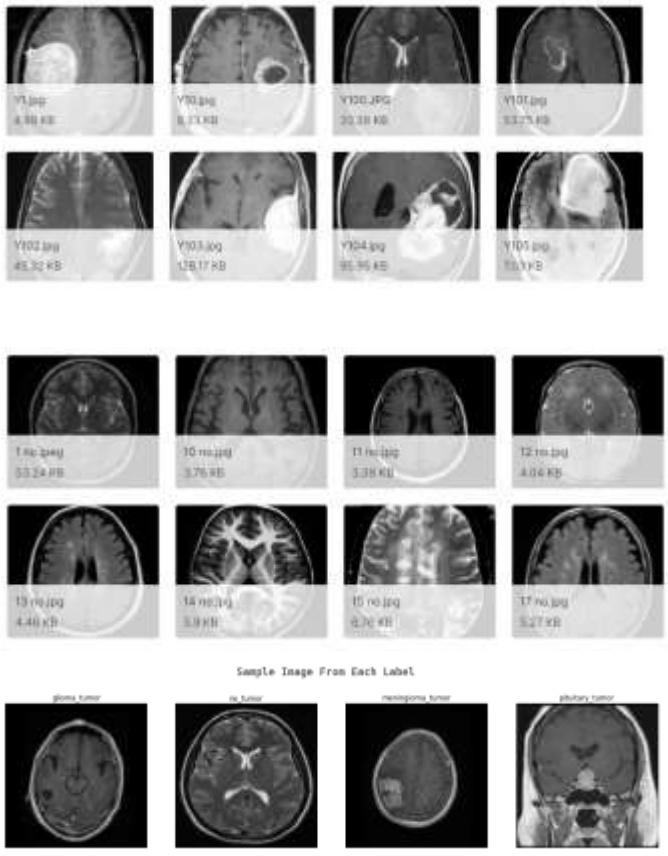

Figure 1. Sample MRI images from data-store

3.2 Pre-Processing and Data Augmentation

In our dataset for the first type of classification, we found that the MRI images are in different dimensions. These images depict the network input layer, thereby normalising it to 128x128 pixels. To augment the dataset, a particular MRI image is taken and several kinds of image enhancements are made, such as rotation, mirroring and flipping, to provide additional images [19]. We will increase the class with fewer images to around the same number of images in both classes. Thus, we have two times expanded our dataset to get 4145 images.

3.3 Convolutional Neural Networks Architecture

CNN model is the most widely used model for deep learning in neural networks. For our first kind of classification, a Convolutional Neural Network (CNN) designed using Python is implemented for the identification of the tumour. It therefore decides whether a patient's given MRI picture has a tumour or not. We have designed a neural network with the TensorFlow and Kera's Libraries and several layers. Generally, CNN consists of three building components: (i) a convolutional layer to learn space and time characteristics, (ii) a max-pooling for reducing input image dimensionality, and (iii) Fully connected layer (FC) for the classification of input images into different classes. Figure 2 shows our proposed CNN architecture for first classification.

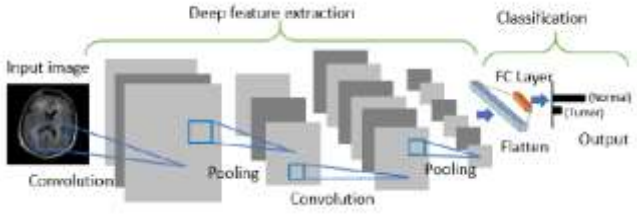

Figure 2. Proposed CNN architecture for binary classification [24]

Grid Search Optimization automatically tunes important hyper-parameters for the CNN models. Grid search is essentially an optimization algorithm which lets you select the best parameters for your optimization problem from a list of parameter options that you provide, hence automating the 'trial-and-error' method. Our CNN model for first classification has 15 layers such as 1 input, 4 convolution, 2 normalization, 2 max-pooling, 3 dropouts, 1 flatten and 2 dense layers. The summary of our proposed CNN model for binary classification is shown in Figure 3.

```
Model: "tumor_model"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
input_1 (InputLayer)         [(None, 128, 128, 3)]     0
_________________________________________________________________
conv2d (Conv2D)              (None, 128, 128, 32)      416
_________________________________________________________________
conv2d_1 (Conv2D)            (None, 128, 128, 32)      4128
_________________________________________________________________
batch_normalization (BatchNo (None, 128, 128, 32)      128
_________________________________________________________________
max_pooling2d (MaxPooling2D) (None, 64, 64, 32)        0
_________________________________________________________________
dropout (Dropout)            (None, 64, 64, 32)        0
_________________________________________________________________
conv2d_2 (Conv2D)            (None, 64, 64, 64)        8256
_________________________________________________________________
conv2d_3 (Conv2D)            (None, 64, 64, 64)        16448
_________________________________________________________________
batch_normalization_1 (Batch (None, 64, 64, 64)        256
_________________________________________________________________
max_pooling2d_1 (MaxPooling2 (None, 32, 32, 64)        0
_________________________________________________________________
dropout_1 (Dropout)          (None, 32, 32, 64)        0
_________________________________________________________________
flatten (Flatten)            (None, 65536)             0
_________________________________________________________________
dense (Dense)                (None, 512)               33554944
_________________________________________________________________
dropout_2 (Dropout)          (None, 512)               0
_________________________________________________________________
dense_1 (Dense)              (None, 2)                 1026
=================================================================
Total params: 33,585,602
Trainable params: 33,585,410
Non-trainable params: 192
_________________________________________________________________
```

Figure 3. Summary of our proposed CNN model for binary classification

Convolution layer is the initial layer to extract the different features from the images. The mathematical computation between the input image and a filter of a specific dimension is conducted in this layer. The result is called a feature map that provides image information on corners and edges. This feature map is later added to other layers to understand more of the input image's features. In most circumstances, a pooling layer follows a convolution layer. The main goal of this layer is to reduce the size of the feature map created in the previous layer to lower the computing costs. Usually, the pooling layer serves as a connection between the convolution and the Fully Connected layers.

The Fully Connected (FC) layer is made up of weights and biases, together with neurons, for connecting the neurons between two separate layers. These layers are generally added before the final CNN architecture and the final layers are formed. The preceding layers' input image is flattened and given to FC layer. The flattened vector subsequently passes through some additional FC levels in which mathematical functions are frequently carried out. In this phase, the process of classification starts. In general, it can lead to overfitting in the training dataset if all functions are linked to an FC layer. A drop-out layer is used to alleviate this problem whereby some neurons are eliminated from the neural network during training, resulting in smaller model size.

As the first step, we created an object for one hot encoder. Then all the data in the directory is read with the label ‘yes’. After this step, the pre-processing is done by resizing all the images into 128 x 128 pixels. The standardized images are then transformed into arrays and manipulated with the help of an encoder. The same process is followed for the data in the directory with the label ‘no’. At this moment, the encoded images are converted into numpy array and stored. Now the resultant array is 3D data. In order to train the data, the 3D array is reshaped to 2D array. Before training, we'll pre-process the data by reshaping it into the shape the network expects.

Finally, the activation function is one of the key elements of the CNN model. They are used to learn and estimate any continuous and complicated connection between network variables. It makes the network non-linear. Several common activation functions are provided, including ReLU, tanH, Softmax and Sigmoid. Each of these functions has a particular use. Sigmoid function is recommended for a binary CNN classification model. Figure 4 displays some results of binary classification.

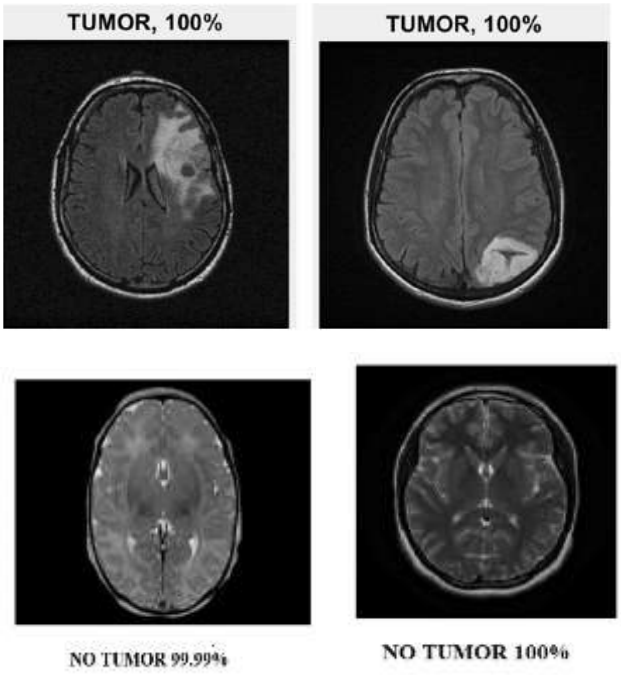

Figure 4. Results for binary classification

3.4 Transfer Learning

The second model of the CNN classifies the brain tumour into into four different categories of brain tumours: normal, glioma, meningioma and pituitary. For this multi-classification, we used the concept of Transfer Learning (TL). The classification capacity of a neural network model is reliant on the quantity and quality of the data for training. The model trained on a larger set will perform better and give more accuracy than a model trained on a smaller dataset. It might take days or even weeks for deep CNNs to train on huge datasets. Transfer learning is a commonly utilised technique through which a network is trained in a large-scale

source dataset and by transferring the acquired information from source to target, the resultant pre-trained network may now be optimised in smaller target data sets. The idea of transfer learning is based on the use of generic characteristics from the source dataset in the previous layers. The target dataset is retrained with a given number of layers at the end of the model. The previous and intermediate layers of a CNN identify edges and general forms, whereas the layers towards the end of a CNN detect domain-specific features. The transfer learning method is shown briefly in Figure 5 [25]. As in the figure, the inner layers are maintained the same and only the last layers are altered according to our classification task.

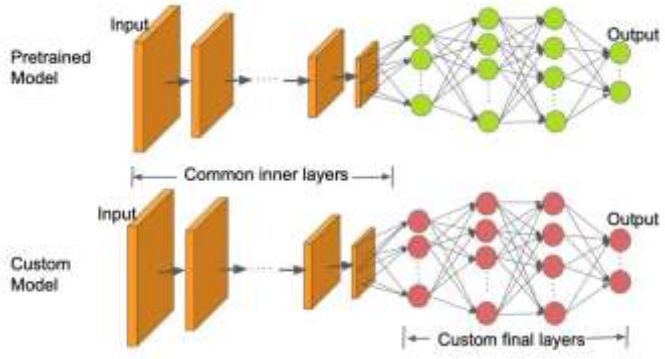

Figure 5. Basic Transfer Learning Model

Transfer Learning's major advantages includes reducing training time, enhancing the neural network's performance, and overcoming the limits of data shortages [26]. Naturally, the application of transfer learning to the categorization of medical images is challenging, as mentioned in [27]. One problem consists of not having adequate amount of annotated data for CNN training [28] in medical image classification applications. Another issue in this field is over-parameterization, referring to the large amount of network parameters. The more parameters in a network needs more training, more epochs and more computation time. This is not optimal for using these models in the real world. One possible method to bypass these obstacles is to utilise smaller and less parameter-rich lightweight models that will make the usage of computing resources more efficient [27]. One of the recently suggested lightweight architectures is EfficientNet [29].

3.5 Deep CNN architecture using Transfer Learning

In this research, we have designed Deep CNN using transfer learning with pre-trained EfficientNetB0 network for our brain tumour multi-classification task. Figure 6 shows the new baseline model for EfficientNetB0. This model accepts an input image of 224x224x3 dimension and extracts features across all levels using several convolution layers. EfficientNetB0 measures each dimension using a fixed set of scaling coefficients compared to other DCNNs. This technique overcame previous state-of-the-art models such as InceptionV3, AlexNet, VGG16 etc., that were trained on the ImageNet dataset. Thanks to its balanced depth, width and resolution, the EfficientNetB0 may be used to build a scalable yet accurate and easy to use model. EfficientNet [29] still produces extraordinary results even with the transfer training, showing its efficiency beyond the standard ImageNet dataset.

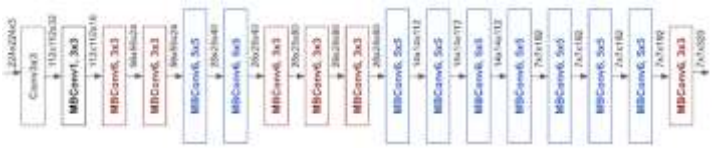

Figure 6. EfficientNetB0 architecture

Our work largely supports the use of the EfficieNetB0 model with changed final layers integrated by layer freezing through fine tuning and trained to deal with multi-classification task. We also compare and assess EfficientNetB0's performance with other contemporary state-of-the-art models.

3.5.1 Proposed DCNN Model for Multi-Classification

In order to activate new weights from the layer, we suggested to replace the last layers of the original baseline EfficientNetB0 model. Figure 7 shows our proposed EfficientNetB0 final layers consisting of a Global Average Pool (GAP), a dropout layer, fully connected dense layer with four neurons to represent our classes and the softmax function. GAP layer is like the Max pooling layer in CNNs; however, the main difference is that the average value is used in pooling instead of the max value. This helps to reduce the computational load on the system during training. The feature map sections were not fully reduced by the GAP. Rather, it averaged all the space characteristics and preserved the most complex patterns necessary for the tumour classification [30]. GAP has also demonstrated its reliable use of DCNNs in dealing with the medical images [31].

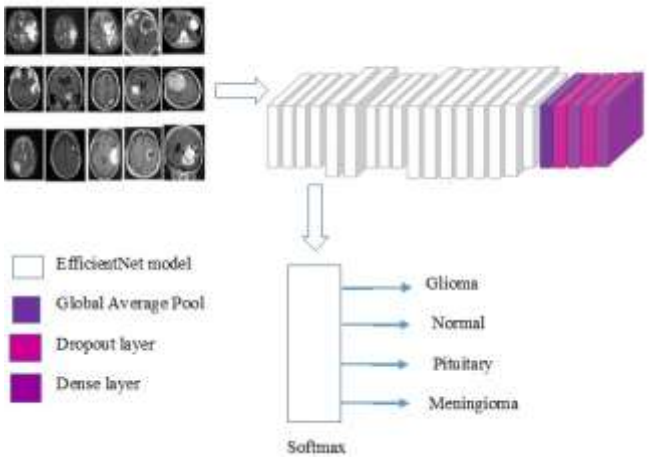

Figure 7. Proposed transfer-learning based DCNN architecture for multi-classification

At each stage, the dropout layer omits some of the neurons of the layer, which allow the neurons to become increasingly independent of their neighbours. It helps to avoid overfitting. Random selection is done for the neurons to be omitted. The rate parameter is the liquidity of a neuron activity set to 0, thereby eliminating the neuron. Dense layer

is the output layer that classifies the image into one of the four potential classes. Softmax activation function is used for multi-classification.

3.5.2 Fine Tuning in Transfer Learning

First, we increased the training parameter size pre-emptively via transfer learning. The base model utilised its features and enhanced the image identification immediately using the pre-initialized weights from ImageNet. The weights of ImageNet provide characteristics for the detection of forms, edges and other essential elements required for the categorization of images [32]. In contrast to randomly initialised weights, this method accelerated the process with reduced effort [33]. Our pre-trained ImageNet database model includes 1000 distinct classes and more than 14 million images [34]. In this context, it is essential to adjust the structure and weight of the EfficientNetB0, as our chosen task cannot be implemented immediately [35]. We have frozen the initial layers of the basic model and then fine-tune our proposed final layers using the MRI image dataset. With this technique, we succeeded to retain and avoid the ImageNet features from being overridden during training inside extraction layers. We then retrained the whole network using MRI dataset and the weights of ImageNet and created the final model, following both the extractor and our layers provided. The algorithm for multi-classification using transfer learning is as follows:

Algorithm: Multi-classification using Transfer Learning

1. Examine, observe and interpret the data.
2. Choose a pre-trained model, EfficientNetB0 in our study.
3. Design your proposed model.

- First take the initial layers, common features and pre-trained weights of pre-trained model.
- Propose additional layers, hyper-parameters, optimizer and loss function based on your target at the end of the model.

4. Train the model.

Evaluate the model.

3.5.3 Hyper-Parameters and Loss Function

Transfer learning is becoming more popular as it significantly reduces training time and requires less data to be trained to enhance efficiency. We utilised all layers in the pre-trained model with the exception of the last layer that is completely related to the ImageNet task. The initial layers of the pre-trained models include the generic features and the last layers consist domain specific features. The chosen hyper-parameter settings and loss function to provide efficient results are presented in this section. The identification of the DL model performance is not only based on precision, but also on loss [36]. The major aim of a DL model is to achieve its lowest feasible error rates [37] which shows the model's improved efficiency. In this work, we have chosen the Categorical Cross Entropy (CCE) as the loss function since our task is multi-classification. For every class label per observation, it is calculated as a total of individual losses. The following equation (1) is presented in mathematical terms for our loss function.

$$CCE = -\sum_{c=1}^{M} y_{i,c} \log (p_{i,c}) \quad (1)$$

Here M denotes the total number of classes, $y_{i,c}$ is a binary indicator that indicates whether c is the correct class or not and p is the probability [38]. We have directly picked Adam as our optimizer to achieve an ideal reduction in losses throughout training. In comparison to others like Stochastic Gradient Descent (SGD) [39] and the RMSProp [40], we have chosen Adam mainly for its easy implementation, efficient memory consumption and faster learning. Recently, Adam has successfully implemented DL models for medical imaging analysis [41].

Table 1 shows our hyper-parameter settings and sets a low Learning Rate (LR) to work well with the other parameters selected. In a little time period than SGD [42], Adam operated efficiently and reached quick convergence. The batch size 32 was a fair burden to send information across the network without our full computer memory being consumed. We have perfected the network using hyper-parameters above and obtained 98% accuracy for our MRI dataset.

Table 1. Selected hyper-parameters for our multi-classification

S.No.	Hyper-Parameters	Value
1	Optimizer	Adam
2	Learning Rate	0.0001
3	Batch Size	32
4	Epochs	12

4. Experimental Results

We experimented with MRI images of brain tumours from Navoneel [43]. The collection is open to the public and includes 253 genuine brain images created by radiologists using actual patient data. The information is available on Kaggle, a shared data platform for machine learning. We have divided our data into training, validation and testing. 60% of images will go to the training set, which our neural network will utilise to learn. 20% for validation and the rest 20% will be tested, with which we use our trained neural network to verify that our neural network is accurate or not. For about 40 'epochs', we have trained the images. An epoch is an iteration where we input training images to the Neural Networks again and again to learn the training images better. In each iteration, the accuracy of the training set continues to improve. This indicates that our CNN model is capable of improving the classification of an MRI image is containing a tumour or not.

Our proposed CNN model showed 97.60% accuracy on training data and 91% accuracy on validation data. Figure 8

shows the precision graphs of the testing and validation phase of our proposed CNN model for binary classification.

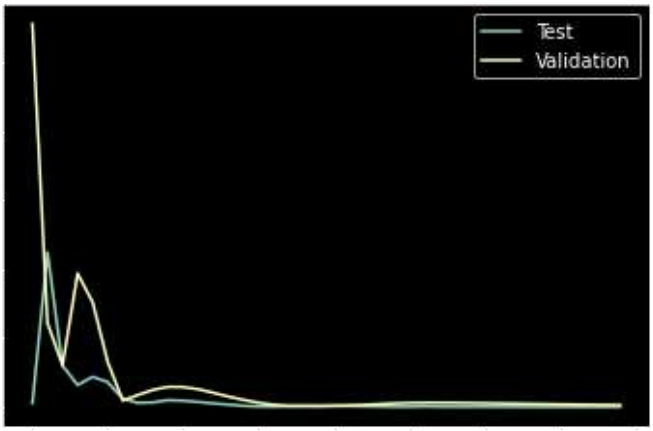

Figure 8. Precision graph for test and validation data

4.1 Performance Evaluation

In image classification, evaluating the performance of classification is extremely crucial to support the research results scientifically. The classification study would otherwise be incomplete. There are many performance assessment methods that have long been used in image classification and have become standard measurements of performance assessment in similar researches. The metrics are precision, recall, sensitivity, specificity, F-score, accuracy and the corresponding formulas are given below.

$$Precision = (TP) / (TP + FP) \quad (2)$$

$$Recall = (TP) / (TP + FN) \quad (3)$$

$$Sensitivity = TP / (TP + FN) \quad (4)$$

$$Specificity = TN / (TN + FP) \quad (5)$$

$$F\text{-}Score = (2 * Precision * Recall) / (Precision + Recall) \quad (6)$$

$$Accuracy = (TP + TN) / (TP + FP + TN + FN) \quad (7)$$

Here, accurate classification is defined by True Positive (TP) and True Negative (TN) while the inaccurate classification is defined by False Positive (FP) and False Negative (FN). TP is positive for irregular brain images, while TN is positive for regular brain images. In FP, regular brain images are shown in a positive tumour, while in FN, irregular brain images are shown in a negative tumour. We did the 5-fold cross validation and calculated the accuracy, precision, recall, F-score, sensitivity and specificity for all the folds. We have shown the evaluation metrics of our proposed CNN model for binary classification in Table 2.

Table 2. Metrics of the proposed CNN model for 5-fold cross validation

Folds	Precision (%)	Sensitivity (%)	Specificity (%)	F-Score (%)	Accuracy (%)
1	98.10	98.51	93.93	98.30	97.41
2	95.36	95.73	86.27	95.54	93.38
3	94.50	92.72	83.89	93.60	90.92
4	93.32	97.41	86.38	95.32	92.88
5	95.36	95.73	79.73	95.54	93.38
Average accuracy					**93.59**

Figure 9 shows the accuracy and loss curves for our second classification i.e., multi-classification.

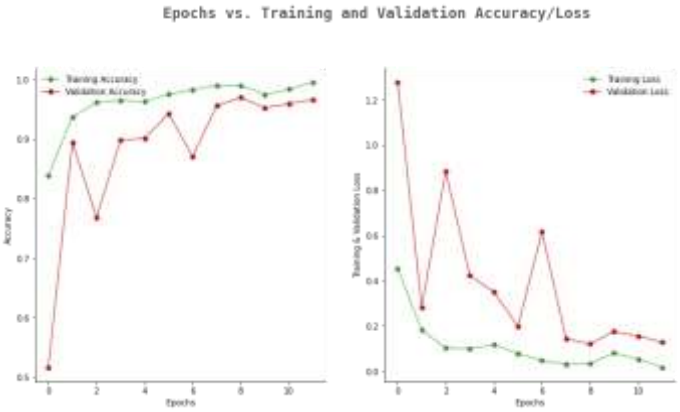

Figure 9. Accuracy and loss curves for multi-classification

Table 3 shows the evaluation metrics for multi-classification.

Table 3. Metrics of the proposed DCNN model for multi-classification

Classes	Precision	Sensitivity	Accuracy
Glioma	0.97	0.91	0.94
Normal	0.96	1.00	0.98
Meningioma	0.92	0.95	0.93
Pituitary	0.98	0.98	0.98

5. Discussions and Comparisons

Classification of images by using the CNN has been often utilised recently to diagnose medical illnesses. An efficient CNN model cannot be developed realistically that can be utilised together for all issues of classification and can deliver satisfactory results. Therefore, for each issue type a unique CNN model is developed. The architecture and complexity of the CNN model depends on the problem type, the inputs and the expected results. In this research, two CNN models were constructed for two types of classifications. The first model detects brain tumours from the MRI images. The second model is for finding the type of brain tumour. The choice of the best model for the particular task is one of the problems encountered in CNNs. The selection of the correct hyper parameters is a major factor, particularly in convolutional neural networks. Satisfactory results of classification are obtained utilising freely available medical datasets. For example, the first constructed CNN model is used to identify brain tumours with a very good accuracy of 97.6% and the second DCNN model classifies the brain tumour types with 98% accuracy. The findings of the models provided are validated with performance assessment metrics.

The results produced by the designed CNN models should be compared with the results obtained in the state-of-the-art CNN models. To do this comparison, the same tests are carried out with the same dataset using the existing pre-trained CNN models like ResNet-50, AlexNet, VGG-16, Google-Net, and Inceptionv3. We have compared the accuracy of both the proposed CNN models and the existing network models. Table 4 shows the results achieved through these networks.

Table 4. Performance comparison between the proposed CNN models and the state-of-the-art CNN models

Networks	Binary Classification Accuracy	Multi-Classification Accuracy
ResNet-50	90.69	93.50
Alex Net	87.12	83.12
VGG-16	88.78	88.87
Google-Net	75.65	86.47
Inceptionv3	85.14	90.01
Proposed CNN model	**97.60**	**98.00**

In every classification challenge, the proposed CNN models exceed other networks. The reason is, the proposed CNN models has been optimised for specific objectives and utilised hyper-parameters which offer the best outcome for certain challenges than the pre-trained models. In literature, some researchers have done the identification of tumour and some have classified the brain tumour into several classes. Since the proposed models are used to carry out all these two objectives, the second proposed model is compared with individual literature research. Table 5 compares the proposed DCNN model with the existing approaches in literatures. This table indicates that the suggested model exceeds existing models since two dense layers are used to improve the higher dimension characteristics.

Table 5. Accuracy comparison for multi-classification of the proposed model with the existing models in literature

Literature	Approaches	Accuracy
Anaraki et al. [44]	CNN + Genetic algorithm	94.20
Sajjad et al. [20]	VGG19 + Extensive data augmentation	94.58
Swati et al. [21]	VGG19 + Fine-tuning	94.82
Gumaei et al. [45]	Regularized extreme learning machine	94.23
Sultan et al. [46]	CNN with 16 layers	96.13
Proposed DCNN model	**EfficientNetB0 + Fine-tuning**	**98.00**

6. Conclusions and future work

A new methodology for the classification of brain tumours was given in this research. First, we used the brain MRIs to classify into normal brain tissue and malignant tumour tissue. Since the dataset is very small, for boosting the quantity of our training data, we employed the data augmentation technique. Secondly, by introducing a simple CNN network with 15 layers, we propose effective approach for the binary categorization of brain tumours. By training the proposed model for about 40 epochs, we achieved an accuracy of 97.60%. Finally, to evaluate our model, we did the 5-cross validation technique and achieved an average accuracy of 93.59%. In our research, we have used two different datasets: (1) The first dataset with two classes such as normal and tumour, and (2) A large dataset with four classes such as glioma tumour, normal, meningioma tumour, and pituitary tumour.

Deep neural networks have become popular image classification methods. In order to achieve the multi-classification of brain tumour into four classes, we have taken the EfficientB0 pre-trained network as our base model and designed a deep CNN. Two dense layers have been designed in the proposed model together with a softmax layer. Due to the usage of Adam Optimizer and a dropout layer the suggested model avoids the concerns of overfitting of the model. With 98% accuracy, our suggested model exceeds the current models.

Our future work will be focused on lowering the number of parameters without compromising the performance of our

model. Our suggested approach can play a predictive role in tumour identification in patients with brain tumours. By tuning the hyper parameters and by using the better pre-processing techniques, the model efficiency can be enhanced. This research provides the help of the CNN models for doctors and radiologists to validate their first screening for brain tumour, breast cancer and lung cancer applications.

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