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Research Paper

Transfer Learning-Based Classification Comparison of Stroke

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Abstract— One type of brain disease that significantly harms people's lives and health is stroke. The diagnosis and management of strokes both heavily rely on the quantitative analysis of brain Magnetic Resonance (MR) images. The early diagnosis process is of great importance for the prevention of stroke cases. Stroke prediction is made possible by deep neural networks with the capacity for enormous data learning. Therefore, in thus study, several deep neural network models, including DenseNet121, ResNet50, Xception, MobileNet, VGG16, and EfficientNetB2 are proposed for transfer learning to classify MR images into two categories (stroke and non-stroke) in order to study the characteristics of the stroke lesions and achieve full intelligent automatic detection. The study dataset comprises of 1901 training images, 475 validation images, and 250 testing images. On the training and validation sets, data augmentation was used to increase the number of images to improve the models' learning. The experimental results outperform all the state of arts that were used the same dataset. The overall accuracy of the best model is 98.8% and the same value for precision, recall, and f1-score using the EfficientNetB2 model for transfer learning.

Keywords : *Cerebrovascular, stroke, brain MR classification, transfer learning, deep learning*.

1. Introduction

Stroke is currently a significant health issue. A stroke, also known as a cerebrovascular event, is a neurological condition that can be brought on by ischemia or bleeding of the brain's arteries. Strokes often cause a variety of functionally detrimental motor and cognitive impairments. Every year, stroke affects around 16 million people globally and has significant economic repercussions. In recent years, machine learning (ML) has rapidly expanded and changed across a number of applications in several different health care systems (Merino, 2014; Savaş et al., 2019, 2022). The most recent estimates for global health from 2000 to 2016 are shown in Figure 1 (Sirsat et al., 2020). The two main global causes of death and disability are listed as ischemic heart disease and stroke (Johnson et al., 2016).

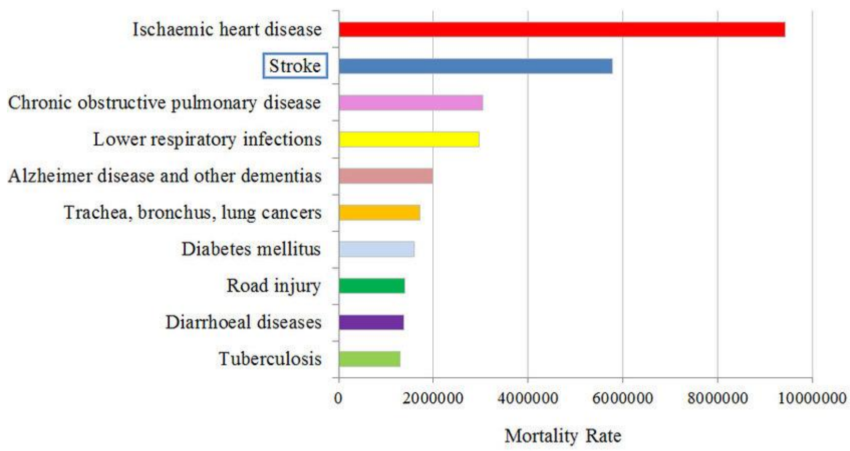


Figure 1. Ranks estimated mortality by cause, recorded in 2016 (Sirsat et al., 2020)

Because stroke has a high fatality rate, it is regarded as a serious health problem by the American Heart Association. Additionally, there is an increased demand for improved technology that can aid in clinical diagnosis, treatment, forecasts of clinical events, recommendations of potential therapeutic approaches, rehabilitation programmers , etc. (Almeida, Y.; Sirsat, M.; Bermúdez i Badia, S. and Fermé., 2020) due to the rising costs of stroke hospitalization (Di Carlo, 2009). For a stroke to be effectively treated, early diagnosis is essential, and ML and deep learning (DL) can be very helpful in this process.

DL is a cutting-edge technology that enables health practitioners to make clinical judgments and predictions. Several research on the enhancement of stroke diagnosis using ML in terms of accuracy and speed have been undertaken over the last two decades. In the last decade, these studies have increasingly focused on DL. DL models produce successful solutions to different classification and segmentation problems. However, the need for a common model with high performance for images in different databases still remains valid. This need has recently led to a tendency to pre-trained deep neural network models that can be adapted to different data types and produce successful results. It is possible to obtain successful results by preserving the feature extraction layers of these models and adapting the classification layers to the problems. This methodology is called the transfer learning method. As far as we are aware, there isn't a enough analysis of the use of transfer learning based DL for brain stroke. For this reason, a comprehensive transfer learning application was carried out in this study and the results were compared.

The following sections of the study are formed as follows. The literature on ML, DL, and brain stroke is reviewed in Section 2. The study selection process, search methodology, and categorization of the research by category are all covered in Section 3. The experimental results of the research are declared and discussed with other studies in Section 4. Finally, the study concluded in Section 5.

2. Related Works

Muhammad Usman et al., (2021) proposed an ensemble learning approach based on DL to predict epileptic episodes. The suggested method uses empirical mode decomposition to preprocess electroencephalogram (EEG) data, then bandpass filtering to reduce noise. Artificial preictal segments were developed using generative adversarial networks (GAN) to address the class imbalance problem. In order to extract automatic features from preprocessed EEG data and combine them with manual characteristics to get a comprehensive feature set, a three-layer customized convolutional neural network (CNN) has been described. The output of a support vector machine (SVM), a CNN, and long short-term memory (LSTM) are combined in an ensemble classifier that is trained using the feature set utilizing model-agnostic meta learning. Average sensitivity and specificity for the trial were 94.2 and 95.8 percent, respectively. On the other hand, Shankar et al. used a well-known DL called CNN and maintained the nonlinear properties of EEG to create two-dimensional (2D) input images from EEG data for certain brain cycles (2021). Two well-known seizure analysis EEG datasets from CHB-MIT (PhysioNet) and Bonn University were examined for experimental validation. With the recommended method, classification accuracy can reach up to 93%. Shoeibi et al., (2021) are doing yet another investigation with EEG. They provided a DL-based method for automatically learning the discriminative EEG features of epileptic convulsions. The time-series EEG data are first segmented into a number of non-overlapping epochs in order to illustrate the relationship between the subsequent data samples. Second, the LSTM network is used to learn high-level representations of both healthy and epileptic EEG signals. These representations are then sent into the SoftMax function for training and classification. The suggested technique beat the competition, with classification accuracies of greater than 90%, according to the results on a well-known benchmark clinical dataset.

In a different study, Oksuz, (2021) presented a deep convolutional neural network (DCNN) with a residual U-net architecture to detect and rectify motion-related brain MR image aberrations. To detect the synthetic artefacts created by employing an MR physics-based corrupting technique, a detection approach based on a DCNN is employed. A residual U-Net network trained on faulty data is used to rectify the discovered artefacts. In trials, the system was verified using a 28-case brain MR image stroke segmentation dataset and exhibited an accuracy of 97.8% for detecting artefacts.

A collaborative DL method for forecasting Alzheimer's disease (AD) clinical scores is suggested in the study by Lei et al., (2022). Reducing dimensions and screening features of brain regions linked to AD is done using a feature selection technique that combines group LASSO and chronotropy. They investigate both the temporal correlation between longitudinal data and the intrinsic connections between diverse brain regions using multi-layer independently recurrent neural network (RNN) regression. The proposed integrated DL network investigates and predicts the link between MRI and clinical score. The overall accuracy of the study is 86%.

Kim et al. (2021) used an ML research with 14 input parameters to forecast motor outcome in hemiplegic stroke patients. In their investigation, they employed DNN, logistic regression (LR), and random forest (RF) and looked at the data of 1,056 stroke patients. The DNN model has a 0.906 area under the curve (AUC) for predicting upper limb function. The LR and RF models' respective AUCs were 0.874 and 0.882. For predicting lower limb function, the AUCs for the DNN, LR, and RF models were 0.822, 0.768, and 0.802, respectively.

Peng et al., (2021) demonstrated a semantic segmentation method that uses a CNN to autonomously segment brain tumors on three-dimensional (3D) brain tumor segmentation (BraTS) image data sets that include four imaging modalities. Their research comprises whole-brain 3D imaging and a comparison of ground truth and anticipated labels in 3D. In terms of tumor prediction, the average prediction ratio was found to be 91.718%.

A pre-trained deep learning model (MobilNetV2) for feature extraction was suggested by Kursad Poyraz et al., (2022). The presented automated brain sickness detection model contains four phases: preprocessing, example deep feature generator, feature selection using iterative neighborhood component analysis, and classification with SVM. An MR image dataset was gathered for evaluating the offered prototype deep feature-based model for brain disease detection. The collection contains 444 MR images, three diseases, and a control (normal) group. SVM was used to classify their model with a 99.10 % accuracy rate.

Lu et al., (2021) offered a DNN-based system for categorizing tumor and non-tumor tissues using magnetic resonance spectroscopy (MRS) data. They build a data cleaning and augmentation architecture that consists of two steps: a data distillation network to filter noisy labelled data and a data augmentation technique that combines samples from both classes is more stable and produces better results. The core-learning model is a deep residual neural network (DRNN), and at the end of all convolutional layers, a global average pooling layer visualizes how much each element of the input contributes to the final classification decision. 435 patients from the University Hospital's Institute for Neuroradiology were used to create a 1H-MR-spectroscopy dataset. ROC curves for the proposed framework are 0.77.

In the study of Ananda Kumar & Mahesh, (2021), CNN is used to predict the automatic classification of brain tumors. This study improved the accuracy of brain tumor classification and experiments reveal that the developed model can detect tumors with a 95.71% accuracy rate. In another study by Kumar et al., (2018) using CNN for the tumor is investigated using alluring reverse images. The characterization of CNNs is used to propose a programmed exploration of mind tumors. The completion of the usage of small pits is the most significant sort of composition. CNN's paper has a lower predictability and accuracy of 97.5%.

Diagnostic studies continue to be carried out on different types of data for the early diagnosis of brain diseases. Recent studies are evolving towards transfer learning studies. Therefore, DCNNs are used in this study. The results obtained were compared with other studies in the literature.

3. Methodology

In the study dataset, brain MR images are in two groups, those with and without strokes, to use the suggested transfer learning-based models. Several preprocessing steps for image augmentation and enhancement are initially applied to the MR images. There were 2376 MR images in the original dataset. 1426 images were collected without a stroke, and 950 of those samples were taken after a stroke. The MRI scans are accessible on the Kaggle website (https://www.kaggle.com/). Figure 2 shows several examples of brain MR images. Notably, this collection has been expanded to produce a bigger MR training dataset. The transfer learning model is tested and evaluated on five pre-trained CNN architectures.

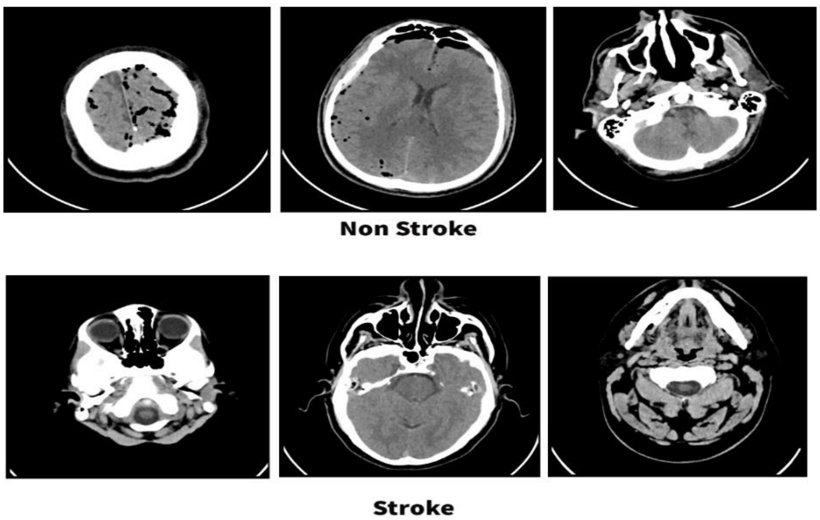


Figure 2. Samples of the dataset stroke and non-stroke MR images

3.1. Preprocessing:

Figure 3 shows the suggested transfer learning-based classification model and the primary preprocessing techniques employed in this study. The first step after reading the dataset is data augmentation which is a key aspect in deciding the performance of DCNNs. The Image Data Generator tool in Keras TensorFlow is used to augment the original picture dataset with a number of random changes (rotations, height and breadth shift, brightness change, etc.) in order to increase the quantity of MR images for training the suggested model. The data augmentation processes' settings are chosen to prevent the proposed classifier from ever seeing the same image again.

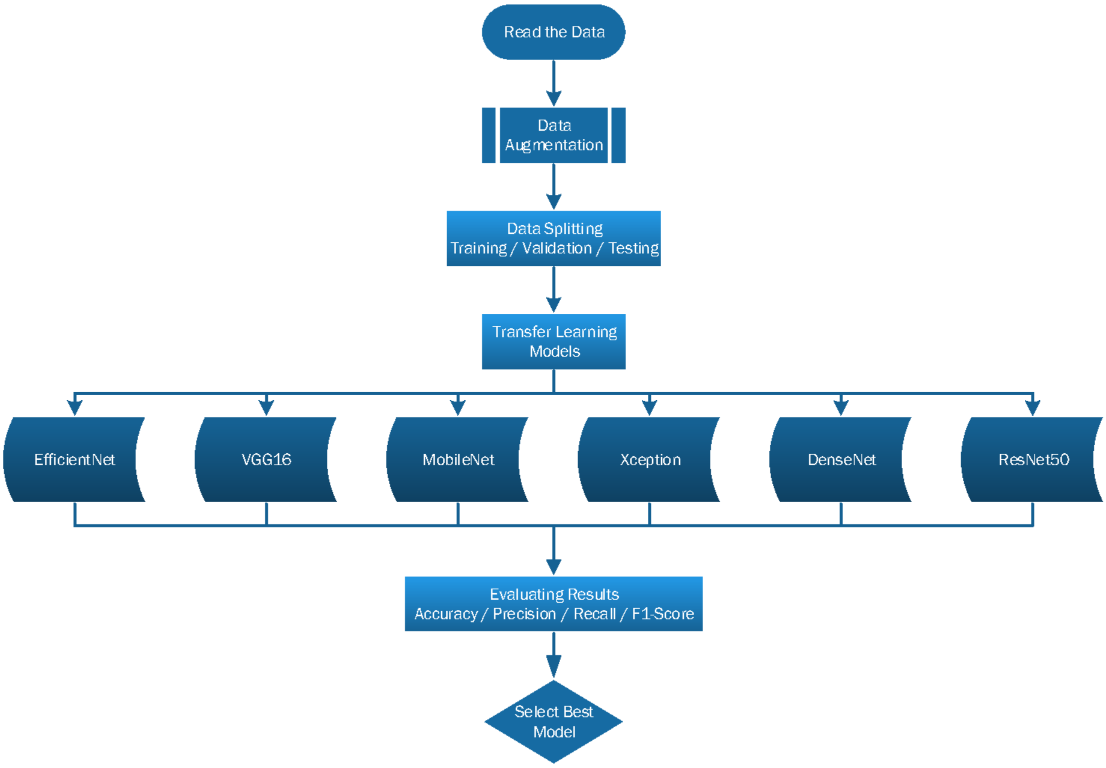


Figure 3. Block diagram of the study

Some of images after augmentation process are represented in Figure 4. This procedure improves the model's ability to generalize and helps avoid overfitting (Tanner & Wong, 1987).

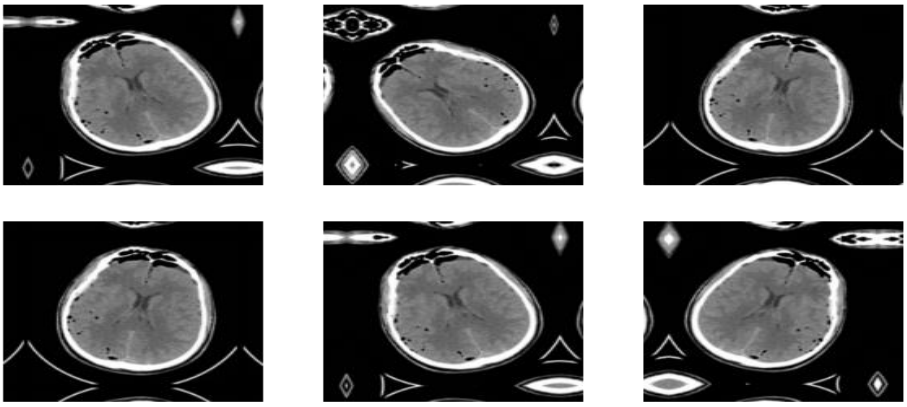


Figure 4. Samples of one image after data augmentation process

The second objective in the preprocessing step is to use a method from the Keras preprocessing techniques to automatically crop the brain out of the background of the image. To normalize the images and make them compatible with the used pre-trained models, they are shrunk to 224x224x3. The final step in the preparation process is the data split, which separates the dataset utilized in this study into three parts for training, validating, and testing the recommended DL model. The first subset, which is used to fit the model, contains 70% of the entire dataset. The remaining amount is equally split between system testing and validation (20 percent for validation and 10 percent for testing).

3.2. Transfer Learning Classifiers:

The pre-trained model is used in transfer learning to learn new, varied data by starting with the features that have already been learned to address one issue. In this study, we used six pre-trained CNN architectures to predict 1000 classes using 1.28 million images from ImageNet: ResNet-50, MobileNet-v2, EfficientNet, VGG16, Xception, and DenseNet. These networks take the entire image into account and then, as probabilistic outputs, supply the labels of each item present in the image.

The top layer's loss function is changed from SoftMax to Sigmoid, and the networks' last two layers are modified to adapt the pre-trained networks to the classification task that distinguishes stroke from non-stroke MR images.

- **ResNet-50**: This network is an exact replica of the 50-layer Residual Network created by He et al., (2015) at the Microsoft Research Center. ResNet uses shortcut connections to perform feature deduction, which is referred to as "residual," in order to speed up training of deeper networks and perhaps reduce errors brought on by complexity development. Deteriorating accuracy is a problem that ResNet also solves.
- **MobilNet-V2**: Two distinct sorts of blocks are offered by this model. The first block consists of a mixture of linear bottleneck operations, whereas the second block is a skip connection. Both blocks contain batch normalization, convolution, and modified rectified linear units. MobilNet-V2 has 16 blocks altogether (Howard et al., 2017).
- **VGG16**: The 2014 ILSVR (ImageNet) competition was won using it. One of the greatest vision model architectures ever developed is thought of as being this one. The most notable aspect of VGG16 is that it consistently used the same padding and maxpool layer of 2x2 filters with a stride 2 and favored having convolution layers of 3x3 filters with a stride 1. Convolution and max pool layers are set up in the same way across the whole design. Two fully connected layers (FC) and a SoftMax for output are included as a conclusion. (Simonyan & Zisserman, 2014).
- **EfficientNet**: EfficientNet is a CNN architecture and scaling technique that uses a compound coefficient to consistently scale all depth, breadth, and resolution parameters. The EfficientNet scaling approach evenly increases network width, depth, and resolution with a set of preset scaling coefficients, in contrast to standard practice, which scales these elements arbitrarily (Savaş, 2022; Tan & Le, 2019).
- **DenseNet**: A DenseNet is a special kind of CNN that uses dense blocks to connect all layers directly with one another (if their feature-map sizes match). To keep the system's feed-forward nature, each layer gets additional inputs from all earlier levels and broadcasts its own feature-maps to all later layers (Huang et al., 2016; Zhu & Newsam, 2018).
- **Xception**: Xception, a Google product that stands for extreme version of Inception (Chollet., 2016). For both the ImageNet ILSVRC and JFT datasets, it outperforms Inception-v3 (Szegedy et al., 2016) (also from Google, 1st Runner Up in ILSVRC 2015) using a modified depthwise separable convolution.

3.3. Evaluation Metrics:

Equations (1), (2), (3), and (4) for accuracy, precision, recall, and F1-score are used to assess the proposed methodology, respectively.

$$\text{Accuracy} = \frac{\text{TP+TN}}{\text{TP+TN+FP+FN}} \tag{1}$$

$$\text{Precision} = \frac{\text{TP}}{\text{TP+FP}} \tag{2}$$

$$\text{Recall} = \frac{\text{TP}}{\text{TP+FN}} \tag{3}$$

$$\text{F1-score} = \frac{2*\text{Recall}*\text{Precision}}{\text{Recall+Precision}} \tag{4}$$

The total samples of the negative and positive classes are denoted by “N” and “P” in the equations below. According to the suggested paradigm, P stands for malignant and N for non-cancerous. True Positive, False Negative, False Positive, and True Negative are represented by the letters TP, FN, FP, and TN, respectively.

The tests examined in this study were carried out using brain MRI stroke detection data. 12 GB of RAM and a Collab GPU were used to implement the research. We used the Keras package to implement the pre-trained CNN models using TensorFlow. With a batch size of 32, all networks are trained over a period of 20 epochs. In this experiment, neural weight updates based on training data are performed using the Adam optimization method

(Kingma & Ba, 2015) as opposed to the conventional stochastic gradient descent optimizer. With a learning rate=0.001, beta 1=0.9, and beta 2=0.999, the Adam optimizer is used.

4. Experimental Results and Discussion

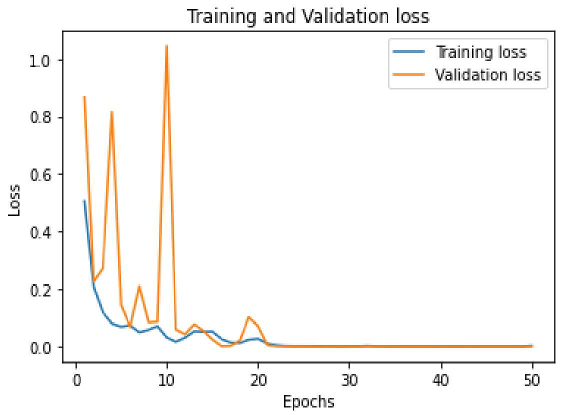
In this section, the measures that were utilized to evaluate the performance of the suggested system are explained. Additionally, the proposed approach is compared with a few other current approaches.

Table 1 shows the comparison between the results of the proposed transfer learning models. The metrics used are the accuracy, precision, recall, f1-score. As shown in the Table 1, the EfficientNetB2 has the highest performance with the best accuracy 98.8% and the best precision, recall and f1-score with the same value on test data.

Table 1. Comparison of performances between proposed models.

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
EfficientNetB2	98.8	98.8	98.8	98.8
MobileNetV2	96	96.19	96	96
VGG16	50	25	50	33
ResNet-50	96.4	96.5	96.4	96.4
Xception	97.6	97.65	97.6	97.6
DenseNet	98.4	98.4	98.4	98.4

As shown in Table 1, the EfficientNetB2 overcome the rest of models in all of metrics, which has 98.8% for accuracy, 98.8% precision, 98.8% of Recall and 98.8% for F1-score on test data. Figure 5.a. represents the relation between training and the validation loss regarding to the progress of number of epochs with the final loss equal to 0.00027 and validation loss equal to 0.0000017. Figure 5.b represents the relation between the training and validation accuracy and the final training and validation accuracy of 100%.



(a)

(b)

Figure 5. EfficientNetB2 performance

Table 2 represents a comparison of the EfficientNetB2 with the state of art models and it is seen in the table that the proposed EfficientNetB2 overcome all of them.

As shown in Table 2, the proposed EfficientNetB2 model overcome other model and previous work for many reasons. The first and the main difference is adapting the pre-trained model and adding global averaging pooling which is a pooling procedure that is intended to replace completely linked layers in traditional CNNs in the final conv layer, one feature map is generated for each matching category of the classification job. The second reason for the performance of the proposed model is making all layers trainable, which improve the performance of feature extraction process and classification. The third reason is not using the EfficientNetB2 model in the previous work. We also implemented data augmentation for the dataset with horizontal fib and random rotation with 10 degree, random zoom with height factor equal to (0.2, 0.3), and also random crop the images with keeping the size of resulted images 224x224. Figure 6 represents the architecture of the EfficientNetB2 model (Agarwal, 2020).

Table 2. Comparison between the proposed EfficientNetB2 with others in the field

Study	Algorithm	Dataset	Results
Sirsat et al., (2020)	FCN	Multimodal MR images ISLES 2015 dataset	Mean Accuracy =70%
J. Liu et al., (2019)	SVM	CT scan images	Sensitivity = 81.3% Specificity = 84.8% Accuracy = 83.3%
T. Liu et al., (2019)	RF	Physiological data	Accuracy =71.6% Sensitivity = 67.4%
Thornhill et al., (2014)	LR	CTA images	Sensitivity = 87.5% Specificity = 71.4%
Vargas et al., (2019)	Artificial Neural Network (ANN)	CTA perfusion images	Accuracy = 85.8%
Bacchi et al., (2020)	CNN, ANN	Clinical data CT brain scans	Accuracy = 0.71%
Ge et al., (2019)	LR, SVM, XGBoost, MLP, and RNN	HER data	AUC = 0.92
Giacalone et al., (2018)	SVM	MR images	Precision = 95%
Hilbert et al., (2019)	ResNet with RFNN	CT angiography images	AUC = 0.71
Proposed work	EfficientNetB2	MR images	Accuracy = 98.8%

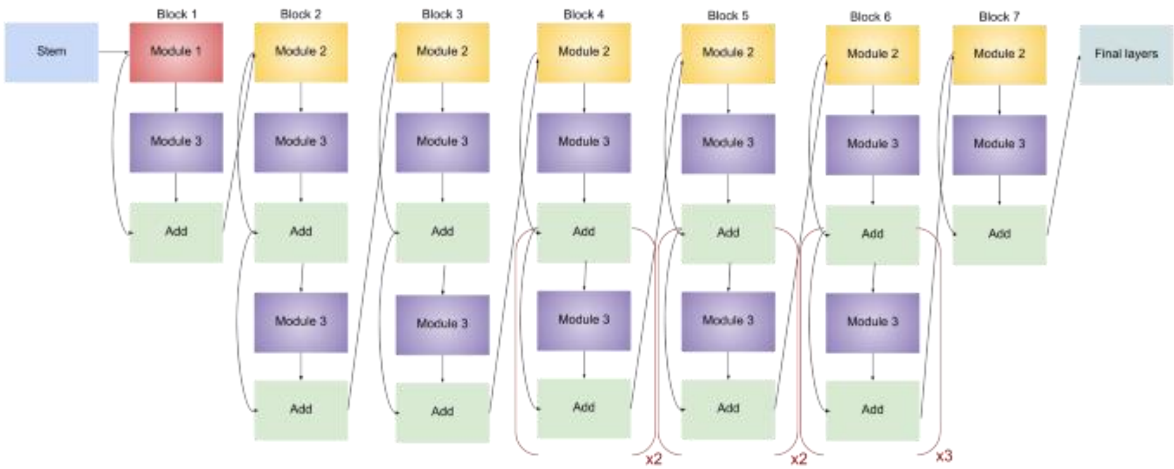


Figure 6. EffiecientNetB2 Model architecture (Agarwal, 2020)

The modules details used in the Figure 6 are illustrated in the Figure 7. Every module has number of layers which help to make the process of feature extraction is efficient.

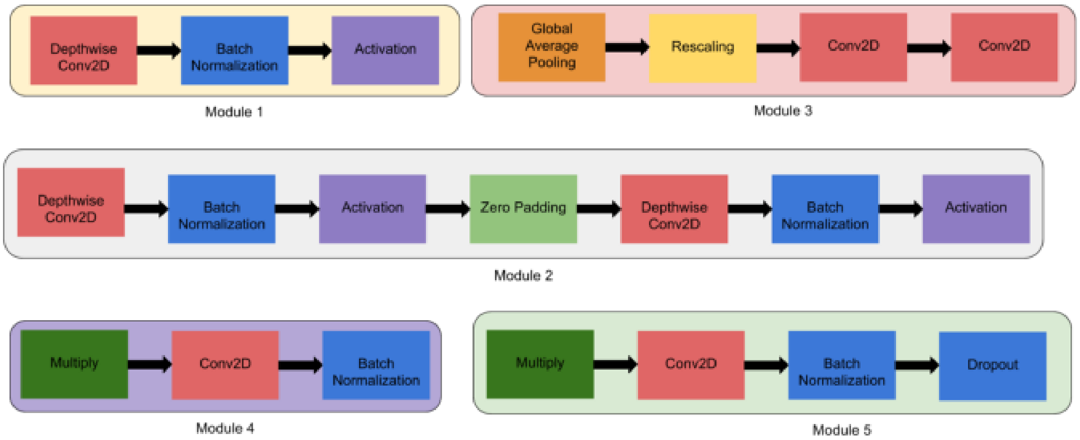


Figure 7. EfficientNetB2 modules description (Agarwal, 2020)

As shown in the Figure 7, module one consists of depthwise convolution2D and batch normalization followed by the second module which contain global average pooling and two convolutions' layers and the module three contains many layers which are very effective in feature extraction process. The other modules contains the same layers but the final one contain dropout which overcome the overfitting problem in the model.

5. Conclusion and Future Work

In this study, an effective technique for automatically classifying brain tumors from MRI scans is presented. The technique uses well-known CNN architectures and is based on transfer learning. The experimental results showed that pre-trained DL models could be utilized to create a classifier that could recognize stroke in brain MR images, despite the small size of the used dataset. Particularly, the EfficientNetB2 DL model demonstrated superiority over the other models by outperforming the state of the art in terms of F1-score, precision, recall, and a very excellent accuracy of 98.8%. In our upcoming study, we intend to develop a unique model for detecting various forms of brain illness using extensive brain stroke datasets and different feature selection methods.

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