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AN INTELLIGENT RESNET50 AND EFFICIENTNET BASED BRAIN TUMOR DETECTION AND DIAGNOSIS

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ABSTRACT

Some of the brain cells grow abnormally and rapidly resulting in tumors in brain tumors. Brain tumor is a major cause of brain diseases. Magnetic Resonance Imaging (MRI) is a mature and consistent diagnostic technique of detection of brain cancer. Nonetheless, the resulting MRI scans yield an enormous amount of images that have to be examined in detail by radiologists. The process of man-handling these images is long and might lead to flaws in detecting the cancer. When it comes to brain cancer diagnosis, the Deep Learning and Machine Learning algorithms of MRI data allow one to quickly obtain a prognosis. Nonetheless, it is essential to consider the increased accuracy to administer the relevant treatment to the patient and enable the radiologists to make timely decisions. In response to this, we suggest that the application of Convolutional Neural Networks (CNN) be used in the detection of brain tumors. We use the dataset that has two classes, three of the classes describe various types of tumors, and one is the non-tumor samples. We introduce a model which uses pre-trained CNNs to classify the cases of brain cancer. Also, there is the use of data augmentation techniques to increase the size of the dataset. Our proposed CNN model is tested based on several measures, such as validation loss, confusion matrix, and the total loss. The suggested model with the usage of ResNet50 and Efficient Net revealed the superior rates of accuracy, precision, and recall in identifying brain tumors.

KEYWORDS: Machine Learning, Deep Learning, Medical Diagnosis, Healthcare Analytics, Tumor, Convolutional Neural Networks.

1. Introduction

The brain is the most important organ as it controls the functionality of all the other organs and is involved in decision-making [1]. It is the main center of the central nervous system controlling all the processes inside the body, voluntary and involuntary, taking place on a daily basis. A tumor is an unregulated growth of fibrous networks of abnormal brain tissue. It has been estimated that about 3,560 children will be diagnosed with brain tumor at the age of fifteen years this year. The signs of brain tumor and its development are important in the prevention and treatment of the condition. This is commonly used by radiologists, who are studying brain malignancies by use of magnetic resonance imaging (MRI). Using deep learning methods, the research performed in the current paper identify whether the brain is healthy or diseased [2].

Detection of brain tumor

The brain is the most significant and the most eloquent organ in the body. Tumours have been rated among the leading causes of brain-related sickness. An overgrowth of cells in the brain is referred to as a tumor. The brain tumor is one of the most perilous and fatal diseases that impose a threat on the mankind. Almost 10,100 individuals are found to be diagnosed with a brain tumor annually. Magnetic resonance imaging (MRI) is an effective method of differentiating brain tumors. The scanning will produce enormous data that can be presented to the analysis of the radiologists. The process of diagnosis undertaken by human beings are time consuming and can be erroneous at times [3]. Nowadays, the edge cutting technologies, such as machine learning, deep learning is considered to make a wise and precise choice in such important spheres as finance, medical and so on. These algorithms have been found to excel in decision makings, fast results and also the evasion of manual interference. And the consistency and reliability has also been greatly enhanced. Automatic classifier was made to detect and classify the brain cancers found in the images of MRI scan. There are number of Artificial based algorithms available in literature to accomplish the task of auto detection and classification. We had guessed a process of deep learning requiring the discovery of the tumors based on the MRI scans [4].

Convolutional Neural Network (CNN)

Deep learning algorithms have been constructed by applying artificial neural networks that have more than one internal layer and learning mechanism. These algorithms are primarily distinguished by the ability to operate very large amounts of data, an opportunity to spend less time on the decision making process and increased accuracy. This is the reason why these algorithms have gained immense popularity. Application of increased internal layers neutralizes the drawbacks of the previous methods in many applications with most of them being in image processing sphere. Deep neural networks that are commonly used with images and regularly operated are known as convolutional neural networks (CNNs). The CNNs are used in detection of objects within an image, segmentation of images and their classification [5]. A CNN is made up of a convolutional layer, which carries out the feature recognition and detection and the results of the convolutional layers are utilized to predict the ultimate choice or kind of group of the image. The CNN is highly preferable in machine learning problems that are related to images [6].

Dataset

The application of weights trained on a different dataset is known as a transfer learning [7]. In this work, 1000 classes were determined with the weights of the model that was trained on the ImageNet Dataset. A model is firstly trained using specific data that is considerable and the specific task is given. In this model, the data is trained to perform another task in which the size of the data is small. This is the core principle. Patterns that we use to complete a similar task have been already established instead of initiating the process of learning. There are various advantages to transfer learning, though the three advantages are the least time to train, better on neural networks, and does not require a lot of data. One of the situations where transfer learning can come in handy is when one cannot always get access to large amounts of data but still has to use it to initiate a neural network. The transfer learning also allows pre-training the model and this allows a practical machine learning model with less training data. The days it takes to train a deep neural network on a challenging problem can be many. Consequently, there is also a reduction of training time. It has been utilized to use ResNet50 and EfficientNet pre-trained models.

Intensification of data

The dataset is to be considered one of the most important and significant constituents to train the model of machine learning. In practice, however, it is impossible to have a large dataset of brain tumor. Therefore, when it happens that there is need to train the model on large number, one is supposed to perform the augmentation. The artificial expansion of the available dataset through the modification of the data is referred to as the data augmentation. The rotation, shearing, flipping, shift and cropping of the images of dataset [8,9] can be re-orientated and re-created as augmented data set. The fact that a lot of images are taken into consideration to train the model may lead to a significant deterioration [10, 11] of its accuracy.

2. Materials and Methods Source Data

Navoneel Chakrabarty's dataset from Kaggle has 253 Brain MRI scans. The images are divided into two files, yes and no, each containing images with and without brain tumors. This dataset is used for the detection of brain tumor. The Kaggle dataset for brain tumor imaging was used. It has 7022 MRI scans of the human brain divided into four categories: glioma, meningioma, no tumor, and pituitary as depicted in

Figure 1. This dataset is used for classification of tumors [16], [17].

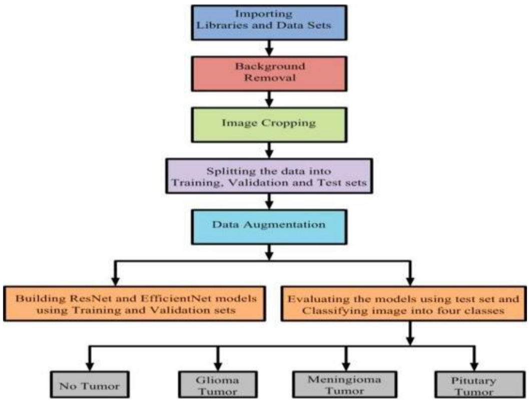

Figure 1: Brain Tumor classification

Tumor Detection Model

The two among the many models employed by CNN are the sequential model and the functional model. The Sequential model and the Functional model are all competent in their field. It allows sharing of layers and branching besides accepting many inputs and outputs. Sequential model each layer is fed with a single input and produces a single output and all the layers are stacked to make the entire network. In the majority of the issues of course, the sequential application programming interface allows us to generate models in layer by layer.

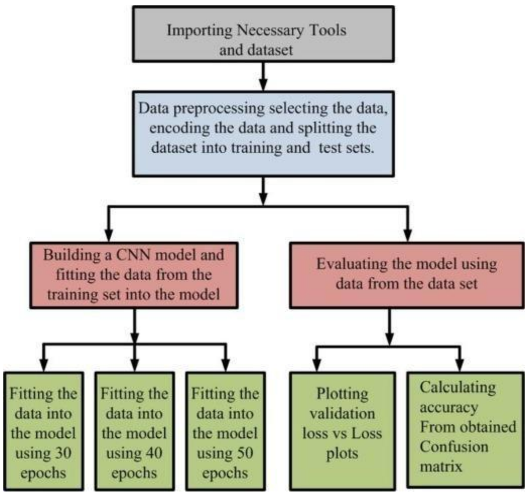

Figure 2: Proposed Model using CNN

The key limitation of this is that it prevents us to develop models that have a large number of inputs / outputs or common layers [18], [19], [20]. Convocation layers extract the features of the input image. The convolved image is obtained as a result of the input image and the appropriate kernel. The kernel is defined by the size of the input image. The input image is convolved with the kernel and this is in the form of a matrix thus referred to as convolution matrix or a convolution mask. The primary goal of taking a pooling layer is to decrease the size of the input image as well as to complete the dimensionality reduction of the network. The reduction of the sample size through pooling reduces the redundant data and the required data is transferred to the next layer of CNNs [21], [22], [23]. The block diagram of proposed method with CNN is represented as illustrated in Figure 2. Feed-forward neural networks are associated with Fully Connected Layers. The pooling or convolutional layer final output is sent over to the fully connected layer before being rounded by the fully connected layer. You can also use the dropout layer to make neurons not encourage the later layers in order to avoid over fitting your training data. A second method that is used regularly in deep learning is the batch normalization method. This normalizing process occurs to the input and the output of intermediate stages [24], [25]. A convolutional neural network (CNN) has an output layer, which is a fully linked layer that is fed with the output of the preceding layers and processes it to an outcome that transforms it to the necessary count of classes. The Loss function is implemented with the help of categorical cross entropy and adamax optimizer as the optimizer. To accomplish a superior accuracy, the fitting method includes changing the characteristics of the model. The information is manipulated through an algorithm. The model is evaluated according to the accuracy of the output of the model, compared to the actual values of the dependent variable. In machine learning, the total number of iterations of the model that use the entire training set is referred to as an epoch. The model was trained on thirty, forty and fifty epochs. The size of the samples that are conveyed through the network is defined by the size of the batch [12], [13], [14]. This work was done using a batch size of twenty-five. Verbose would be the best choice to see the output of any Neural Network throughout the training process. The modeling of Model was conducted in two phases one prior to the data augmentation and another following the augmentation of the data.

3. Results

A machine learning model must be evaluated to know how it works so that its advantages and disadvantages can be identified. The training loss is the measure of the fit of training data set. A certain section of the dataset that is set aside to check the performance of the model is referred to as the validation set. The loss of validation is used to identify and analyse the performance of a deep learning model on the validation data set. A confusion matrix is a table that is used to make decisions on how a best classification system should perform. Many parameters of the model such as True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN) and accuracy are calculated with the help of confusion matrix.

Data augmentation may also prove as an effective approach to enhancing the employment of a tumor detecting model, particularly when the accessible data is small. The objective of data augmentation is to use several transformations on the original images in order to artificially expand the range of the training data. This is capable of assisting the model to generalize better to various variations of the input data.

3.1 Detection of Brain tumor

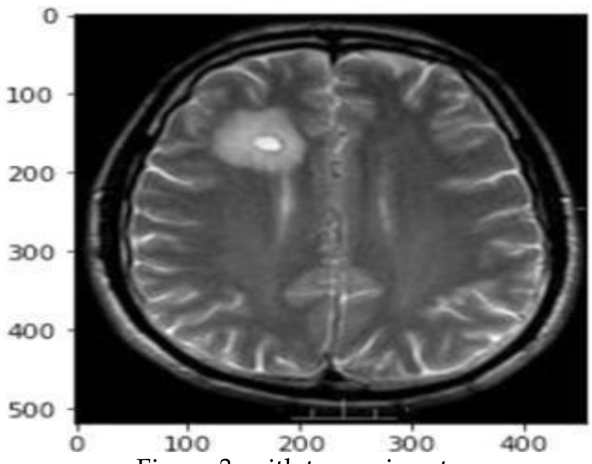

Figure 3: with tumor input

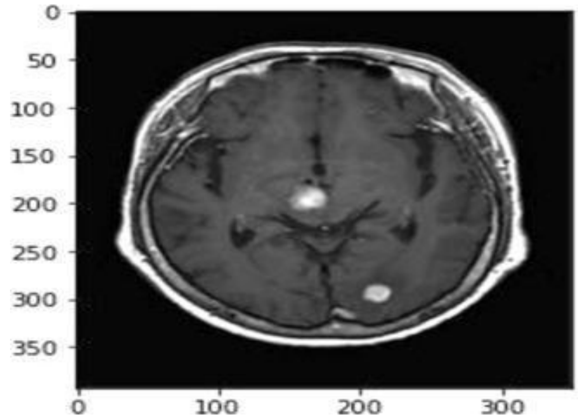

Figure 4: without tumor input

The appropriate application of data augmentation can increase the robustness and generalization of the model, and the performance of tumor detection is improved.

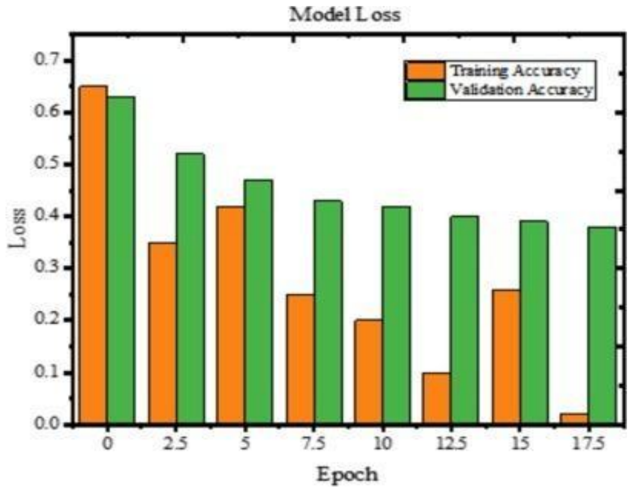

Figure 5: Training Accuracy Vs Validation Accuracy Plot

4. Discussion

Test augmentation methods to identify the one that best suits your particular dataset and task. Figure 5 presented the Training Accuracy Vs Validation Accuracy Plot. Training Loss Vs Training Loss Plot is shown in Figure 6.

Table 1. Proposed CNN

Empty Cell	**For 30 Epochs**	**For 40 Epochs**	**For 50 Epochs**
True Positive (TP)	15	21	21
True Negative (TN)	15	12	11
False Positive (FP)	9	3	3
False Negative (FN)	3	6	7

Tables-2 illustrates the comparison of the parameters of different classes of brain images. Model accuracy is used to describe the accuracy of a model on a given dataset in terms of percent correct. Loss or cost or model loss Model loss is the measure of the difference between the predicted values and the true ground truth values. The model accuracy is normally inversely related to the model loss. The model has a training and validation accuracy of 97 and 71.3 respectively without augmentation. Nevertheless, these accuracies are raised to 99 percent during training and 80 percent during validation when data augmentation is used. The larger the model accuracy, the smaller is the model loss and the other way around. Based on the Table 2, it can be seen that model has less loss in training without augmentation as opposed to with augmentation being applied.

Table 3. Comparison of brain images

Empty Cell	ResNet50				EfficientNet			
	TP	TN	FP	FN	TP	TN	FP	FN
GLIOMA	167	0	1	0	175	0	3	0
NOTUMOUR	201	0	5	0	200	0	3	0
MENINGIOMA	147	0	5	0	152	0	2	0
PITUITARY	163	0	4	0	162	0	6	0

Table 4. Brain tumor detection and classification

S.No	Model	Accuracy	Precision	Recall
1	CNN without data augmentation	78.57%	75%	87.5%
2	CNN with data augmentation	85%	82%	88%
3	ANN [10]	91.72%	89.2%	89.2%
4	ResNet50 (Proposed1)	96%	97%	98%
5	EfficientNet (Proposed2)	98%	98.5%	99%

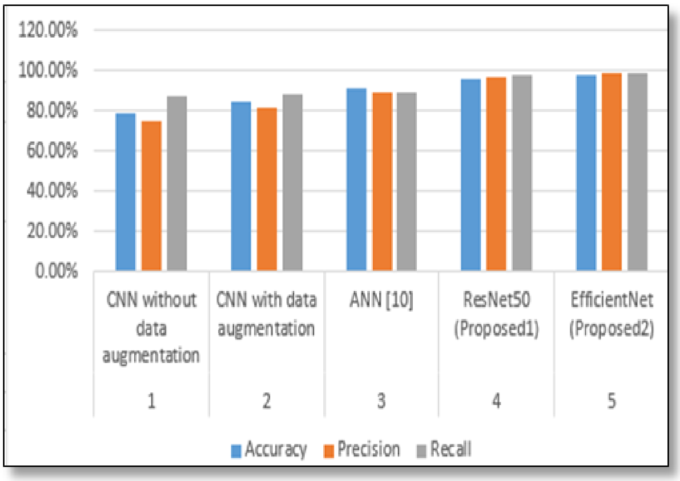

Figure 6: Brain tumor detection and classification

5. Conclusions

The main aim of this research paper is to use deep learning to detect and classify brain tumors. To resolve the problem of a small data set and computing power, we used transfer learning and image augmentation methods. A Convolutional Neural Network (CNN) was applied to tackle the brain tumor detection problem with a validation accuracy of 78.57% and a training accuracy of 97.00% in the absence of data augmentation. The model with data augmentation had a validation accuracy and training accuracy of 85% and 99% respectively. In case of tumor classification, transfer learning models were used. The ResNet50 model had a testing accuracy of 96% and testing loss of 9.4, precision of 97 and recall of 98 and EfficientNet model had testing accuracy of 98 and a testing loss of 5.09, precision of 98.5 and recall of 99. This implies that more data needs to be collected in order to achieve more specific classification in subsequent studies. In addition, it is advisable to explore the other models and architectures other than the one used which is the fully connected architecture to determine the best way of achieving high accuracy in classification of brain tumors. The research on the comparison of different models should be developed in the future to inform the choice of the most efficient architecture. It is also necessary that more data should be collected in the future to complement classification accuracy and brain tumor detection. Furthermore, the investigation of alternative models and architectures to the one that is currently in use, fully connected architecture, can be employed to find out which approach can be best utilized to improve the accuracy of brain tumor classification.

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