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Brain Tumor Classification Using Deep Learning

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***Abstract*—Brain tumor is a very common and destructive malignant tumor disease that leads to a shorter life if it is not diagnosed early enough. Brain tumor classification is a very critical step after detection of the tumor to be able to attain an effective treatment plan. This research paper aims to increase the level and efficiency of MRI machines in classifying brain tumors and identifying their types, using AI Algorithm, CNN and Deep Learning. We have trained our brain tumor dataset using five pre-trained models: Xception, ResNet50, InceptionV3, VGG16, and MobileNet. The F1-scores measure of unseen images were 98.75%, 98.50%, 98.00%, 97.50%, and 97.25% respectively. These accuracies have a positive impact on early detection of tumors before the tumor causes physical side effects, such as paralysis and others disabilities.**

Keywords— Brain Tumor, Deep Learning, Classification, Artificial Intelligence

I. Introduction

There is a very large group of people, whose exact numbers are unknown but they continue to increase, who are diagnosed with a type of brain tumors called secondary brain tumor. Early detection is always likely to accelerate the process of controlling and eliminating the tumor at early stages, with the help of highly efficient clinical imaging devices. Meanwhile, patients who suffer from brain tumors face the problem of MRI machines inability to precisely detect and classify the brain tumor, which could lead to physical complications that cause disability [1].

Brain tumors as collected data**:** are classified into four types: glioma tumor, meningioma tumor, no tumor, and pituitary tumor.

This research paper discusses the limitations caused by the inability of MRI machines in identifying and classifying tumors. These tumors could cause complications such as physical disabilities, which would then force patients to seek proper extensive and usually painful rehabilitation in order to treat or reduce the induced disabilities. Moreover, the complications of brain tumors on brain's functionality varies subject to its magnitude, location and type.

A patient may become unable to move because a tumor could put pressure on the area that controls the body's movement in the brain. It could also cause loss of sight or hearing [2-3].

II. Background

A. Deep Learning

Deep learning is a training-based artificial intelligence (AI) method, which allows creating multiple layers of computation to teach multi-level machine representations of data. This approach enhanced up-to-date technologies, such as speech recognition, identification of objects and many other domains. Training can be supervised or unsupervised. The Input data at all levels is transformed into a more abstract and organized representation in deep learning. In a Tumor recognition applications, the raw input will represent pixel matrix, the first layer in the representation could abstract the pixels and put them into a code that detects edges of tumor, in next layer it put the code of the arrangement of tumor edges, the third representation layer put into the code of the representation of circles, and the next layer might be able to identify that the image comprises tumor. Essentially, a process in deep-learning is capable to pick up features and fit them in the proper place by itself [4].

B. Supervised Learning

Supervised model learning is built to give predictions. An algorithm in the supervised learning process receives dataset as an input and the labels to the recognized output to acquire the classification and/or regression of the model. A deep learning procedure trains a model for generating an expectation for the reaction to original dataset or the unseen images of the dataset as an open loop chain. Impact of the output is connected to the dishonorable by a single chain of kinematics. In the instance of parallel exploiters, the connections are bound in a way that is a closed loop chain is produced. At the end of the chain, the part which makes the effect can be found, however it is bound to the base by at least two or more kinematics chain. Thus, none parallel manipulators could have the benefit of additional elastic and broader occupied interplanetary matched to manipulators that are connected in parallel [4-5].

C. Unsupervised Learning

Unsupervised learning is a technique which belongs to machine learning. In unsupervised learning one is not required to supervise the model. As an alternative, one is required to permit the model to work by its own to ascertain material. It largely works with data that is not labeled.

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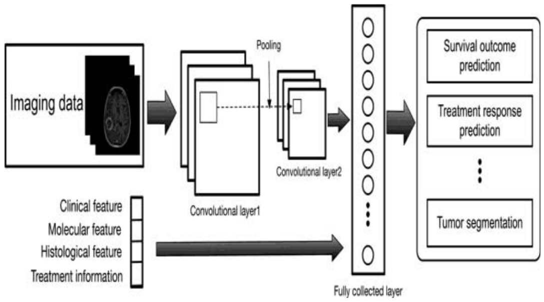

Fig. 1. CNN of Training for Brain Tumor Adapted from [25].

Algorithms under unsupervised learning permits one to do more sophisticated processing when associated to supervised learning. Unsupervised learning might largely be impulsive when compared with other approaches in natural learning [6, 7].

D. CNN

Convolutional neural networks, (CNNs or sometimes called ConvNets) is considered one of the key classes for recognition and classifications of images. Some of the areas where CNNs are widely used are detection of objects, face recognition, image classification etc. Researchers sometimes use Matlab or Python Libraries (tensorflow, pandas, openCv, Keras, etc) to create and train CNN [8-12]. Fig. 1 outlines the architecture of CNN for training brain tumor as an example.

E. Pituitary Brain Tumors

Abnormal developments that grow in one's pituitary gland is called Pituitary Brain tumors. Specific pituitary tumors outcome in a lot of the hormones which control significant tasks of one's body such as growth and development, organ function (kidneys, breasts and uterus), and gland function (thyroid, gonads and adrenal glands). Specific pituitary tumors may cause one's pituitary gland to yield lesser levels of hormones. The most common pituitary tumors are benign (none cancerous) growths (adenomas). Adenomas stays in one's pituitary gland or nearby tissues and don't blowout to other chunks of one's body. Pituitary tumors are irregular developments that grow in one's pituitary gland [2-3].

F. Glioma Brain Tumor

Glioma is a kind of tumor that happens in the spinal cord and brain. Gliomas starts in the sticky supportive cells that border nerve cells and assist them in performing their functions. Three kinds of glial cells may yield tumors. Gliomas are categorized conferring to the kind of glial cell shared in the tumor, in addition to the tumor inherited topographies, which may assist in predicting how the tumor will act with time and the conducts which may work. The symptoms of a Glioma tumor consists of imbalance, Nuisance, queasiness or vomiting, misperception or a weakening in brain function, Loss of memory, Behavior changes or touchiness, irregularity in urination, visualization problems, such as indistinct vision, dual vision or peripheral vision loss, talking problems and seizures, particularly in somebody deprived of a history of seizures [2-3].

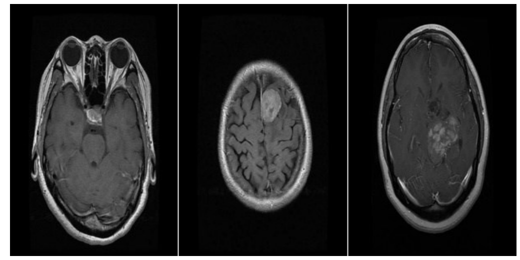

Fig. 2. Brain Tumors Adapted from [23].

G. Meningioma Brain Tumor

A meningioma is a tumor that ascends from the meninges — the films that surround one's spinal cord and brain. Though not theoretically a brain tumor, it is comprised in this class since it might pad or crush the nearby brain, vessels and nerves. Meningioma is the utmost shared kind of tumor that grows in the head. The symptoms of a meningioma naturally start slowly and might be much understated in the beginning. Dependent on location in the brain or, infrequently, backbone the tumor is located, signs and symptoms may comprise: variations in vision, such as sighted double or vagueness, headaches, particularly those that are not as good as in the morning, hearing problems or buzzing in the ears, recollection loss, seizures, faintness in one's arms or limbs, difficulty in language [3]. Fig. 2 shows sample images of brain tumors.

H. Pre-Trained Deep Learning Models

Pre-trained deep learning models are used for extracting features from images, giving improved performance accuracies over the traditional models, increasing interpretability, understanding and processing of the data. The most famous pre-trained deep learning modes are:

1) Xception

The pre-training model which is called Xception is an architecture that belongs to deep convolutional neural network. It was developed by Google cooperation and it involves depth wise separable convolutions, and it was developed to give clarification of Inception modules in CNN. Pictures head into the entrance flow, then go to the middle flow that is iterated eight rounds, and lastly by the departure flow as seen in Fig. 3 [13].

2) ResNet-50

ResNet-50 was developed by Kaiming for residual learning that could be construed effortlessly as deduction of input characteristics acquired from specific layer. That can be done by ResNet by means of shortcut acquaintances to every pair of the thirty three filters, straight linking the input of kth layer to (k + x)th layer. The reason behindhand avoiding layers is to retain absent the problematic vanishing gradients thru re-exploiting initiations from the previous layer until the neighboring layer that has learnt its weights [15].

During the training of the artificial neural network, weights will intensify the neighboring layer and will similarly alter the weights to preserve the previous layer. ResNet-101 is 101-layer Residual Network and it is a modification of the 50 layer ResNet model.

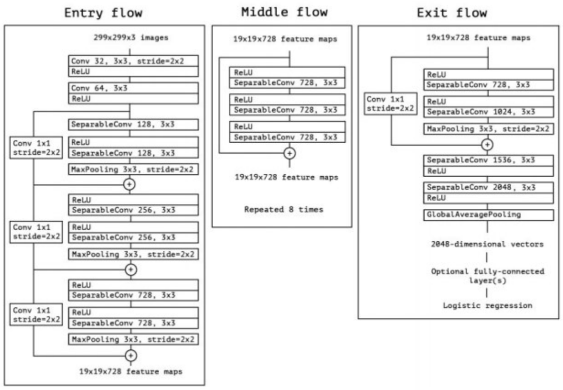

Fig. 3. Xception Architecture Adapted from [13].

3) Inception-v3

Inception v3 is one of CNN popular architectures, see Fig. 4. It is used in the current research. Inception v3 system piles eleven inception models in which every model contains layers of type pooling and filters that are convolutional with units of type rectified linear as the function of activation in our research. The model receives as input an image of two dimensions which consists of sixteen flat pieces of the brain positioned on 4-3-4 gridirons as shaped by the preprocessing phase. Three completely linked layers of size 256 by 256, and three are added to the last layer of concatenation. 60 percent is used as a dropout prior to the fully connected layers by way of regularization. It is a pre-trained model which was implemented on Image-Net dataset and additionally was perfected with eight as size of the batch and 0.0001 as rate of learning [13-14].

4) MobileNet

MobileNet is a CNN building model for image classification and mobile phones. There are other models, but what makes MobileNet special is that it has less processing power to create or implement transfer learning. This makes it perfect for low-end IT installations with cell phones, integrated systems and non-GPU computers or a significant commitment to accuracy of results. It is also more suitable for browsers because the browser has limits on calculations, graphics processing and archiving.

MobileNet is designed for mobile and integrated visual applications, based on an optimized architecture that uses deeply separable resolutions to build a light terrestrial nervous system. The main layer of MobileNet is a deeply separable filter, called a deeply separated solid. The structure of the network is another success factor. Finally, the width and resolution can be changed to improve accuracy and precision of prediction [16].

III. Related Works

Lately, Deep Learning approaches have been used for classifying and detecting brain tumors using different imaging methods, particularly those with MRI. The most recent studies on the brain tumor are outlined.

Muhsen et al. [17] proposed a system that combines deep learning and discrete wavelet transform features techniques. They used fuzzy c-mean method to segment the brain tumor, and for every detected lesion the wavelet transform features was used to extract the features, then these features are fed into the principal component analysis for feature dimension reduction and lastly the selected features are then fed to deep neural networks. The results showed that they achieved an accuracy rate of 96.96% and a sensitivity rate of 97.1 %.

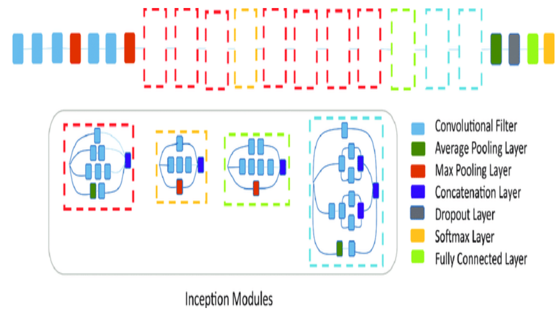

Fig. 4. Inception-v3 architecture Adapted from [23].

Widhiarso et al. [18] proposed a brain tumor classification system by using convolutional neural network and Gray Level Co-occurrence Matrix (GLCM) based features. They extracted four features (Correlation, Contrast, Energy, and Homogeneity) using four different angles (0°, 45°, 90°, and 135°) for every image and these features are supplied into the CNN, they evaluated the proposed system using four different datasets (Gl-Pt, Mg-Gl, Mg-Pt, and Mg-Gl-Pt) and the highest accuracy obtained was 82.27% for Gl-Pt dataset using two sets of features; contrast with homogeneity and contrast with correlation.

A CNN system, was presented by Seetha et al in [19], for brain tumo detection and classification. The system is based on Fuzzy C-Means (FCM) for brain segmentation and based on these segmented regions a texture and shape features were extracted then these features were supplied to the SVM and DNN classifiers. The results of evaluating the system obtained 97.4% accuracy.

Sasikala et al. [20] presented a genetic algorithm feature selection for feature dimension reduction of wavelet features set. The method is based on selecting optimal features vector that can be supplied into the selected classifier such as ANN. The results showed that the genetic algorithm selected only four out of 29 features and achieved an accuracy of 98% using only the selected features.

Khawaldeh et al. [21] proposed a system for non-invasive classification of glioma brain tumors using a modified version of AlexNet CNN. The classification process was performed by dint of MRI images of the entire brain and the labels of the images were at the image level, not the pixel level. The result of evaluating the system showed an accuracy of 91.15%.

Sajjad et al. [22] suggested a data augmentation method CNN for brain tumor classification. The approach adopted for classification of brain tumors using segmented brain tumor MRI images. They used pre-trained VGG-19 CNN architecture for classification and achieved accuracies of 87.39% and 90.66% for data before and after augmentation respectively.

IV. Methodology

A. Convolutional Neural Network

It is the most popular deep-learning neural network that can work with different types of images. Typically, CNN contains different layers such as: input, convolution, RELU, fully connected, classification, and output [4, 20].

B. Datasets

The dataset is imported from Kaggle website [24]. It has 4480 images, 2880 for training and validation. Each brain tumor type has 520 images for training and 200 images for validation. 800 unseen images (each type has 200 images) for testing were used to test the final trained models.

C. Proposed CNN Architecture

We have adopted five pre-trained CNN architectures: Xception, Inception v3, ResNet-50, VGG16, and MobileNet for brain tumor classification. And these models are available on Keras, as open-source neural network library written in python [25], and the data augmentation was used to overcome the overfitting problem due to the limitation in images of the dataset.

D. Performance Measure

In this paper we have used F1-score accuracy. F1-score takes into account recall and precision. F1-score is the vocal average of the recall and precision. F1-score is the best if there is a balance between recall (R) and precision (P) in the dataset. On the other hand, it is not so good if either measure is enhanced at the price of the other one.

$$F_1=\left(\frac{2}{\text{Recall}^{-1}+\text{Precision}^{-1}}\right)=2.\frac{\text{Precision . Recall}}{\text{Precision + Recall}} \tag{1}$$

where,

$$\text{Precision}=\frac{tp}{tp+fp} \tag{2}$$

and

$$\text{Recall}=\frac{tp}{tp+fn} \tag{3}$$

Precession and recall uses four different statistical indices namely True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN).

V. Evaluation and Discussion of Results

The dataset we gathered from Kaggle website consists of 4480 images. We split the images into three groups: training, validation, and testing (unseen images). The training group has 2880 images where each brain tumor type has 520 images. The validation group has 800 images where each brain tumor type consists of 200 images. The testing group has 800 images where each brain tumor type consists of 200 images. We resized the brain tumor images to 256 x 256 pixels.

The number of images on meningioma tumor dataset was not balanced like other brain tumor types; thus we had to use data augmentation and python language to create new images for it.

During training we used data augmentation and resizing for the images to increase the number of images and overcome the problem of overfitting due to the limited number of images provided from Kaggle.

We replaced the original classifier of these architectures with our brain tumor classifier. Each model was trained with 50 epochs, then, final accuracy and error loss of each model was noted. The F1-score accuracies and error losses of each model are shown in Table I and in Fig. 5 to 9.

We have tested the five trained models with the unseen images and the accuracies were 98.75%, 98.50%, 98.00%, 97.50%, and 97.25% respectively as seen in Table I. These accuracies gave us two indications: (1) the five trained models were capable of generalizing and not memorizing the images. (2) The five trained models have a positive impact on early detection of tumors and, therefore, can contribute to lessening the potential causes of tumors physical side effects, such as paralysis.

TABLE I. F1-Scores and Accuracies of Used Models

Algorithm	Training F1-score Accuracy	Validation F1-score Accuracy	Training F1-score Loss	Validation F1-score Loss	Testing Accuracy
Xception	100.00%	97.04%	0.0004	0.1381	98.75%
ResNet50	99.50%	96.76%	0.0291	0.2006	98.50%
InceptionV3	99.29%	95.12%	0.0236	0.2281	98.00%
VGG16	100.00%	0.9478	0.00004	0.3316	97.50%
MobileNet	100.00%	92.35%	0.0014	0.2829	97.25%

(a) Learning (b) Loss

Fig. 5. VGG16 Model Results.

(a) Learning (b) Loss

Fig. 6. Xception Model Results.

(a) Learning (b) Loss

Fig. 7. MobileNet Model Results.

(a) Learning (b) Loss

Fig. 8. ResNet-50 Model Results.

(a) Learning (b) Loss

Fig. 9. InceptionV3 Model Results.

VI. CONCLUSION

In this paper we have used five pre-trained models to classify brain tumors: Xception, ResNet50, InceptionV3, VGG16, and MobileNet. We had four rankings in the model: glioma tumor, meningioma tumor, no tumor, and pituitary tumor. Our aim in this paper was to increase the level of efficiency of MRI machines in classifying brain tumors and identifying their type. After training and validating the five pre-trained models, we tested the five models with keeping aside (unseen) images we achieved accuracies between (97.25% and 98.75%). The Xception model gave the highest accuracy rate of 98.75%. This high accuracy will have a positive impact on the early detection of brain tumors before the tumor can cause physical side effects such paralysis, other disabilities or death.

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