A Deep Learning Based Classification Model for the Detection of Brain Tumor using MRI

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***Abstract*: The diagnosis of a brain tumor requires high accuracy, as even small errors in judgment can lead to critical problems. For this reason, brain tumor segmentation is an important challenge for medical purposes. The wrong classification can lead to worse consequences. Therefore, these must be properly divided into many classes or levels, and this is where multiclass classification comes into play. The latest development of image classification technology has made great progress, and the most popular and better method is considered to be the best in this area is CNN, so this paper uses CNN for the brain tumor classification problem. The proposed model successfully classifies brain images into two distinct categories, namely the absence of tumors indicating that a given brain MRI is free of tumors or the Brain contains Tumor. This model produces an accuracy based on the results of a study that was conducted on a group of volunteers.**

***Keywords:* Convolutional Neural Network, Kaggle, Segmentation, Classification, MRI**

I. INTRODUCTION

A tumor is a mass of tissue that is caused by abnormal cells grouping together. A brain tumor is a mass or lump in the brain which is caused by uncontrolled cell division in the brain. A brain tumor is considered malignant if it contains cancer cells, or if it consists of harmful cells located in areas that inhibit one or more important functions. Magnetic resonance imaging (MRI) is a medical imaging technique used in radiology to form images of the anatomy and physiological processes of the body. MRI scanners use strong magnetic fields and radio waves to create images of parts of the body. Healthcare professionals use MRI to detect the presence of brain tumors and to assess their location, size, and other features. The contrast agents used in MRI provide better image detail that can help us identify abnormal cells in our brain tissues. Nowadays, there are various ways to classify MRI scans, such as the Fuzzy method, neural network, and differential segmentation. The medical image processing system has provided many helpful methods that help to speed up the classification task in a shorter amount of time and with greater accuracy. The most significant steps in medical image processing are feature extraction and feature selection, image segmentation, and image classification. Feature selection is even more essential than feature extraction because it allows you to get a smaller, more accurate subset of features. Most of the methods used to classify brain tumors are based on segmentation. This means that the problem of classification and feature extraction is not as important as it may seem, and can help to improve the performance of CAD systems. These methods are now combined with imaging techniques to give the best results in the diagnosis of many critical diseases such as lung cancer and image analysis of breast cancer. Although machine learning techniques have proven to be useful, recently the need for more accuracy and the real-time process has forced users to dive into a new area - deep learning.

Recently, deep learning techniques have become very popular in the fields of medical analysis, object recognition systems, and object detection. In Deep Learning, the accuracy and efficiency of the data model depend on the datasets and training used to create it. To overcome the training process and obtain more timely results, Deep Learning employs a concept called transfer learning. Transfer learning is a data learning technique that can be used to transfer knowledge and skills from large data sets to smaller sets. Pre-trained models are the main reason we use them because they don't need large datasets to work well.

There are many studies about the detection of brain tumors, from [18], it is observed that the authors proposed a non-invasive system for the detection of brain tumors. The texture and morphological features are used to detect objects in the image. JMCD delivered on its promise, achieving 97.37% success on JMCD and 98.38% on BraTS. Paper [21] proposes a clinical support system to improve the accuracy of brain tumor detection and classification from the BraTS dataset using imaging. The GLCM extraction technique was used to acquire features of the tumor region and LOBSVM was used for classification purposes. Its accuracy is close to 97%. Researching Paper [25] found that using social media can lead to a decrease in physical activity. This individual worked on brain tumor images, segmentation, and classification. Use discrete wavelet decomposition and SGLDM methods to extract text features without using wavelet transforms. It is observed that the SVM classification method is accurate 96% of the time. The Authors of the Paper [24] developed a method to classify pituitary adenoma tumors using multinomial logistic regression and k-nearest neighbor algorithms. The approach achieved an accuracy of 83% on multinomial logistic regression and 92% on a k-nearest neighbor algorithm with an AUC curve of 98.4%.

According to Pereira [29] three different pre-trained neural network models classify brain tumors into pituitary, glioma, and meningioma. Using this Transfer learning approach, VGG16 achieves the highest accuracy of 98.67%. Febrianto [30] proposed a framework for classifying brain MRI images as healthy and unhealthy, and a grading system for classifying unhealthy brain images into low-grade and high-grade, by modifying the Alex-Net CNN model, the model showed 91% accuracy.

However, a new three-dimensional convolutional neural network for automatic segmentation of brain tumors in multimodal MRI (2014). This is computationally intensive, but 3D imaging allows radiologists to easily understand tumor growth. The $3 \times 3 \times 3$ convolution filter was used to reduce the feature map size with batch normalization, ReLU, and 3D maximal clustering layers. The 3D input is stacked in a 4D set, the four dimensions representing the height, width, image channel, and the number of modes. This architecture achieved an accuracy of 87%, 77%, and 73% for the whole tumor, core tumor and active tumor region in the BraTS dataset, respectively. Salma X Sun [32] presented a Seg-Net for automated brain tumor segmentation, which was trained separately using multiple modalities. The Seg-Net was then used post-processing to combine the outputs of the different methods. The MRI data is pre-processed to remove unwanted artifacts, which improves segmentation performance. The Segment Net algorithm is used to train each of the four different MRI modalities separately.

Over the last decade, many scientists and researchers have praised meta-heuristic methodologies for their ability to solve real-world challenges. The use of MH approaches to solve various issues is growing rapidly. On the one hand, a heuristic algorithm is designed to solve a specific type of problem. A meta-heuristic is a high-level method that can tackle a broader range of problems. Meta-heuristics use random processes to help solve a problem with a set of randomly generated solutions. Therefore, they can find reasonable solutions to problems in an acceptable time when using the standard optimization method is not feasible. Meta heuristics have recently become popular for three reasons:

1. Derivative independence,
2. Reasonable computation time, and
3. High local optima avoidance.

II. LITERATURE REVIEW

A literature review is an important section of a project report, providing a comprehensive overview of the research in your field and the results already published. This information is considered along with the parameters of the project and the scope of the work. The focus of your report is important because it will help steer your research in the right direction. Convolution involves developing an addiction to each component of the picture towards its neighboring prejudiced elements. This is in addition to the form of mathematical convolution. It must be known with the value of the life form of the average process that performs the rollup, which is not a normal development of the environment, even though it is also denoted by with exemplary condition, we keep two three with matrix first of all at the moment when the complexity of image fragment will be reversing row and column procedure the kernel added to the subsequent increase, similar to the tolerance added to the summation. The constituent on the coordinate of the resultant picture would be biased in grouping everyone the entry of the picture medium pool is an appetizer base discretization procedure. The purpose of this trial is to tumble the input illustration's dimensionality in order to allow for its assumption.

Wahid [1] proposed an automated three-step model for classification. In the first step (pre-processing), noise is removed from the image. Two types of features: color moments and textures extracted in the second step are classified using a probability classifier. The classifiers used were based on the logistics function and a total of 150 images were reviewed, of which 66% were used for model training and 34% used for model testing. The overall accuracy obtained is 90.66%.

Kyong Hwan Jin [2] proposed a novel deep convolution neural network (CNN) algorithm for solving ill-posed inverse problems. Regularized iterative algorithms produce excellent results, but can be challenging to deploy in practice due to factors such as the high computational cost of forward and adjoin operators and the difficulty of hyper parameter selection. The starting point of this paper is to observe that the unrolled iterative method has the form of a CNN (filtering followed by point nonlinearity) when the normal operator (H*H, where * is the adjoin of the forward imaging operator, H) and the forward model is a convolution. Based on this observation, we propose to use direct inversion, and then use CNN to solve the normal convolution inverse problem. The proposed network outperforms total variation-regularized iterative reconstruction for realistic phantoms, requiring less than a second to reconstruct a 512×512image on the GPU.

Nandpuru [3] proposed a technique that could be used to distinguish between MRI images that are affected and those that are healthy. The median filter was used to remove salt and pepper noise and unwanted components such as the scalp and skull. Image quality has been improved by reducing noise. Four types of features were extracted, namely power law transform, texture, symmetric features, and grayscale features, respectively. PCA is used to reduce these features to an optimal set of features, which are then classified using SVM in the classification step. For evaluation purposes, they used Linear Kernels (LK), Quadratic Kernels (QK), and Polynomial Kernels (PK), which were 74%, 84%, and 76% accurate, respectively.

Different sub-regions (achieving performance comparable to human rater variability), but no algorithm ranks high in all sub-regions at the same time.

Heba Mohsen [6], proposed the architecture for the CAD Brain MRI system shown in Figure 1. It consists of four main processes: (i) image acquisition, (ii) ROI segmentation, (iii) feature extraction and selection, and (iv) classification of selected ROIs. Image acquisition techniques such as magnetic resonance imaging (MRI), X-rays, ultrasound, mammography; CT scans are highly dependent on computer technology to generate digital images. After obtaining digital images, image processing techniques can be used to analyze a chosen region of interest.

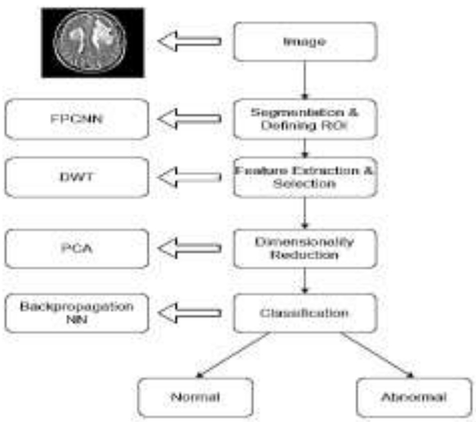

Fig. 1. FPCNN Classification model.

Sobhaninia [7], proposed a new method for CNN to automatically classify the most common brain tumor shapes, i.e. pituitary tumor, glioma, and meningioma. They applied the Link Net network for tumor segmentation. 2100 images are networked for training purposes. Twenty percent of them are validated and the remaining data is used for tests. Empirical network tests show that the dice score is 0.73 for one net and a score of 0.79 is achieved for multiple nets. In sagittal imaging, this relatively high score was obtained by tumor segmentation. Sagittal images with no specific features of other organs and tumors are more visible than other images.

III. METHODOLOGY

This section illustrates the detailed methodology that is used to classify brain tumors. It consists of the following steps:

- Dataset collection and description
- Proposed System
- Image pre-processing
- Brain tumor classification using CNN and system performance indicators.

A. Dataset collection and description:

We included images from the microdata set [16] in the proposed algorithm to perform all necessary investigations. The dataset includes MRI scans from several patients which are arranged into training, testing and validation. This dataset contains images of healthy brain and brain tumors, which were labeled into two types. Adding on, “Brain Tumor” and “Healthy Brain” contain around 2090 pictures for every class for preparing and roughly 440 pictures for each class for testing as well concerning approval. The variety of this dataset helped in giving more precise and dependable expectations.

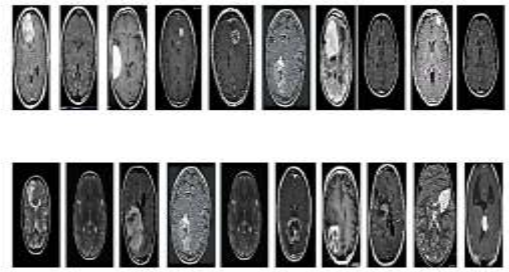

Fig. 2. Dataset of Brain Tumor.

B. Image Pre-processing:

Pre-handling performs to make smooth preparation since there are various variations of power, difference, and size in pictures [16]. Input picture will be handled in the first pre-process which is the interaction of wrapping and trimming. In wrapping, the info picture is checked against the edge of the principal object in the picture. From the edge of the picture, the greatest edge is resolved so that when the consequence of trimming, the item in the picture stays in one piece. After trimming, resize the picture to shape (224, 224, 3) = (image width, image height, number of channels) in light of the fact that the pictures in the dataset have various sizes. Apply standardization: to scale pixel values to reach 0-1 to work with the learning process.

C. Proposed System:

This paper uses CNN for automated brain tumor detection. This study used labeled input images from the raw data and then used these samples to distinguish between tissues that did not contain tumors and those that did. CNN was trained to use 2090 sample images consisting of 1045 images containing tumors and 1045 images without tumors. Therefore, the proposed system illustrated in Figure 4 method is proposed in this study.

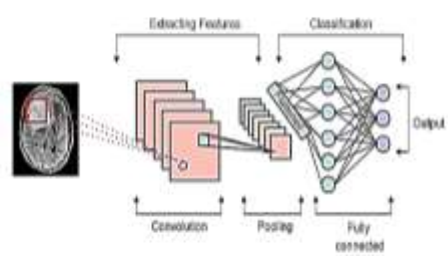

Fig. 3. Data Training Process.

Figure 4 shows the CNN classification model. It is separated into 3 stages. In Brain, Tumor order takes a few pieces of information from our dataset. After picking information it will apply Homomorphic Wavelet Filter and send it to the Inception V3 layer. Feature Extraction will choose the best component for the information here we pick the ADAM optimizer. 2 portions will come subsequent to utilizing classification.

Stage II Brain Tumor Localization will again send it to a layer and Redv2 will identify the place of the tumor. In the photos white imprints cannot specifically detect the situation thus the layer will confine the place of the tumor in the brain by Redv2.

Stage III Segmentation of the Localized Tumor Region will be the result of the tumor position.

D. Brain tumor classification using CNN and system performance indicators:

In this Research, the CNN model has several layers, including the convolution layer, the pooling layer, the flatten layer, the dropout layer, and the dense layer. Besides the layers used in the CNN process, there is also a rule activation function in this study.

In this study, two different CNN models were used as comparison material. The CNN model design can be seen in Table 1. An image 224x224 pixels in size is composed of a sequence of numbers. Kernels that are 3x3 in size, with a thickness of 3, match the shape of the image data and filters. After receiving the results of the operation, the model will perform activation and pooling data functions. The Pooling layer process helps to reduce the size of the feature map. The convolution process produces a feature map that is used for the subsequent convolution process multiple times.

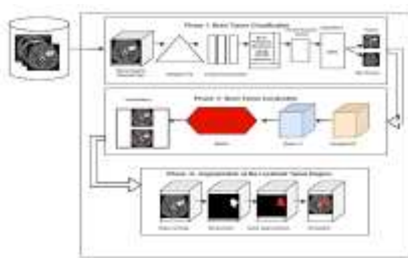

Fig. 4. CNN Classification Model.

Table. 1. CNN model with different parameters with their output shape.

Layer (type)	Output Shape	PARAM #
conv2d (Conv2D)	(None, 222, 222, 16)	448
conv2d_1 (Conv2D)	(None, 220, 220, 32)	4640
max_pooling2d (MaxPooling 2D)	(None, 110, 110, 32)	0
conv2d_2 (Conv2D)	(None, 108, 108, 64)	18496
max_pooling2d_1 (MaxPooling 2D)	(None, 54, 54, 64)	0
conv2d_3 (Conv2D)	(None, 52, 52, 128)	73856
max_pooling2d_2 (MaxPooling 2D)	(None, 26, 26, 128)	0
Dropout (Dropout)	(None, 26, 26, 128)	0
Flatten (Flatten)	(None, 86528)	0
Dense (Dense)	(None, 64)	5537856
dropout_1 (Dropout)	(None, 64)	0
dense_1 (Dense)	(None, 1)	65
Total PARAM's: 5,635,361 Trainable PARAM's: 5,635,361 Non-trainable PARAM's: 0		

IV. IMPLEMENTATION AND RESULT ANALYSIS

To get the most accurate results, we used Google Collaboration as our software. You'll need Windows 10 or a compatible operating system to install the software. We use "sigmoid" and "relu" as our activation functions and a CNN as our algorithm. All the tasks were done with full concentration and valid data.

The experiments in this article were conducted on 2090 images consisting of 1045 samples containing tumors and 1045 samples containing no tumors. The data is divided into 70% of it as data training, 15% of it as data validation, and 15% of it as data testing. The data is run 16 times, each using the CNN model that has been made before, each experiment using 30 epochs and 32 batches. The results are compared using standard deviations (a measure of variability), the mean (a measure of central tendency), and the mean of the loss, accuracy. In the tables below, you can see the results of the experiments that were conducted in this study. In the CNN model built with 1 convolutional layer, the accuracy was 98.72% with a loss of 0.0321 on the training data. However, the accuracy of the test data was much lower, averaging 89% and an average loss value of 0.4111.

Phase	Accuracy	Loss
Training	95.45%	0.1123
Testing	98.72%	0.0321
Validation	89%	0.4111

a. Classification Report:

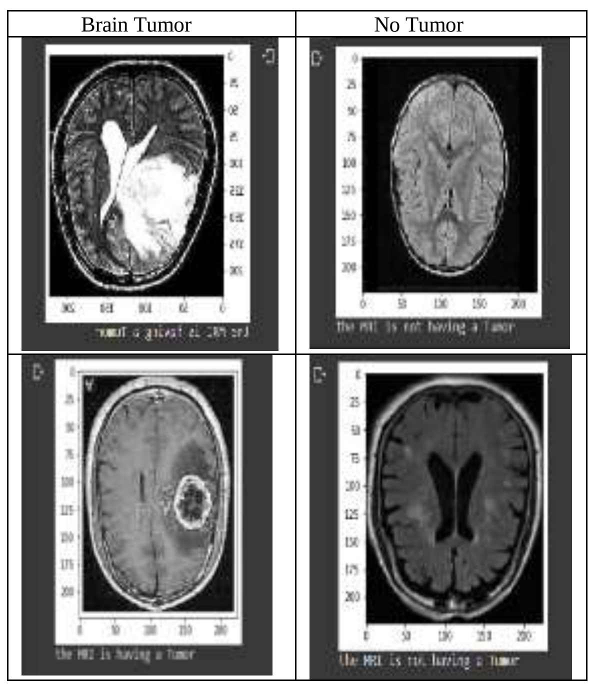

Fig. 5. MRI of brain tumor and no tumor stage.

After conducting extensive research on brain tumors, we developed a model that can be used to effectively classify them. CNN's method results in us being satisfied. A comparison of our CNN methods with others is shown in the following table

Table. 2. Comparative analysis with previous work and different algorithms.

Authors	Classes	Method	Accuracy (%)
[4]	3	CNN	98
[19]	6	GA-SVM, GA-ANN	GA-SVM:89 GA-ANN:94.1
[31]	3	CNN, Caps Net	86.56
Proposed model	4	CNN	98.72

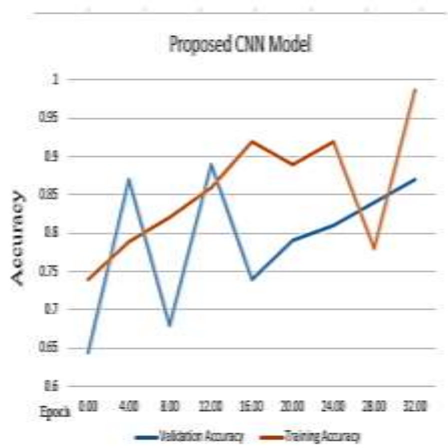

Fig. 6. Graphical representation of accuracy measurement.

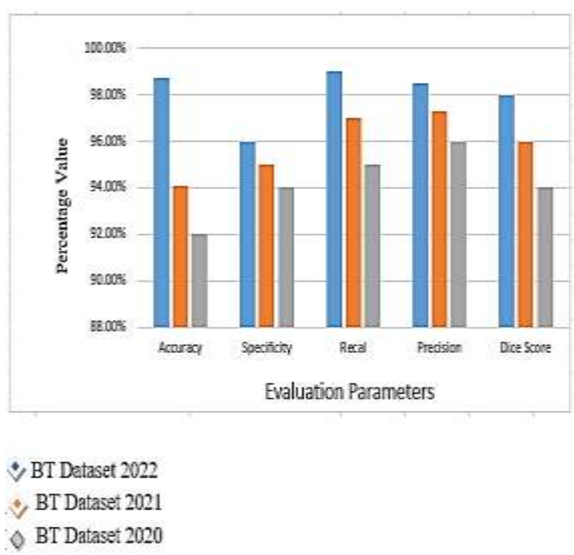

Fig. 7. Comparative analysis on dataset.

V. FUTURE WORK

In this paper, the existing strategy might confront troubles like accuracy, growth of the tumor, and position of the tumor. In future we will work on advanced novel brain tumor identification procedures and preprocessing MRI pictures, the first preprocessed portion applies middle separating techniques. CNN strategies are best for the precision level with a slower pace of error. So the objective district is the assurance of the presence of the tumor utilizing the method proposed here allows specialists to make the treatment arrangement and state of the tumor reconnaissance in the determination. So in this future work like working on the precision with a low rate of blunder utilizing different classifier procedures.

VI. CONCLUSION

This paper discussed how deep learning algorithms can be used to identify brain tumors. We used a CNN pre-trained model to segment MRI scanned images. This model was chosen based on various parameters, and it was used for the segmentation of images in this study. The MRI brain scan showed either cancerous tumor cells or no tumor cells. The number of parameters of the model is too high, and the model is only trained on a small amount of data. There is a risk of overfitting the data if you are using too many of the same data points to predict future outcomes. To prevent overfitting, a regularization technique, namely the dropout regularization algorithm is used on the model. The model is better able to focus on important patterns during training if it is kept stable. This helps to ensure generalization, which makes the model more reliable in the long term. The model achieves 98.72% accuracy. The CNN classifier will be very important in the medical field, and it will be able to save precious lives.

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