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Mobile Application to Detect Brain Tumor Using Transfer Learning

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Abstract— In this paper, Classification of Brain Tumor (BT) is a vital obligation for assessing Tumors and making a suitable treatment. There exist numerous imaging modalities that are utilized to identify tumors in the brain. Magnetic Resonance Imaging (MRI) is generally utilized for such a task because of its unrivalled quality of the image and the reality that it does not depend on ionizing radiations. The relevance of Artificial Intelligence (AI) in the form of Deep Learning (DL) in the area of medical imaging has paved the path to extraordinary developments in categorizing and detecting intricate pathological conditions, like brain tumor, cancer etc. Deep learning has demonstrated an astounding appearance, particularly in segmenting and classifying brain tumors. In this work, the AI-based classification of BT using Deep Learning Algorithms is proposed for the classifying types of brain tumors utilizing openly accessible datasets. These datasets classify BTs into (malignant and benign). The datasets comprise 696 images on T1-weighted images for testing purposes. The projected arrangement accomplishes a noteworthy performance with the finest accuracy of 99.04%. The achieved outcome signifies the capacity of the proposed algorithm for the classification of brain tumors.

Keywords: Artificial Intelligence, CNN model, Deep Learning, Image classification, Image processing, Transfer Learning

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I. INTRODUCTION

Brain cancer (tumor) can be characterized as abnormal and unrestrained development in the synapses. As the individual head is an inflexible and volume constrained, any startling development in the brain may influence a human capacity; besides, it might bulge into various body parts and influence individual capacities (DeAngelis, 2001). As indicated by the WHO, in its cancer report Brain Tumor (BT) represents less than 2% of cancers in humans; nevertheless, serious austerity and difficulties are reported (Stewart & Wild, 2014). United Kingdom's cancer research corporation referenced that there are around five thousand two hundred causalities reported every year due to brain diseases and tumors within the skull in the United Kingdom (Brain, other CNS and intracranial tumors statistics | Cancer Research UK. (n.d.), 2020).

BTs are arranged under two significant heads; The one that is developed within the brain, termed as a primary brain tumor corresponds to 70% of all BTs and the other tumors that swells into the brain from some other body parts, called secondary brain tumors form the residual 30%, with majority belonging to malignant type (Tandel et al., 2019). The tumor area, its type as well as where it is situated in the brain decides the type of treatment required. As a rule, surgery of the brain is deemed as the way of handling tumors (American Brain Tumor Association, Chicago, I.L., U.S.A., 2015). Most frequently occurring brain tumors are of Glioma types that incorporate approximately 30% of all BTs, attack Central Nervous System, and around 80% of these are harmful BTs (Gooden Berger).

Amid various clinical advances, MRI gives data about the location and tumor size. Its working depends upon the activity of protons contained in an enormous magnetic field, by maneuvering radiofrequency waves and reclamation of their stable state (Pereira et al., 2016) To decisively separate delicate tissues with high precision MRI technology is quite proficient and is increasingly responsive to change in tissue solidity,requisite for pathological consultation. The MRI images are classified into T1-weighted (T1-w) that are frequently utilized in non-invasive brain investigations. Since they portray high contrast and less fragments, they are referred for anatomy purposes. Whereas, T2-weighted (T2-w) are significant MRI slices that are reasonable for perceiving the boundary structures of the medical images (Zimny et al., 2015). The major downside of the T2-weighted pact is that tumors in the brain, cerebrospinal fluid (CSF), and Gray Matter (GM) bind together. Pathologically, the utilization of these MRI tasks is fundamental in identifying BTs however these can create few problems in separating tumorous from non-tumorous zones besides grading (Bahadure et al., 2017). Accordingly, to estimate the tumor boundary evaluated against a non-tumorous area on T1-w and T2-w pictures using a contrast medium are significant. BTs are sometimes confounded as they remain unimproved with contrast enhancement. Subsequently, the FLAIR procedure is utilized along with T2-w to show the upgraded BTs (Jalab& Hasan, 2019). Fig. 2 shows the types of MRI images generally utilized.

Deep Learning (DL) is a type of AI technique that emulates the functioning of an individual brain in data processing and generating prototype useful in making suitable choices. DL calculations make use of various non-linear layers that are well organized for extracting features from an image. The outcome of every ordered layer is the contribution of the following one, and that helps in information deliberation as we dive deep inside the system (Deng & Yu, 2014). Convolutional Neural Network (CNN) is a part of the DL family and is usually utilized in scrutinizing visuals and intended to entail negligible pre-processing (LeCun, 2015). It is motivated by the biological progression of the human brain (Matsugu et al., 2003) and used to deal with information that comes in groups (LeCun et al., 2015). Deep CNN was first used when LeCun et al. (1998) presented a DL network 'LeNet' for document identification in 1998. Many years later, it came up substantially when utilizing a DL network was utilized to identify images by making use of a pre-trained network (PTN) called AlexNet (Krizhevsky et al., 2012). It showcased remarkable outcomes when compared with other systems of that time. Later, its prosperity prompted back-to-back triumphs of CNNs in the area of DL.

The primary points of interest of Convolutional Neural Networks are their ability to learn features and to give boundless precision as opposed to conventional AI techniques by increasing the number of samples used for training and hence leads to a much powerful and precise model (Litjens et al., 2017). In the design of Convolutional Neural Networks, the features are extracted by convolutional filters and as we dive deep, much more intricate features are mined. Extraction of features takes place by convolving small size filters with the patterns of input and thereafter determination of the most distinctive features and hence training the network for classification. Zacharaki et al. (2009) put forward a framework to identify glioma other than a classifying high level and low-level utilizing Support vector Machine and k-Nearest Neighbour. They achieved a precision of 85% for multiple classifications and binary identification 88% accuracy is obtained. El-Dahshan et al. (2010) projected a technique to identify 80 BT images both abnormal as well as normal utilizing the Discrete Wavelet Transform (DWT) technique for feature extraction, PCA for feature reduction, and thereafter Artificial Neural Network (ANN) and k-NN to identify images with a precision of 97% and 98% individually.

Cheng et al. (2015) presented a technique to upgrade the BT identification by using dilation of image and thereafter by parting them into sub-sections. They utilized three ways for feature extraction; Bag of Words (BOW), Gray Level Co-event Matrix (GLCM), and intensity histogram, and lastly accomplished the finest precision of 91.28%. Ertosun and Rubin (2015) utilized Convolutional Neural Networks to identify grades of glioma as well as high and low grades of glioma. They acquired exactness's of 71% and 96% separately. Paul et al. (2017) utilized transverse BT images for training and create two principal methods for identification using CNN and accomplished the utmost exactness of 91.43%. Afshar et al. (2019) introduced CapsNet, a capsule network that encapsulates MR images of the brain with the boundary of the coarse tumor to characterize the BT and obtained a precision of 90.89%. Anaraki et al. (2019) put forward a network of two consolidated regulations to identify BT from MR images using Genetic Algorithms and Convolutional Neural Network. They achieved a precision of 90.9% and 94.2% in identifying glioma and its grades respectively.

A Wavelet-based Auto Encoder utilizing ANN was presented by Chen et al. (2018) that breaks down the input image into an image with low resolution for classification. These images are then given to CNN as input for reducing complexity in computation without affecting the precision. Shalini et al. (2014) proposed a technique in which the weighted fuzzy system was utilized to separate BT from the image and to increase the segmentation process kernel matrix was utilized. It gave high effectiveness and precision when contrasted with some other widespread techniques. A successful neural system-based BT identification procedure was put forward by Damodharan and Raghavan (2015) which concentrated on the segmentation of tissues in the brain. The said technique gave ideal effectiveness and precision in significance to tissues in the brain and segmentation of tumor, extraction of features and identification, etc. (Chelghoum et al., 2020) in their work utilized nine PTN which includes AlexNet, VGG19, GoogleNet, ResNet18, VGG16, ResNet50, ResNet-Inception-v2, ResNet101 and SENet for BT classification through Transfer Learning (TL). Firstly, they customized the three end layers of PTNs so as to acclimatize them to their task of classification. Subsequently, the fully connected layer in their originally taken PTNs is substituted by new layers, in which the types of BT is characterized by its output size. Lastly, they utilized TL based fine-tuned PTN for experimentation with MR data. Their elucidations verify that TL had provided results that are unswerving even with the dataset of small size. Their projected network outperformed the state-of-the-art techniques and achieved an accuracy of 98.71% for the classification of BTs.

Rehman et al. (2020) conducted experiments utilizing three PTNs (AlexNet, GoogLeNet, and VGGNet) for classifying BTs such as glioma, meningioma, and pituitary. They then discover the TL methods that are, fine-tuning and freeze by means of MR slices of the BT dataset. They utilized these PTNs to dig out features through the use of TL techniques. Lastly, the classification of features is done through a support vector machine (SVM) and a log-based SoftMax layer. They have accomplished the utmost exactness of 98.69% through fine-tuned VGG16 network as compared to AlexNet and GoogLeNet. On the other hand, in the freeze method of TL, the top most accuracy of 95.77% utilizes the freeze Conv5 layer of AlexNet as contrasted to its other layers as well as to all the architectural layers of VGG16 and GoogLeNet. Their experiment on the classification of BTs had attained the utmost exactness of 98.69% by utilizing a fine-tuned VGG16 network.

II. RELATED WORKS

Artificial intelligence and deep learning are primarily used in image processing techniques to segment, identify, and classify MRI Images and are also used to classify and detect brain tumors. So many works have already been done on the classification and segmentation of brain MRI images. Some of the international journals we reviewed on the detection and classification of brain tumor using deep learning are Sheikh Basheera et al.,proposed a method for classifying brain tumors where the tumor is initially segmented from an MRI image and segmented portion is then extracted through a pre-trained convolutional neural network using stochastic gradient descent.

Muhammad Sajjad et al. suggested classification of multi-grade tumors by applying data augmentation technique to MRI images and then tuning it using a pre-trained VGG-19 CNN Model. Carlo, Ricciardi et al., presented an approach for classifying pituitary adenomas tumor MRIs by 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 with an AUC curve of 98.4%. Khwaldeh, saed et al. presented a framework for classification of brain MRI images into healthy and unhealthy, and a grading system for categorizing unhealthy brain images into low and high grades, by modifying the Alex-Net CNN model which revealed 91% accuracy. Nyoman Abiniwanda et al., trained a convolutional neural network to classify three specific brain tumors classes, namely Meningioma, Glioma, and Pituitary, which achieved 98.51% training accuracy and 84.19% validation accuracy. Sunanda Das et al., also trained a CNN model with an image processing technique to identify various brain tumor types and achieved 94.39% accuracy with an average precision of 93.33%. Romeo, Valeria et al., presented a radiomic machine learning approach to predict tumor grades and nodal status from CT scans of primary tumor lesions and got the highest accuracy of 92.9% by Naive Bayes and k-nearest neighbor. Muhammed Talo et al., used the ResNet34 pre-trained CNN model a transfer learning approach along with Data Augmentation to classify normal and abnormal brain MRI images and got 100% accuracy. Arshia Rehman et al., used three different pre-trained CNN models (VGG16, AlexNet, and GoogleNet) to classify the brain tumors into pituitary, glioma, and meningioma. During this Transfer learning approach, VGG16 acquires the highest accuracy that is 98.67%. Ahmet Çinar et al., modified the pre-trained ResNet50 CNN model by removing its last 5 layers and adding 8 new layers instead and comparing its accuracy with other pre-trained models such as GoogleNet, AlexNet, ResNet50. The updated ResNet50 model showed effective results by achieving 97.2% accuracy.

The unavailability of labelled data is one of the major obstacles in the penetration of deep learning in medical healthcare. As recent development of deep learning applications in other fields has shown that the bigger the data would be the better accuracy result will be. Data segmentation and data augmentation are done using deep learning in the mentioned literature, and different pre-trained CNN Models using the transfer learning approach to classify brain tumors had been used. Most of the literature addresses the classification efficiency using transfer learning approach. The pre-trained models that are mostly used in the mentioned literature are VGG-16, ResNet-50 and Inception-v3, which are pre-trained on a mass number of datasets such as ImageNet. And for radiology research and experiments, we have to do fine-tuning by freezing the layers to reduce parameters if the dataset is small, we also have to replace the fully connected layers according to the dataset labels, Besides transfer learning requires high processing power from specialized processors (GPUs) to train smoothly, which is cost consuming, and one of another drawback in transfer learning is that the image input size is fixed so, we have to adjust our images according to the pre-trained model's input size. So, in our experiment, we took a very small dataset of Brain MRI Images. We applied the data augmentation technique along with the image processing technique on those MRI images and then trained a CNN model from scratch on that augmented pre-processed image data to determine whether the MRI image contains a tumor or not. And at last, we compared the diagnostic performance and computational consumption of our model with the VGG-16 and ResNet Model.

III. PROPOSED METHOD

In this research, we applied Image Processing and Data Augmentation techniques on a small dataset of 253 brain MRI images. We trained them through a simple 8 Convolutional layers CNN model and compared our scratched CNN model accuracy with pre-trained VGG-16, ResNet-50, and Inception-v3 models using transfer learning approach. The dataset includes 155 images of malignant cancer and 98 of benign non-cancerous tumors. We split our dataset into 3 separate segments for training, validation, and testing. The training data is for model learning, validation data is sample data for model evaluation and model parameters tuning. Test data is for the final evaluation of our model. Our proposed method is composed of various phases shown in Figure 1.

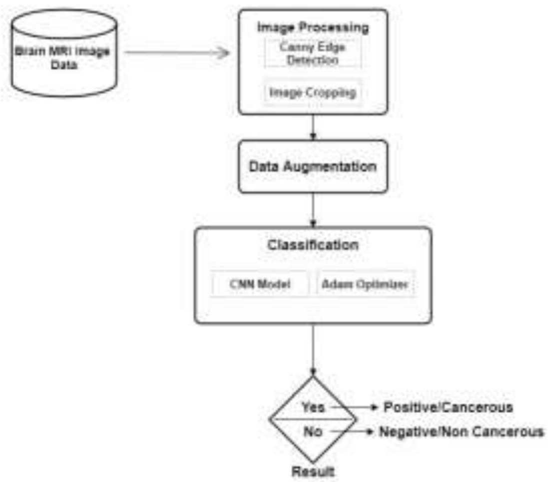

Figure 1: An overview of the proposed methodology

A. Image Processing

First, we cropped the dark edges from the images and took only the brain portion from MRI images shown in Figure 2 by using Opensource Computer Vision (CV) Canny Edge Detection technique. Canny Edge Detection is a multi-phase algorithm used to identify the edges of an object in an image. The edges of the Real MRI brain have shown using the canny edge detection technique and then only the brain part of the image has been cropped.

Figure 2: MRI Images

B. Data Augmentation

Data Augmentation is a strategy for artificially increasing the quantity and complexity of existing data. We know that training a deep neural network needs a large amount of data to fine-tune the parameters. But our dataset is very small, so we applied the technique of data augmentation on our training dataset by adding modifications to our images by making minor changes, such as flipping, rotation, and brightness. It will increase our training data size and our model will consider each of these small changes as a distinct image, and it will enable our model to learn better and perform well on unseen data. Fig.3 displays the numerous augmented images from a single image.

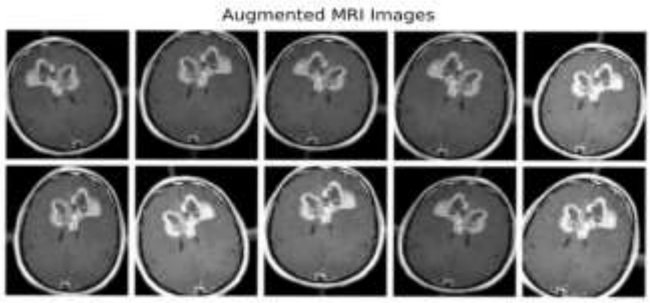

Figure 3: Augmented MRI Images

C. CNN Model

In our study, we proposed a simple CNN model,we extracted the augmented MRI image data of 224×224224×224 input size having RGB Color channels with a batch size of 32 through our CNN model. Initially, we added a single 16 filters convolutionallayer having a filter size of 3×33×3. The reason for placing a small number of filters as 16 is to detect edges, corners, and lines. And then a max-pooling layer with 2×22×2 filter was added on it to get the max summary of that image, then we increased the number of convolutional layers and the number of filters to 32, 64, and 128, having the same filter size of 3×33×3. This combines these small patterns as the number of filters increases and finds bigger patterns like a circle, a square, etc. And we applied max-pooling layers on top of those convolutional layers to get the most of it. Finally, we applied a fully connected dense layer of 256 neurons along with the SoftMax output layer that calculates the probability score for each class and classifies the final decision labels that either the input MRI image contains cancer or does not contain cancer in Yes or No. Figure. 4 displays the layout of the proposed CNN Architecture.

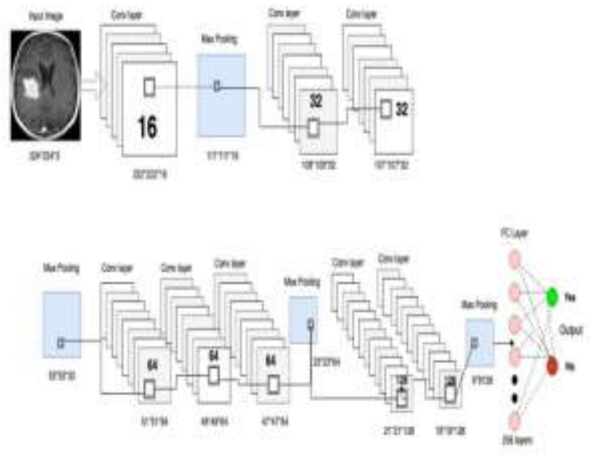

Figure 4: CNN architecture

IV. MOBILE APPLICATIONS

The Mobile application got very simple GUI to make easy to use by any type of user. In the asset folder trained model and label are placed for mobile application to access it. Take photo accesses camera for user to take picture live and camera roll is used to access downloaded images. When the image is uploaded the output appears saying Brain tumor detected / not detected based on the input image. When the system emerges each and every individual can know what is happening inside their head. It allows normal people can know whether they are affected by tumor or not. We do not need to travel to hospital each and every time, this application reduces your visit to hospital. the home screen of the application. Since it is going to be used by normal people the User Interface was design simple and elegant for any normal people can understand.

The Home Screen consists of two buttons, as shown in Figure 5, one is Take a photo button and the other one is Camera roll button. The Take a photo button allows user to take photo of the MRI scan real-time. The taken photo can be pre-processed and sent to the model in the application to

Figure 5: Home Screen of Mobile Application

detect brain tumor. The camera roll button allows user to explore the file manager and gives access to drive images If there is any. The User can explore and select any of the desired image which will then sent to the model to detect brain tumor. when the image is uploaded to the model either from take photo or camera roll it goes the CNN model where detect process takes place and it prints the output on the screen just as shown in the Figure 6. Application also shows the selected image in the output screen for user to check if they selected correct image. Below the selected image detection of brain is printed. Confidence level also can be printed if needed. Confidence level is nothing but the rate at which it detected is shown.

Figure 6 CNN architecture

V. RESULTS AND DISCUSSION

We experimented on brain tumor MRI Images dataset by Navoneel. The dataset is publicly available, consists of 253 real brain images developed by radiologists using data from real affected patients. It's available on Kaggle, a shared data platform used for machine learning competitions. We split our data into training, validation, and testing. There are 185 images for training, 48 images for validation, 20 for testing to evaluate our model accuracy. First, data augmentation is done to enhance our dataset by doing minor changes in our MRI images and extract these augmented images from our proposed CNN model. We trained the models for 15 epochs with a batch size of 32. The experiment is done using TensorFlow and Keras libraries in python on a CPU having a 2.3 GHz core i5 processor with 8 Gb of ram.

The proposed model showed 96% accuracy on training data and 89% accuracy on Validation dataset. While using the transfer learning approach, we trained pre-trained VGG-16, ResNet-50, and Inception-v3 CNN models on the same dataset to compare the accuracy of our CNN model. VGG-16 showed 90% on training data and 87% accuracy on validation data, ResNet-50 showed 92% on training data and 87% on validation data and Inception-v3 showed 93% on training and 83% on validation data. Displays the accuracy graph of the testing and validation phase during the iterations of our proposed CNN, VGG-16, ResNet-50, and Inception-v3 model.

We evaluated our model on unseen testing data True Positive and True Negative categorize correct classification, where TP showing abnormal brain images positive and TN showing Normal brain images positive, while False Positive and False Negative categorize incorrect classification, while FP showing the normal brain images into a positive tumor and in FN showing the abnormal brain images into a negative tumor. The mobile application is developed too easy and handy.

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