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Convolutional Neural Network-Based MRI Brain Tumor Classification System

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Abstract

A brain tumor, the cause of more death rates among all cancers, is diagnosed using uncontrollable cell growth and abnormal brain cell partitioning. The recent progress in Deep Learning (DL) neural network aids the health service in medical image diagnosing. The visual learning of image recognition may result in fault detection and that can be solved using machine learning. The Convolutional Neural Network (CNN) model is used in our study to categorize distinct brain tumor types. There are three main phases namely; image pre-processing, feature extraction and classification. In pre-processing stage, the image processing is done by edge detection and cropping of MRI brain images. Then feature extraction employing the Transfer Learning (TL) approach is followed by CNN model classifier layers for the classification of brain tumor images. The experimental results demonstrate that our model is extremely effective at minimal computing power with less complexity. In the performance comparison of our suggested CNN model with VGG16, achieves greater accuracy even with less dataset.

Keywords: MRI image, Deep learning, Brain tumor, CNN, Transfer learning, VGG-16

1. Introduction

Several death-causing diseases evolved especially brain tumor in the brain affects the fundamental functions and qualities of our human body. Since, brain is the most sensitive organ in our body [1]. Brain cancer is not more prevalent compared to

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other malignancies such as breast cancer or lung cancer. Tissue anomaly occurs inside the brain or the central spinal cord, that interrupts the correct operation of the brain. A tumor of the brain gets tagged and progressively develops. These tumours do not spread and usually remain in one area of the brain, whereas malignant brain tumours include cancer cells, swiftly develop and expand into other areas of the brain and spine. A tumor that is cancerous and dangerous to life [2]. The brain tumor is diagnosed using several techniques such as CT scan, EEG, but Magnetic Resource Image (MRI) is the most effective and widely used method. MRI uses powerful and effective internal images of the organs in the body [3]. MRI provides more detailed information on the internal organs and is more effective than CT or EEG scanning.

Significant advancements in medical research results in DL a medical image processing technique to diagnose the brain disease early. It was challenging and time-consuming prior to then. So, in order to overcome such restrictions, computer-assisted technology is developed in the medical field. In order to provide, efficient and reliable methods to detect the life-threatening diseases such as cancer, the top cause of death for patients worldwide a CNN model is proposed in our work. This presents a DL method for classifying brain cancers employing data augmentation technique and optimizer using the brain MRI images.

2. Related Works

AI and DL are primarily used in image processing techniques to segment, identify, and classify MRI Images and are also used to classify and detect brain tumors. Some of the international journals we reviewed on the detection and classification of brain tumors using DL are [4] 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 CNN using stochastic gradient descent. Classification of multi-grade tumors is suggested by applying the data augmentation technique [5] to MRI images and then tuning it using multinomial logistic regression. K-nearest Neighbor (KNN) algorithm is presented in [6]. This approach achieved utilizes the multinomial logistic regression and KNN with an AUC curve.

A framework for classifying brain MRI images into healthy and unhealthy is presented in [7], a grading system for categorizing unhealthy brain images into low and high grades by modifying the Alex-Net CNN model. Meningioma, Pituitary, and Glioma are the three types of brain tumours that the pre-trained NN model is used to categorize [8]. This image processing approach combined with a trained CNN model assists in detecting different types of brain tumours with great accuracy and precision [9]. The Naive Bayes (NB) and KNN [10] were used in a radiomic machine learning technique to predict tumor grades and nodal status from CT images of primary tumor lesions. A highly precise TL approach [11] is used in a pre-trained CNN model. The brain tumor categorization into the pituitary, glioma and meningioma is supported by three distinct pre-trained CNN models (VGG16, Alex Net, and GoogleNet).

During this TL technique VGG16 gains the maximum precision by modifying the

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pre-trained CNN model by eliminating its final five levels and adding eight new layers [12]. One of the most significant impediments to DL adoption in medical healthcare is the lack of labeled data. The accuracy rate of DL applications in other domains has been demonstrated that the greater the data, the better [13]. In the cited research, distinct pre-trained CNN Models utilizing the TL method are utilized to classify brain cancers, and data segmentation and data augmentation are done using DL. The TL method's classification efficiency is the subject of the majority of the literature.

The TL-based VGG-16 pre-trained CNN models are commonly utilized in the literature. Furthermore, in order to train smoothly, TL requires a lot of processing power from specialized processors, which takes a long time. The image input size in TL is fixed, thus we must adapt our images to fit the input size of the pre-trained model. So we used a limited collection of brain MRI images in our experiment. We applied the data augmentation technique along with the image processing technique on those MRI images. We then trained a CNN model from scratch on that augmented preprocessed 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 model.

3. Proposed Methods

Image Processing and Data Augmentation techniques are applied in this paper with less number of samples dataset of the brain MRI images [14]. Then through the simple eight convolutional layers network model with the pre-trained VGG-16 model database utilize the TL approach. The dataset includes 155 images of cancer and 98 of benign non-cancerous tumors. We split this collection contains 155 cancer pictures and 98 non-cancerous benign tumors. Our dataset is divided into three independent training, validation and test parts. The training data is used for model learning and sample data are used to analyze the model and adjust the models. Test data are for our model's final evaluation. The strategy we suggest consists of different stages. Figure 1 provides an overview of the suggested technique.

3.1 Image Processing

First, we cropped the dark edges from the images and took only the brain portion from MRI images using the Open source Computer Vision (CV) Canny Edge Detection [15] technique. Canny Edge Detection is a multi-phase algorithm used to identify the edges of an object in an image. In Figure 2, 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.

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3.2 Data Augmentation

Data Augmentation is a strategy for artificially increasing the quantity and complexity of existing data. The over fitting problem is solved by using the data augmentation approach [16]. 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. Figure 3 displays the numerous augmented images from a single image.

3.3 CNN Model

$$f(z) = \max(0, z) \quad (3.1)$$

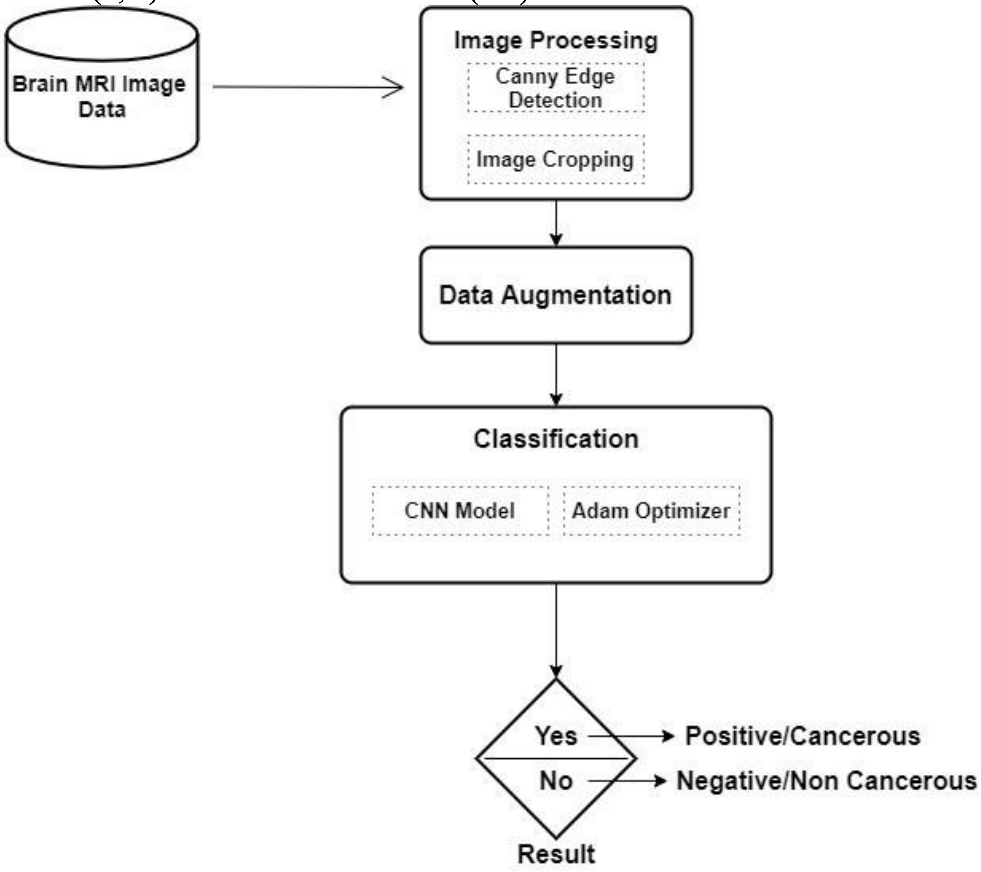

Figure. 1Overview of the proposed methodology

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Our study proposed a simple CNN model; we extracted the augmented MRI image data of 224x224 input size having RGB Color channels with a batch size of 32 through our CNN model. Initially, we added a single 16 filters convolutional layer having a filter size of 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 a 2x2 filter was added to 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 3x3. 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 Soft-max output layer that calculates the probability score for each class and classifies the final decision labels

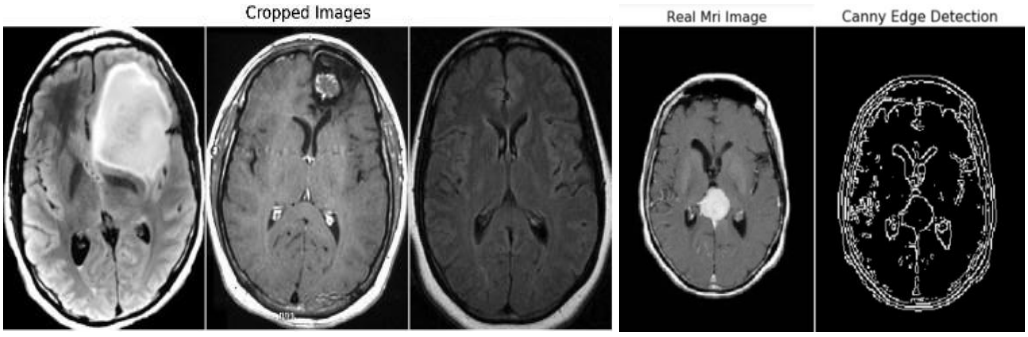

Figure. 2Identifies corners utilizing the detection of the canny edge of brain

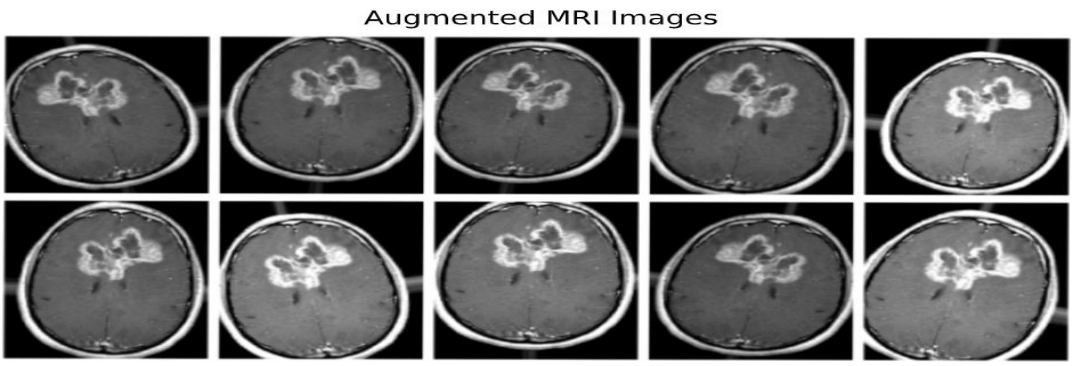

Figure. 3Data augmentation applied

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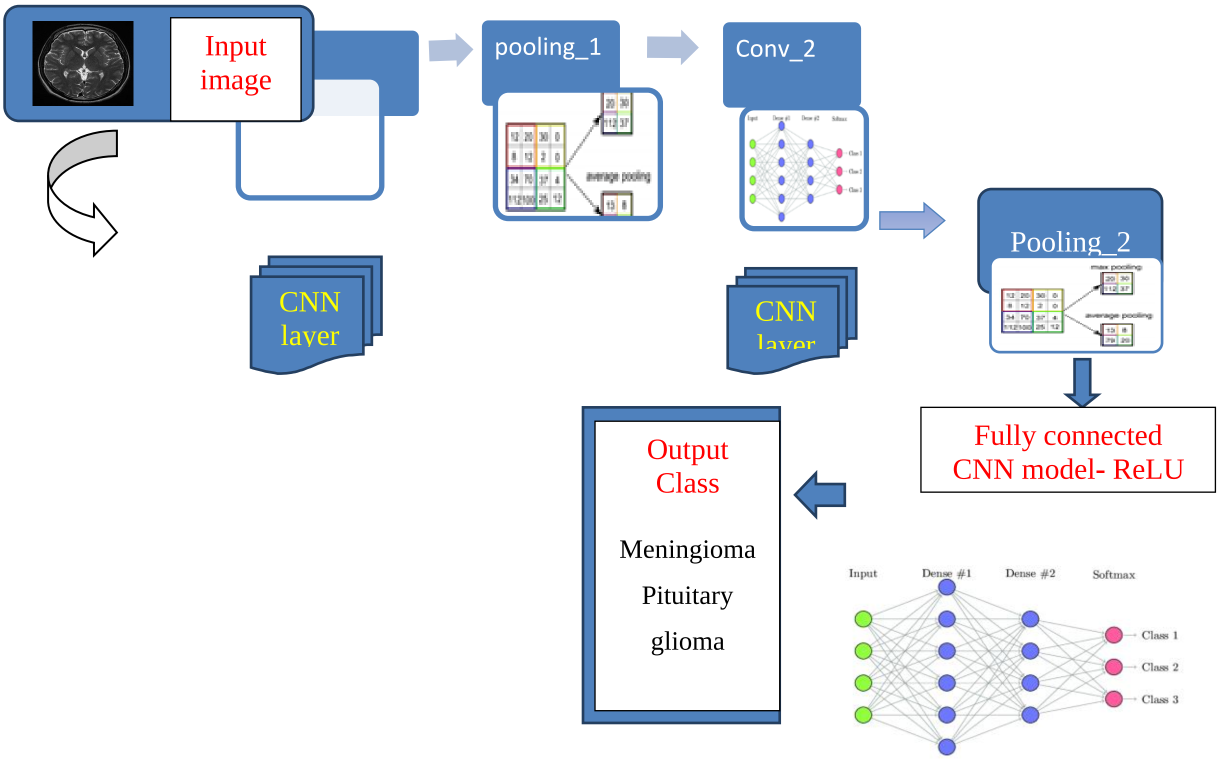

Figure. 4Proposed CNN model architecture using TL

3.4 Transfer Learning

Figure 4 shows at DL, we occasionally apply a transfer learning strategy to the picture classification issue instead of creating a new CNN model.

3.4.1 VGG-16

To prevent over-fitting of sample data set our experiment employed a pre-trained VGG-16 model, which is precisely calibrated with the freezing of certain layers. VGG-16 is the CNN model with sixteen layers as shown in Figure 5 forming the network is 224x224x3. Sixteen convolutional layers are included with a fixed 3x3 filter size with five Max pooling layers. VGG-16 model is a large network with many convolutional layers built with deep neural networks that also extract the hidden layer features. In Figure 5, the VGG-16 network architecture is shown.

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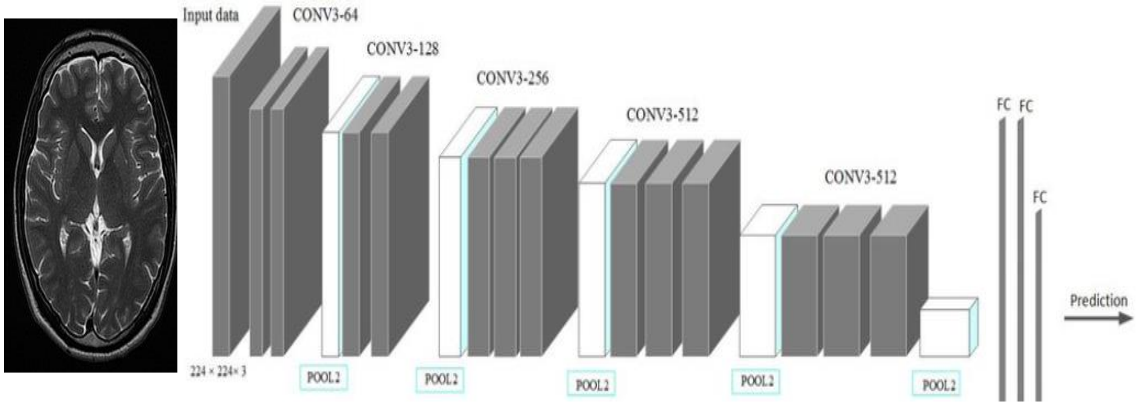

Figure. 5VGG-16 network architecture

4. Results and outcomes Discussed

The brain-tumor experiment MRI Popularly accessible files contain 253 actual brain imaging data from real-world patients generated by radiologists. We divide our data into training, testing and validation. There are 185 training pictures, 48 validation pictures and 20 test samples to assess our model correctness. First, data augmentation is done to enhance our dataset by doing minor MRI images and extracting these augmented images from our proposed CNN model. We trained the models for 15 epochs with a batch size of 32. Our proposed CNN model showed 96% accuracy on our training data and 89% accuracy on our Validation dataset. While using the TL approach, we trained pre-trained VGG- 16 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 is depicted from Figure 6.

Our model is assessed on inconspicuous testing information as shown in Table 1.

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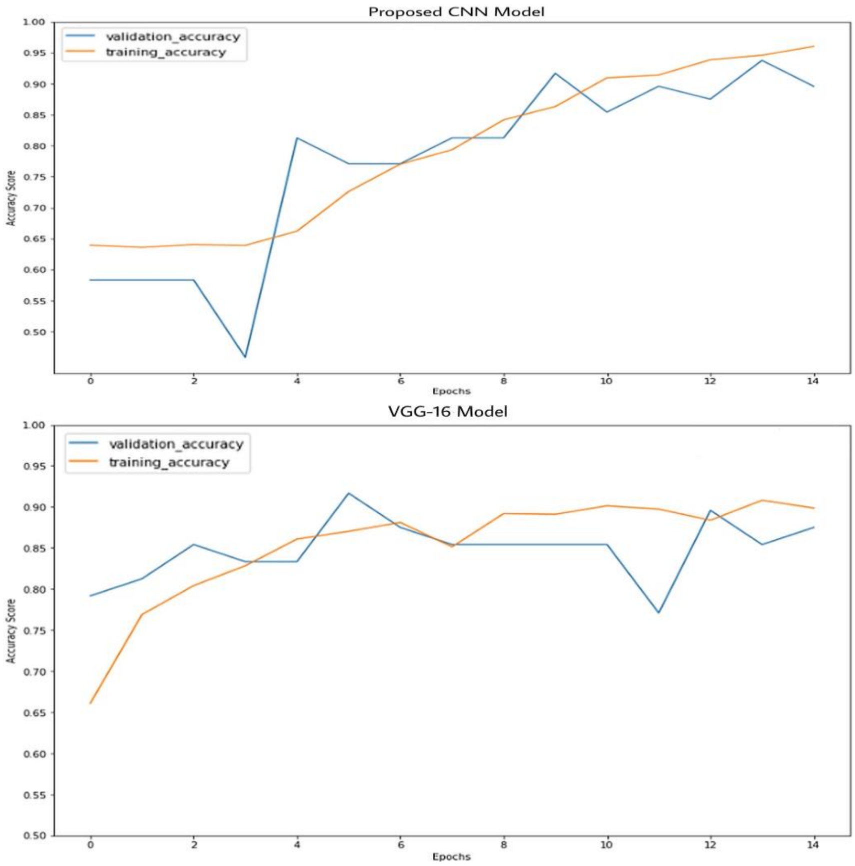

Figure. 6Proposed CNN and VGG-16 model accuracy graph

Table. 1Classification of Model performance

Model	True Positive	True Negative	False Positive	False Negative	Accuracy
Proposed C	14	14	0	0	1.0

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NN					
VGG-16	14	13	1	0	0.96

The accuracy is calculated for proposed CNN and VGG-16 pre-trained models. Accuracy is the measurement of classifications.

$$Accuracy = \; True\ Negative\ (TN) + True\ Positive\ (TP)\ /(Total\ No\ o\,f\,Samples)(4.1)$$

5. Conclusions

This study describes the deep learning network model's transfer technique for classifying brain cancer types. Initially , we crop the scanned sample images and utilize the obtained MRI brain image edge detection approach to locate the ROI. Then, to get extra datasets for our training database model, we employ the data augmentation approach to enhance the amount of samples. Second, we developed a lightweight CNN network to give an efficient VGG-16 approach for the brain tumor classification system. Large datasets are required to train the neural networks for sophisticated and accurate results, however our results suggest that even with a limited dataset, more accuracy can be achieved. The methodology we are proposing plays an essential role in identifying brain cancers and in classifying brain tumor kinds including glioma, meningioma and hypophysical pituitary tumours using the same TL approach.

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