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Research Article

Brain tumor Detection with Optimized Deep Features: A Machine Learning Approaches Using Deep CNN & Transfer Learning

Md. Moinuddin[1], and Prince Mahmud[1]

[1]Department of Computer Science and Engineering , School of Engineering, Khwaja Yunus Ali University,Sirajganj, Bangladesh

***Corresponding Author**: mohinmbstu15020@gmail.com (Md. Moinuddin, Lecturer, Department of Computer Science and Engineering, Khwaja Yunus Ali University, Sirajganj, Bangladesh)

Abstract

Brain tumors are very harmful for human beings, leading to even death. Early detection of brain tumors can be the possible solution to reduce the death rate and threats. Thus, this research reflects on a unique brain tumor detection and classification method through the mechanism of Deep Convolutional Neural Networks (DCNN) on 1255 Magnetic Resonance Imaging (MRI) images. The proposed research has been applied some image processing techniques like image filtering techniques on the publicly available dataset. The dataset is classified into two identical classes: with-brain and without-brain tumours. The research also applied the mechanism of data image augmentation to enlarge dataset size. After a set of pre-trained Convolutional Neural Networks (CNN) architectures, including VGG-19, ResNet50, Inception V3, and Xception, have been adopted to build the model and extract the features from each particular image. Then, we have applied the Principal Component Analysis (PCA) and Linear Discriminant Analysis (LDA) on the extracted features to reduce the dimension and the components. After that, we have applied conventional machine learning models with the six classifiers to find the accuracy of the detection and classifications. To gain goal of the research, a set of experimental data have been enumerated and interpreted. The study achieved the highest accuracy of 99% while working with ResNet50 pre-trained architecture and ensemble classifiers. Thus, we assume that the proposed solution can effectively detect and classify brain tumors.

Keywords: Convolutional Neural Networks (CNN), Magnetic Resonance Imaging (MRI), Principal Component Analysis (PCA) and Linear Discriminant Analysis (LDA)

1. Introduction

The sensitive and most complex organ ofthe human brain which manages all the fundamental functionalities. Interrupting the proper brain function, brain tumor is occured by tissue abnormality that develops within the brain or in the central spine[1].Among all types of cancer, the brain tumor is in the 10th position leading in the worldwide cause of death [2]. In 2018, according to the Global Cancer Registry results there were 18,078,957 registered cases of cancer in both genders, of which 29,681 were related to brain tumors [3].Brain tumors can be cancerous (malignant) or noncancerous (benign), whereas the cancer cells are contain by the malignant brain tumors and this cell grows quickly and spread through to other brain and spine regions as well [1, 4]. DNA mutation, radiation exposure, previous history of the family,etc., can all cause people to suffer from brain tumors. In brain tumor diagnosis, as the first symptom in patients, headaches were found 35%, 50-70% experienced a seizure and 15-20% cognition [5]. The after-effects of brain tumors such as gradual loss of movement or sensation in an arm or a leg, difficulty with balance, speech difficulties, difficulties in everyday matters, hearing problemsand making decisions etc. could be directed early by using our proposed method.

Nowadays, brain tumors are mainly detected by the magnetic resonance imaging (MRI).It is a very difficult task to evaluating MRI images manually for any human being due to the considerable number of images produced [6]. So, there is a need for using an Artificial Intelligent (AI) system for early detection and classification. From MRI images, our model will classify if it is cancerous or noncancerous. In our proposed method, we used Deep Convolutional Neural Network(DCNN) and Transfer Learning(TL). CNN has significance effect in medical diagnosis, which performs classification of the image by extracting features directly from raw images via pooling layer and tuning the convolutional parameters. Various pre-trained DCNNs, namely VGG-16, VGG-19, Alexnet, Resnet50, GoogLeNet, Resnet101, Inceptionv3, and ResNetV2, were used in the present study [7].
Thus, this research fucus on to detect and classify the brain abnormalities based on deep learning system. The proposed methodperform the given contributions are as follows:

- The proposed system can detect brain abnormalities through the mechanism of the deep learning system.
- The proposed solution is implemented with the optimized deep features with the mechanism of Linear Discernment Analysis (LDA) and Principal Component Analysis (PCA).

The manuscript is classified into five interconnected parts. Where section 2 present the study of the existing related works, section 3 shows the overall proposed methodology and section 4 shows the results associated with the proposed methodology. Finally, section 5 shows the conclusion of the manuscript.

2. Related Work

Transfer learning (TL) is the machine learning (ML) technique that focuses on storing knowledge where a model is trained from one task and applying it to different task but related problems. Many works have already been done on segmentation and classification of MRI images using transfer learning. Using deep transfer learning, some international journals we reviewed on the detection and classification of brain image are Taranjit Kaur et al.,[7] proposed a model to perform the prominent pre-trained DCNN models like Alexnet, GoogLeNet, ResNet50, ResNet101, Vgg-16, Vgg-19, Inceptionv3, and InceptionResNetV2 have been used for efficient brain tumor classification.Esraa Salah Bayoumi.,[8]works five CNN Models described in this paper: Transferred AlexNet Models, Transferred Vgg16 Models, Transferred GoogLeNet Models, Transferred Resnet50, Transferred Inceptionv3 Models. Among all those models, the best models have resulted from AlexNet because network capacity is simpler in computations and runtime compared to other models. AkilaGurunathan., [9]presentedan automated computer-aided method using three sub-modules as segmentation, preprocessing and classifications for detecting and locating the brain tumors in brain MRI images using deep learning algorithms and also diagnosis the “Severe” and “Mild” cases with CNN architecture. Hassan Ali Khan at al., [1] provides an efficient methodology for brain tumor classification. The proposed model compared the performance with the scratched CNN model, where CNN model was pre-trained with Inception-v3,VGG-16 and ResNet-50.In the detection of brain tumors the proposed model can play a prognostic significance. Firstly to find the region of interest in MRI images the image edge detection technique was used and also cropped them. This model showed 96% accuracy on training data and 89% accuracy on Validation dataset. Alireza Fazelnia at al., [10] trained a Convolutional neural networks (CNN) model to classifies the brain tumor types. Different low- and high-level features are extracted usingCNN method of ALEXNetGoogLeNet and VGGNet. Alex network obtained the best classification accuracy result which is 99.84%.Zar

Nawab Khan Swati., [11],authors focused on multiclass brain tumor classification for MRI images using block-wise fine-tuning and transfer learning (TL). This method only works for the CE-MRI dataset, not in natural images. Training parameters are a time-intensive procedure, even on high-speed GPUs. To get sub-optimum parameters for all blocks, the authors designed a new training manner, ensuring fast and proper convergence. Under five-fold cross-validation, VGG19 achieved an average accuracy of 94.82%. Arshia Rehman., [12]presented a pioneer study for brain tumor classification using AlexNet, GoogLeNet, and the VGG16 model of CNN. The system also used transfer learning techniques like fine-tune and freeze for accurate evaluation. To reduce the over-fitting and increase the dataset samples, data augmentation techniques are applied to the generalization of the results of MRI slices. In the freezing technique of transfer learning, the highest accuracy, 95.77%, was gained from Conv5–AlexNetlayer.Mohd at al., [13] proposed a 3-class deep learning model for classifying Meningioma, Pituitary and Glioma tumors which are regarded as three prominent types of brain tumor. By adopting the concept of transfer learning this proposed model uses a pre-trained InceptionV3 model that extracts features from the MRI images and deploys a softmax classifier for classification. This model achieved an average accuracy of 99%.Sinan Alkassar at al., [14]presented a method for brain tumor segmentation in Magnetic Resonance Imaging (MRI). To achieve robust tumor segmentation, fully convolution network (FCN) and transfer learning have been utilized with the VGG-16 network. This proposed method accurately achieved 0.97785% accuracy, which outperformed the present methods in terms of the whole brain tumor segmentation. Deepak S., [15]focused on a 3-class classification problem of brain tumor glioma, meningioma and pituitary tumors. The proposed system adopts the concept of deep transfer learning and to extract features from brain MRI images the system uses a pre-trained GoogLeNet. The proposed models uses k-nearest neighbours(KNN) classifiers and SVM. For an improved performance, the features were used with proven classifier models. **:** The proposed classification system achieved a classification accuracy of 98%.Roohi Sillea, Piyush Chauhan at al.,[16]build a model that have revised, implemented, and observed the segmentation process of tumors from MR images and trained the CNN to perform automatic segmentation.Total 11 layered convolutional neural network that incorporates transfer learning the proposed model consists. Due to the transfer learning, the model has achieved high dice score coefficients such as 0.78 in the whole tumor, 0.74 in the core tumor, and 0.74 in the active tumor. Ruqian Hao at al., [17] design aactive learning framework based on transfer learning for brain tumor classification, the proposed system combines active learning and transfer learning which can reduce the number of required training samples while maintaining robustness and stability of CNN performance. On a separate test dataset of 66 patients, the proposed model achieved AUC of 82.89% , which was 2.92% higher than the baseline AUC while the model also saved at least 40% of labeling cost. Mohamed Arbane et al., [18] proposed a deep learning model using a convolutional neural network (CNN) based on transfer learning (TL) for the brain tumors classification from MRI images. The implemented system explores CNN architectures, namely MobilNet-V2,ResNet and Xception. This model achieved the best results with 98.24% and 98.42% in terms of accuracy.Jonas Wacker et al.,[17]implement Convolutional neural network architectures based on transfer learning model for brain tumor segmentation. The authors showed that they can stabilize the training process this way and produce more robust predictions. The authors got average results for UCL-TIG- 0.7256, AlbuNet3D (pre-trained)-0.7493, AlbuNet3D (no pre-trained)-0.7169, AlbuNet2D(pre-trained)-0.7407, AlbuNet2D(no pre-trained)- 0.6993. Table 1 presents the corresponding comparison among the related works

Table 1: Comparison with related work

References	Method Used	Result	Strength
[7]	Transfer Learning (TL) and Deep convolutional neural networks (DCNN)	Automated brain image classification	Applying noise filtering, ROI delineation

[8]	CNN, Transfer Learning	Automatic Brain Tumor detection for accuracy of 100.00% from the AlexNet models.	Finetuning to classify brain tissues.
[9]	Deep learning algorithms, CNN, Morphological based segmentation.	Diagnosis and detection of brain tumors	Diagnosed the “Severe” and “Mild” cases using CNN architecture.
[1]	CNN, Transfer Learning(TL)	Classify brain tumors	Applying edge detection technique
[10]	Convolutional neural networks (CNN), Transfer Learning (TL).	Brain Tumor Detection using ALEXNet and the accuracy is 99.84%.	For average accuracy, 4 data sets were used.
[11]	VGG16, and VGG19, CNN, Transfer Learning, and pre-trained AlexNet	Brain tumor classification with VGG19.	Used block-wise fine-tuning.
[12]	Transfer Learning (TL) and Deep convolutional neural networks (DCNN).	Automatic Brain Tumors Classification usingALEXNet and the accuracy is 95.77%	Reducing the over-fitting and increasing dataset data augmentation techniques are applied
[13]	Data Driving, Data Pre-processing, Transfer Learning	Brain Tumor Classification	Contrast-enhanced magnetic resonance images (CE-MRI) dataset are used.
[14]	Fully Convolution Networks (FCN),Deep Neural Networks (DNN) and VGG-16	Automatic Brain Tumor Segmentation and accurately achieved 0.97785% accuracy	Used manual segmentation technique
[15]	Transfer Learning (TL), CNN, SVM	Brain Tumor Classification by SVM and accuracy is 98%	Used proven classifier models.
[16]	Transfer learning, CNN, Intensity Normalization	Automatic brain tumor Segmentation	Segmentation algorithms and MSE,SNR
[17]	Transfer Learning (TL), active learning, CNN	Classification of brain tumor with CNN.	Used 2D slice–based approach
[18]	Transfer learning-ResNet-50, Xception, MobilNet-V2	Brain Tumor Classification and achieved 98.42% accuracy with ResNet-50	Used data augmentation technique.
[19]	AlbuNet architecture-ResNet34, Transfer Learning.	Predicted brain tumor.	Used FCNs.

3. Proposed Methodology

This section presents the overall methodology of our proposed solution. Section 3.1 offers images dealing with medical image datasets and analysis through image preprocessing techniques. Section 3.2 shows image augmentation techniques. Finally, section 3.3 presents the structure orientation and setup of the deep learning mechanism.

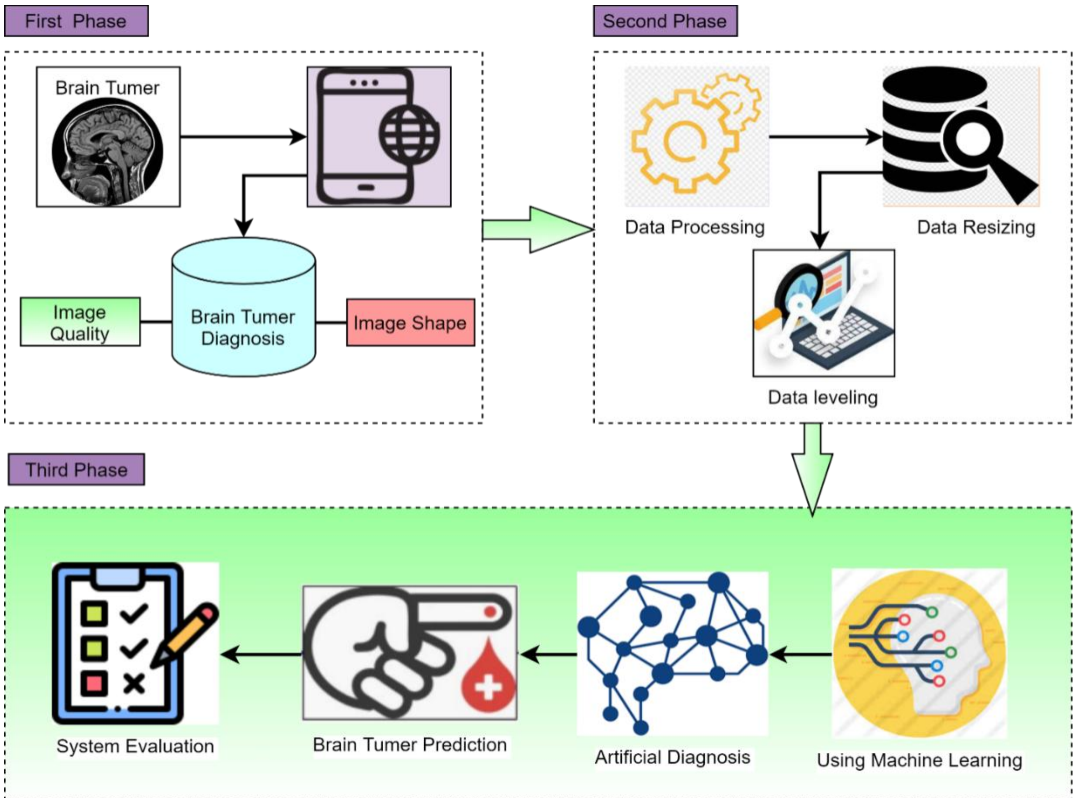


Figure 1: The overall proposed methodology

The prime mechanism of the proposed methodology is depicted in the combination of two parts, namely, architectural design of smartphone and brain tumor detection using transfer learning with artificial diagnosis. Two structural models are merged to detect brain tumors and find excellent results. In this article, we divide the whole working mechanism into three broad categories: first, second, and third.In the first phase, the smartphone architecture uses multiple sensors to take data reading and data transmission for monitoring. It also ensures the image quality and image shape.In the second phase, mainly three functionshave occurred here. The data processing part is to collect and manipulate the data items to produce meaningful information. Data resizing is the process of changing partitions of image size. You can either increase the size of a partition or split partitions, and data levelling is the process that collects the data and specifies its order.In the third phase, transfer learning mechanism is used to extract features from the levelling images and apply the artificial diagnosis technic to detect the brain tumor excellently. Finally, system evaluation evaluates the whole prediction system for model justification.

3.1. Dataset &Image processing

A dataset is a collection of instances with a common trait, such as being female. The majority of machine learning models are made up of various distinct datasets, each of which plays a particular function in the system overall. To run machine learning algorithms, datasets must be provided to the algorithm first, followed by validation datasets (or testing datasets), which are used to ensure that the model correctly interprets the data it is being fed. Our dataset was compiled using Kaggle, which is a well-known publically available dataset source. The dataset is classified into two identical classes with brain tumors and without brain-tumor. Each data class contains 1275 and 1255 Magnetic Resonance Imaging (MRI) image data, respectively. Table 2 shows the corresponding image dataset for brain tumor detection and classification.

Table 2: Image dataset of MRI for our research

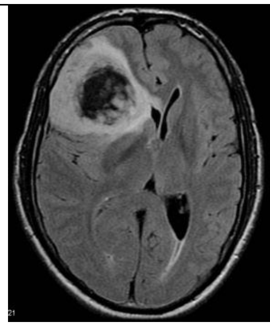
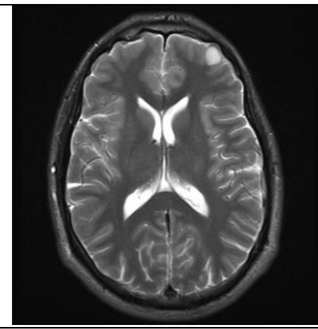
Class Type	With Tumor	Without Tumor
MRI Images		

Image Filtering

The image filtering approaches have been adopted to remove the existing noise in the image to achieve a better result in model training and testing. A set of image filtering techniques will be applied, such as:

Average Filter: The mean filter is a simple sliding window that replaces the center value with the average of the window's pixel values. It is used in many applications. Window or kernel is often square in shape however it can take on any shape.

Median Filter: The median filter is similarly a sliding-window spatial filter, but it substitutes the center value in the window with both the median of all the pixel values in the window. In the case of the mean filter, the kernel is generally square but can be any form.

Gaussian Filter: In the world of linear filters, a Gaussian filter is one of the most common. To decrease noise or blur an image, this technique can be adopted. The Gaussian filter alone will blur edges and diminish contrast. Eq. 1 shows the corresponding equation for Gaussian blur.

$$G(x) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{x^2}{2\sigma^2}} \qquad (1)$$

3.2. Data Augmentation

In image augmentation, an artificially enlarged dataset is created by employing several different techniques. While working with a tiny dataset, this method is really successful. It comprises a traditional way of picture augmentation, which incorporates rotation, horizontal flipping, and vertical flipping, acontrast increase of 20%, shear and reflection effects, and emphasizing brightness. The researchers carried out this technique in a sequential manner to generate a huge dataset for insect detection in the field. Table 3 shows the size of the dataset after image augmentation techniques have been used.

Table 3: Image dataset after augmentation

Class	Dataset size before augmentation	Dataset size after augmentation
With brain Tumor	1275	1574
Without brain Tumor	1255	1572

3.3. Structural Setup for deep learning

3.3.1. Loss function

To calculate the error between the true label values and the algorithmic predicted values, we use the loss function. By using any optimization method then, this error is minimized. We used the Cross-Entropy loss function in our experiment. We used binary cross-entropy to classify binary MRI Images. The error rate is calculated between 0 and 1 in binary cross-entropy. It is represented as mathematically.

$$J(z) = [y\log P(y) + (1 - y)\log(1 - P(y))] \qquad (1)$$

Where P(y) is the predicted labels, and y is the actual labels. The first term will be zero while the actual labels y will be 0 because log multiplies with y. The second term will be zero (1-y), while when y will be 1, it is reproduced with log. Finally J(y) (Loss) will be zero if y = P(y).

3.3.2 Transfer learning with pre-trained CNN architecture

Transfer learning (TL) is a popular approach in machine learning where a model is developed that focuses on storing knowledge form one problem while solving this problem and applying this knowledge to a different but similar problem. For example, knowledge gained from a trucks while learning to recognize this trucks and this knowledge could apply when trying to recognize cars. There are some popular pre-trained such as ResNet50, Inception V3, Xception and VGG19 are used in this research work.

- **VGG-19**

Three conventional pre-trained Convolutional neural network (CNN) architectures will be used to extract the deep Feature Vector (FV) from MRI images. At the beginning stage, the VGG-19 model will be adopted to extract the feature from the MRI image. To discard the overfitting for a small dataset, Vgg-19 model is fine-tuned with some of the layers. This pre-trained model is comprised with the single or multiple fully connected layers and a series of convolutional layers. This model are classified into two significant parts. The first part of this model extracts the feature from the input layer to the last max-pooling layer. The second part of this model is known as the classification part, which includes the model's residual network. The proposed VGG-19 model will accept the MRI image of 224 x 224 x 3 and assemble 4096 features for each MRI image. The above figure discusses the VGG-19 model in detail.

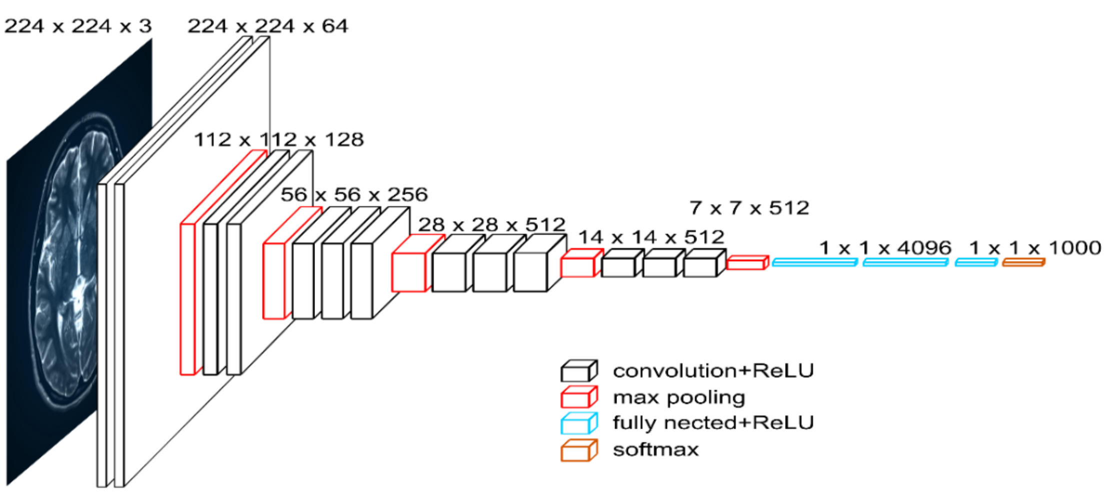


Figure 2: Brain-Tumor image feature extraction with VGG-19

- **Inception V3**

After that, the Inception V3 architecture will be used to extract the feature from the MRI image. The Inception V3 model extracts the feature through max pooling with a filter size of 1x1,3x3 and 5x5 and this model has 22 layers with 5M parameters. The Inception V3 model itself is a pre-trained network model, and this model is known as GoogleNet. To diminish computation discarding performance of the network, the Inception V3 model replaced the 5x5 convolutional filters with the two 3x3 filters. To avoid overfitting, the Inception V3 model consists of 48 layers and fine-tunedstructure. Figure shows Inception V3 architecture to extract the deep feature from the MRI image data.

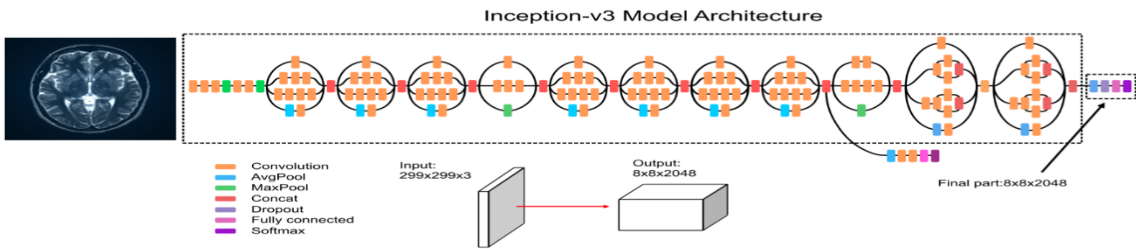


Figure 3: Brain-Tumor image feature extraction with Inception V3

- **ResNet-50**

The pre-trained ResNet50 architecture is used to extract deep features from the MRI image and this architecture consists of 50 layers with 2M parameters. To constitute the model, ResNet50 architecture has several parts. In the first part of this model contains a convolution layer, 64 kernels with a max-pooling layer and a fully connected layer. The proposed Inception V3 architecture will accept the MRI image of 224 x 224 x 3 and extract total 4096 features for each MRI image. Without including the classifier part to extract feature the research only uses the ResNet50 architecture.

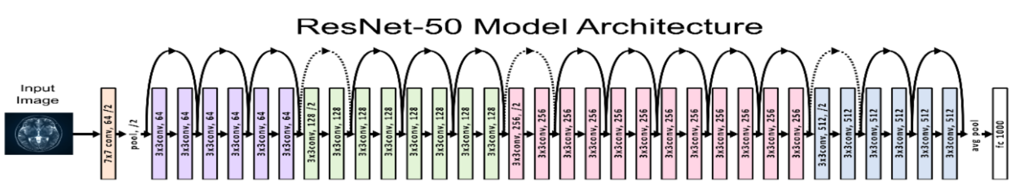


Figure 4: Brain-Tumor image feature extraction with ResNet-50

4. Result analysis and discussions

This section present results from our proposed solution. We have interpreted the data according the proposed model. In the first step,We have evaluated the ResNet50 model with different numbers of component found from Principle Component Analysis (PCA). Table 1 shows the performance matrices for the Model. The accuracy increases while the number of principle components decreases. When the amount of PCA components is 700, the model results in an accuracy of 99% and the precession is also high. Table 4 shows the corresponding data analysis with ResNet50 architecture and Figure 4 shows the confusion matrix of this results.

Table 4: Experimental data analysis with ResNet50 architecture

Experiment No	PCA Component	Accuracy (%)	Precession (%)	Recall (%)	F1-Score (%)
1	1300	0.98	0.99	0.98	0.99
2	1200	0.98	0.98	0.98	0.98
3	1100	0.98	0.98	0.98	0.98
4	1000	0.98	0.99	0.98	0.99
5	900	0.99	0.98	1.0	0.99
6	800	0.99	0.99	0.98	0.99
7	700	0.99	1.0	0.98	0.99

Figure 4 illustrated the confusion matrix of ResNet50 implementation. It shows how the model detects the Brain Tumor into the test dataset. It is clear that ResNet50 can easily detect the brain with tumor with 100% accuracy while it may generate positive (detects tumor) output although the brain does not contain any tumor.

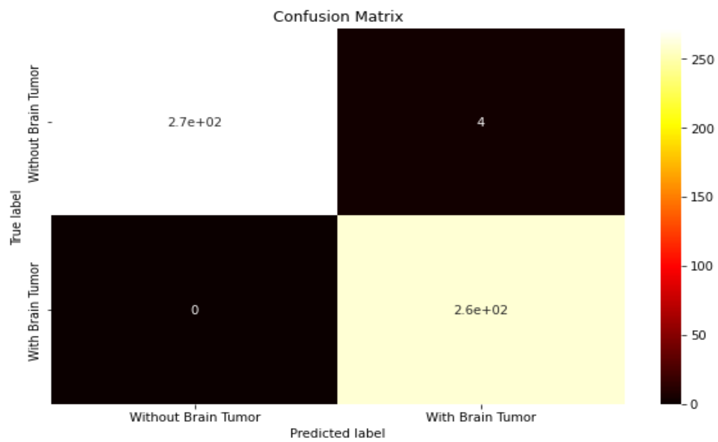


Figure 5: Confusion matrix for ResNet50 data analysis

We show the accuracy, precession, recall and f1-score from the InceptionV3 model with different numbers of component found from Principle Component Analysis (PCA). Table 2 shows the performance matrices for the Model. The accuracy is almost same while the number of principle components decreases. When the amount of PCA components is 700, the model results in an accuracy of 97% and the precession is also high. Table 5 shows the corresponding data analysis with Inception V3 architecture.

Table 5: Experimental data analysis with Inception V3

Experiment No	PCA Component	Accuracy (%)	Precession (%)	Recall (%)	F1-Score (%)
1	1300	0.97	0.98	0.95	0.97
2	1200	0.96	0.98	0.94	0.96
3	1100	0.96	0.97	0.95	0.96
4	1000	0.96	0,97	0.96	0.97
5	900	0.96	0.96	0.97	097
6	800	0.96	0.96	0.97	0.97
7	700	0.97	0.96	0.97	0.97

Figure 5 illustrated the confusion matrix of InceptionV3 implementation. It shows how the model detects the Brain Tumor into the test dataset. It is clear that InceptionV3 can't easily detect the brain with tumor with 100% accuracy while it may generate positive (detects tumor) output although the brain does not contain any tumor.

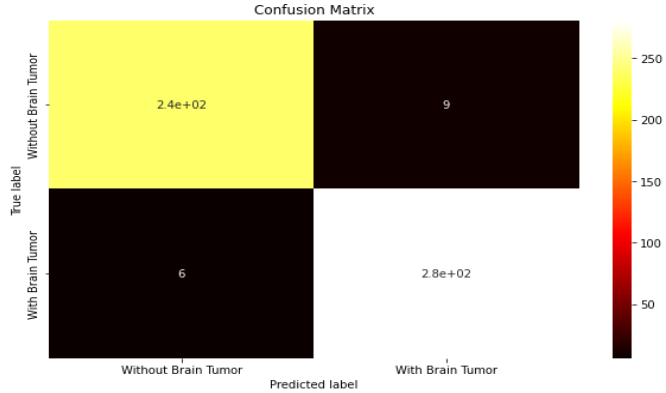


Figure 6: Confusion matrix for Inception V3 data analysis

We show the accuracy, precession, recall and f1-score from the Xception model with different numbers of component found from Principle Component Analysis (PCA). Table 3 shows the performance matrices for the Model. The accuracy is continuously changes while the number of principle components decreases. When the amount of PCA components is 700, the model results in an accuracy of 97% and the precession is also high. Table 6 shows the corresponding data analysis with Xception architecture.

Table 6: Experimental data analysis with Xception

Experiment No	PCA Component	Accuracy (%)	Precession (%)	Recall (%)	F1-Score (%)
1	1300	0.97	0.98	0.95	0.97
2	1200	0.95	0.96	0.94	0.95
3	1100	0.96	0.95	0.97	0.96
4	1000	0.95	0,94	0.96	0.95
5	900	0.96	0.97	0.96	096
6	800	0.97	0.98	0.97	0.97
7	700	0.97	0.97	0.97	0.97

Figure 6 illustrated the confusion matrix of Xception implementation. It shows how the model detects the Brain Tumor into the test dataset. It is clear that Xception model can't easily detect the brain with tumor with 100% accuracy and it appear some false value while it may generate positive (detects tumor) output although the brain does not contain any tumor.

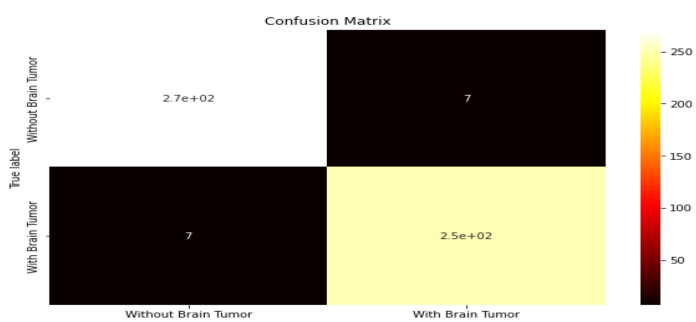


Figure 7: Confusion matrix for Xception data analysis

5.Conclusion

Brain tumors are extremely dangerous to human health and can even result in death. Early diagnosis of a brain tumor may be a viable option for lowering the death rate and dangers associated with the tumor. The result of this investigation is a novel approach of brain tumor identification and classification using the Deep Convolutional Neural Networks (DCNN) mechanism on 1255 magnetic resonance imaging (MRI) data, which is described in detail below. On a publically accessible dataset, the suggested research has employed several image processing techniques, such as image filtering approaches, to get the desired results. Both kinds of patients, those with and those without brain tumors, are included in the classification of the dataset. In addition, the process of data picture augmentation was used to increase the amount of the dataset in this study. After a collection of pre-trained Convolutional Neural Networks (CNN) architectures including VGG-19, ResNet50, Inception V3 and Xception have been applied to create the model and extract the features from each specific image, the model and features are extracted from the photos. After that, we used the Linear Discriminant Analysis (LDA) and Principal Component Analysis (PCA) on the retrieved features to minimize the dimension and the number of components in the dataset. Following that, we used traditional machine learning models in conjunction with the six classifiers to determine the accuracy of the detection and classifications made by the system. A collection of experimental data has been compiled and analysed in order to achieve the research's purpose. Working with the ResNet50 pre-trained architecture and ensemble classifiers, the researchers were able to reach the greatest accuracy of 99 percent in their research. As a result, we believe that the suggested method will be extremely effective in the identification and categorization of brain tumors.

While dealing with proposed solution a set of drawbacks have noticed. Firstly, the research can only classify into binary classes. Secondly, noisy images effect a lot in rendering the fine details of the each images. In future, we will solve these two issues and build a model to classify the brain tumor in multi-class nature.

6. Conflict of Interest:

All the authors in this research project hereby declare that there are no conflicts of interest.

7. Acknowledgement

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9. Authors Contributions

The concept of this present research was initiated by Md Moinuddin. All the authors participated in designing a questionnaire for the purpose of collecting and editing data. Thereafter, edited data was tested and analyzed with the cooperation of all authors. Finally, Md Moinuddin. took part in writing the manuscript and the rest of the authors approved the final manuscript after careful readings.

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