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► To cite this version:

Menaouer Brahami, Kebir Nour El-Houda, Dermane Zoulikha, Sabri Mohammed, Matta Nada. Detection and Classification of Brain Tumors From MRI Images Using a Deep Convolutional Neural Network Approach. International Journal of Software Innovation, 2022, 10 (1), pp.1-25. 10.4018/IJSI.293269 . hal-04449729

HAL Id: hal-04449729

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Submitted on 20 Feb 2024

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Detection and Classification of Brain Tumors From MRI Images Using a Deep Convolutional Neural Network Approach

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Brain tumor is a severe cancer disease caused by uncontrollable and abnormal partitioning of cells. Timely disease detection and treatment plans lead to the increased life expectancy of patients. Automated detection and classification of brain tumor are more challenging processes that are based on the clinician's knowledge and experience. For this fact, one of the most practical and important techniques is to use deep learning. Recent progress in the fields of deep learning has helped the clinicians in medical imaging for medical diagnosis of brain tumor. In this paper, the authors present a comparison of deep convolutional neural network models for automatically binary classification query MRI images dataset with the goal of taking precision tools to health professionals based on fined recent versions of DenseNet, Xception, NASNet-A, and VGGNet. The experiments were conducted using an MRI open dataset of 3,762 images. Other performance measures used in the study are the area under precision, recall, and specificity.

KEYWORDS

Brain Tumor, Deep Learning, Image Processing, Knowledge Management, Medical Decision Support System, Medical Informatics, MRI Image

1. INTRODUCTION

With the improvement of modern medical standards, medical imaging technology plays an increasingly important role in research on the medical diagnostic. Similarly, a human brain is centre of the nervous system (Choudhury et al. 2020; Anitha & Raja, 2018). A tumor of brain is a collection of uncontrolled increasing of these cells abnormally found in a different parts of the brain. However, brain tumor has become a key research topic in the medical field. For (Mittal & Kumar, 2019), the symptoms of a brain tumors may range from severe headaches and seizures to problems with vision and mental changes, depending on different parts of the body. In fact, early detection of tumor cells plays a major role in the treatment and recovery of patients. Diagnosing a brain tumor usually undergoes a very complicated and time-consuming process. In the medical imaging era, different medical imaging techniques namely X-ray, Magnetic Resonance Imaging (MRIs), Ultrasound, MRS (Magnetic Resonance Spectroscopy),

and Computed Tomography (CT), have a great influence on the brain tumor detection and treatment process of patients (Jalali & Kaur, 2020; Amin et al. 2020). Furthermore, MRI (Magnetic Resonance Imaging) has demonstrated out as an effective instrument in the location of brain tumor with the assistance of MR Images (Kumar et al. 2017). Besides that, Magnetic Resonance Imaging (MRI) is the preferred way to diagnose a brain tumor, as it generates more detailed pictures than Computerized Tomography (CT) scans (Sarhan, 2020). MRI images help physicians study and diagnose diseases or tumors present in the brain (Ruba et al. 2020). This technique produces clear and high-quality images in various medical image formats. According to several researchers, a brain tumors can be classified into two types: benign and malignant. Benignant tumors have a homogeneous structure and don't contain disease cells while malign have a heterogeneous structure and contain malignancy cells (Jain & Godara, 2017).

Meanwhile, automated and accurate classification of MRI, X-ray, and CT brain images is extremely important for medical analysis and interpretation. Over the last few years, numerous techniques are devised for brain tumor classification using different deep learning methodologies considering imaging modalities like MRI, CT, and so on. According to (Deepak & Ameer, 2019), the classification of tumors using brain images is a challenging task due to two issues. The first issue is that the brain tumor pose high variations in contrast to size, intensity, and shape. The second issue is that the tumors poses many pathological types, which pose the same manifestation. Moreover, brain tumor classification is an important problem in computer-assisted surgery systems, healthcare artificial intelligence systems in order to give yield more advantages for the medical diagnosis. Apart from this, Deep Learning (DL) has also been able to obtain significant results in the domain of medical diagnosis. Deep Learning has become one of the most common techniques that have achieved better performance in many areas, especially in medical image analysis and classification (Al ayoubi et al. 2020). According to (Ali Khan et al. 2020; El Kader Isselmou et al. 2019), because of Deep Learning, significant advancement has been made in medical science like the medical image processing technique which helps doctors to diagnose the disease early and easily. For (Kaur & Singh, 2020), Deep learning (DL) techniques are widely used in the automatic analysis of radiological images. Likewise, Deep Convolutional Neural Networks (DCNNs) has been used in the medical imaging classification and grading since it does not require preprocessing or features extraction before the training process (Sasikala & Kumaravel, 2008). For (Alqudah et al. 2019), DCNNs are designed to minimize or canceling in sometimes the data pre-processing steps and usually are used to deal with raw images. Deep Convolutional Neural Networks (DCNNs) models is a class of deep, feed-forward artificial neural networks that has successfully been applied to analyzing visual imagery (Zabalza et al. 2016). DCNNs use relatively minimal pre-processing compared to other image classification algorithms.

Motivated by making a contribution to improving the analysis of the medical images, this paper introduces a complete automatic brain tumor detection and classification as fast, accurate and supervised method for clinicians. The remainder of this paper is organized as follows. Section 2 introduces the literature review on deep learning methods and brain tumor detection and classification techniques proposed by various researchers. Section 3 presents the proposed methodology used for automatic detection and classification of brain tumors using deep learning models. The experimental results and discussion are covered in Section 4. Finally, Section 5 concludes and summarizes the key findings and future works.

2. LITERATURE REVIEW

Nowadays, medical treatments have witnessed a tremendous development of new advanced systems with high standard new technologies for medical investigation. In the right context, a variety of work recently is done for brain tumor detection and classification. In the medical and health arenas, image classification plays a significant role in medical image processing as medical images have different diversities. For brain tumor classification, they have used MRI and CT scan images. MRI is most vastly

used for brain tumor classification. Numerous works have been done on brain tumor classification in recent years. In a previous study, (Suganthe et al. 2020) have proposed CNN and RNN models for developing a high accuracy system for detecting brain tumor from MRI images. The network that resulted in the highest accuracy during testing has been selected and used as the classifier for brain tumor detection. The proposed work increased the accuracy and reduces the loss when compared to the existing system. Another study by (Ramadevi et al. 2020), it is to use deep learning techniques for brain tumor classification. BRAT's dataset is used in this process. Recurrent Neural Network (RNN) is used for features extraction and Decision Tree classifier is used for predictive analysis for precision, accuracy and specificity values of normal and abnormal images in dataset. Yet, (Arunnehrhu et al. 2020) have presented an approach to improve tumor detection and classification performance. Initially, the tumor area is clustered with the fuzzy c-means algorithm for discovering the surrounded tumor tissues and also gives important clues for tumor types. Second, the Canny Edge detection applied for the tumor region. Third, the spectral residual for saliency map from the tumor region. In other words, (Kalaiselvi et al. 2020) have developed six convolutional neural networks (CNN) models for finding optimal brain tumor detection system on high-grade glioma and low-grade glioma lesions from voluminous magnetic resonance imaging human brain scans. (Li et al. 2019) have proposed a method with three-dimensional MRI brain tumor detection combining multimodal information fusion and CNN is proposed. Moreover, the experimental results show that the three evaluation indexes of dice, SN and SE are optimized respectively, and the two-dimensional brain tumor detection network and the original single-mode brain tumor detection method are compared. A study was conducted by (Uczal et al. 2019) in order to develop web-based software that can classify brain tumors (glioma, meningioma, pituitary) based on high-precision T1 contrast magnetic resonance images using the convolutional neural network from deep learning algorithm. According to the experimental results, all the calculated performance metrics are higher than 98% for classifying the types of brain tumors on the training dataset. In other words, (Alqudah et al. 2019) have used Convolutional Neural Network (CNN) which is one of the most widely used deep learning architectures for classifying a dataset of 3064 T1 weighted contrast-enhanced brain MR images for grading (classifying) the brain tumors into three classes (Glioma, Meningioma, and Pituitary Tumor). In the work done by (Özyurt et al. 2019), to combine the CNN with neutrosophic expert maximum fuzzy (NS-CNN) sure entropy for brain tumor classification using the neutrosophic set – expert maximum fuzzy-sure method for brain tumor segmentation. They achieved an average success of 95.62%. Likewise, (Sajjad et al. 2019) have proposed an extensive data augmentation method fused with VGG-19 CNN architecture for brain tumor classification. The method used for multi-grade classification of brain tumors using segmented brain tumor MRI images. The authors used pretrained VGG-19 CNN for classification using transferee learning and achieved an overall accuracy of values 87.38% and 90.67% for data before and after augmentation respectively. Moreover, (Das et al. 2019) have proposed a system in order to develop a CNN model for classifying brain tumors in T1-weighted contrast-enhanced MRI images. The system consists of two significant steps. First, preprocess the images using different image processing techniques and then classify the preprocessed image using CNN. Besides that, Siar & Teshnehlab, (2019) have used a Convolutional Neural Network (CNN) to detect a tumor through brain Magnetic Resonance Imaging (MRI) images based on the combination of feature extraction techniques with CNN. The accuracy of the Softmax Fully Connected layer used to classify images obtained 98.67%. In (Samadi et al. 2019), a deep learning-based supervised method is introduced to detect synthetic aperture radar (SAR) image changes. This method provided a dataset with appropriate data volume and diversity for training the DBN using input images and the images obtained from applying the morphological operators on them. The detection performance of this method indicates the appropriability of deep learning based algorithms for solving the change detection problems. In an earlier work, (Seetha & Raja, 2018) have proposed a deep CNN based system for automated brain tumor detection and grading. 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

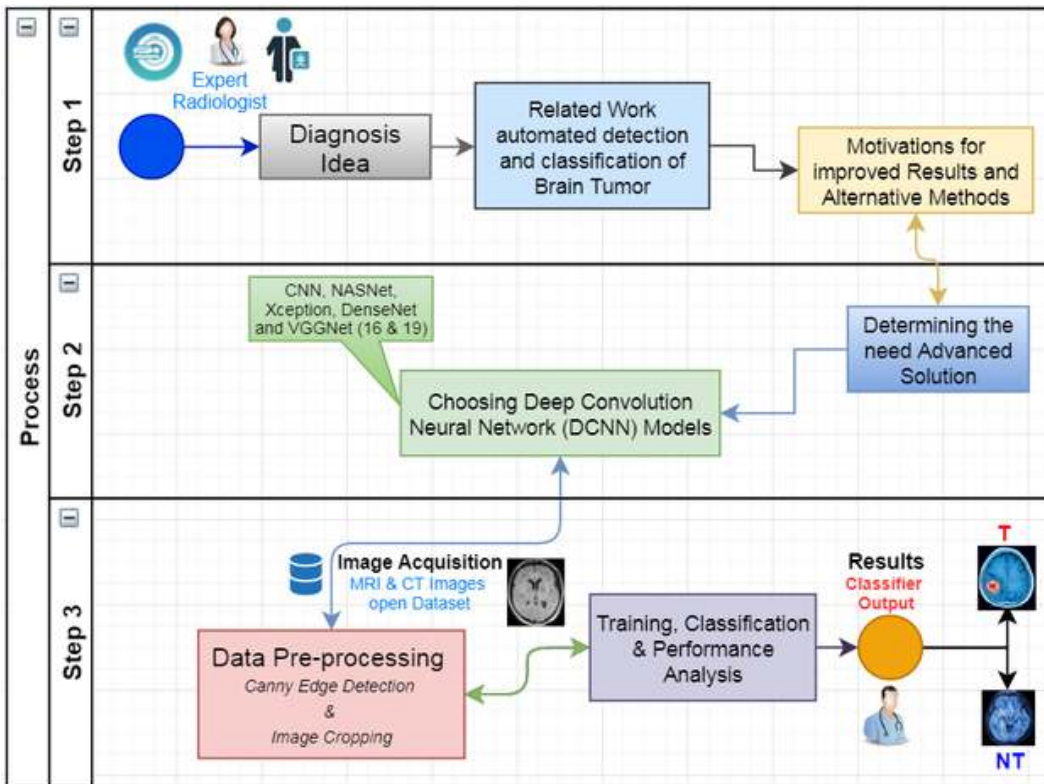
were fed into SVM and DNN classifiers. The results showed that the system achieved a rate of 97.5% accuracy. (Mohsen et al. 2018) have proposed a system that combines Discrete Wavelet Transform (DWT) features and deep learning (DL) techniques using fuzzy c-mean method for segmenting the brain tumor. The authors was applied DWT to extract the features in order to feed into the principal component analysis (PCA) for feature dimension reduction. The results show that they achieve an accuracy rate of 96.97% and a sensitivity of 97.0%.

Therefore, to overcome the issues associated with the existing models, deep Convolutional Neural Networks models are proposed in this paper to detect and classify brain tumor from MRI images of infected patients.

3. APPROACH PROPOSED

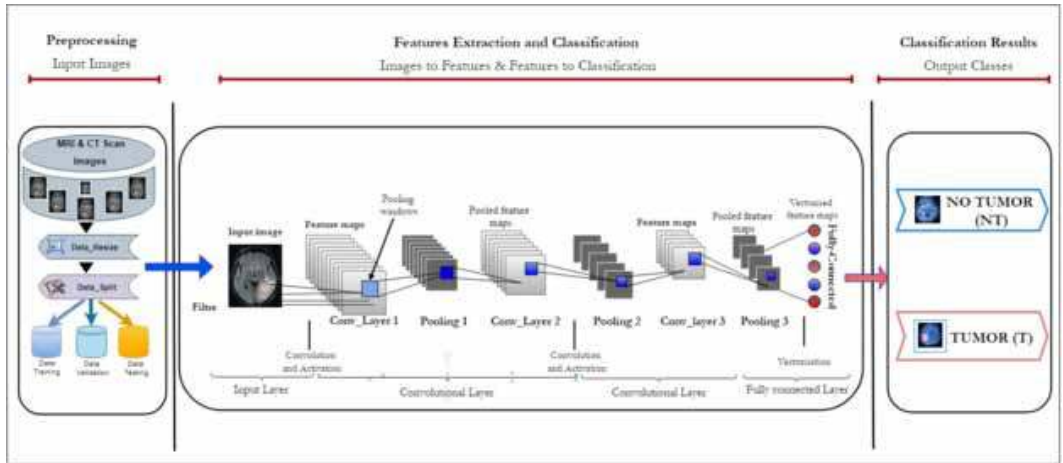
As per our objective and the motivations, this study is associated with some background ideas and research efforts as shown in Figure 1. Briefly, especially using deep CNN models for detection and classification (Brain Tumor) and supporting it with image processing has been remarkable ideas to follow. As general, widely followed automatic binary classification and detection approach performed with Deep Learning models such as CNN, NASNet-A, Xception, DenseNet, and VGGNet have been directed to the disease of brain tumor (see Figure 1).

Figure 1. Ideas and research efforts on the background of this study



In the context mentioned above, this study followed an easy-to-design image pre-processing and deep learning approach for automatic detection and classify brain tumors, by considering MRI & CT Images as input data. In this respect, Figure. 2 represents the stages within the flow of the introduced deep learning approach. After the image pre-processing based enhancement, the classification was made by using Deep Convolutional Neural Networks (DCNN) models (NASNet-A, Xception, DenseNet, and VGGNet). In next stages, we evaluate our introduced deep learning approach by using 3762 T1-weighted contrast-enhanced MRI images, which are performed as part of patients' routine clinical care. Meanwhile, the image processing technique is important for good image enhancement, which will be effective for better detection and classification at the end. The whole flow is a deep learning approach applied to target image data, which is essential for detection from medical inputs in the form of visual elements (see Figure 2).

Figure 2. Main Steps of the proposed hybrid approach

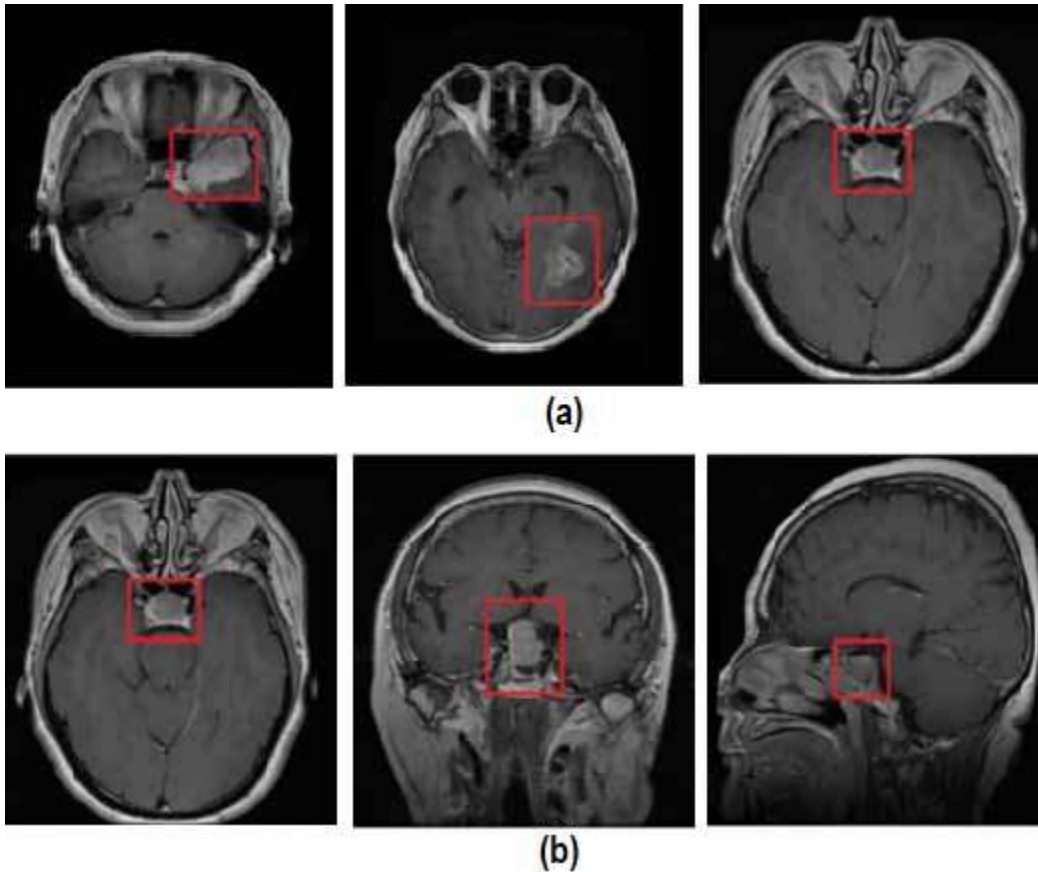


3.1. MRI Images Datasets

In our work, MRI images used in this study are publicly available image datasets available at Kaggle (Badža & Barjaktarović, 2020). The image dataset, provided as a set of slices, used in this study contains 3762 T1-weighted contrast-enhanced MRI images acquired with three kinds of brain tumor, Meningioma, Glioma, and Pituitary tumor (Sultan et al. 2019; Ismael & Abdel-Qader, 2018). All images were acquired from 285 patients in three planes: Sagittal (1259 images), Axial (1224 images), and Coronal (1279 images) plane. Likewise, the images are different for each patient. The images have an in-plane resolution of 512×512 with pixel size $0.49 \times 0.49 \text{ mm}^2$ (Avşar & Salçin, 2019). In Figure 3, three different MRI images are presented along with their tumor region. The tumors are marked with a red outline.

As per our objective, this dataset (3,762 MRI images) has been used for analyzing the performance of deep learning algorithms used for automated detection and classification of brain tumors. The dataset is organized into three folders (Training, Testing, and Validation) and contains subfolders for each image category (Tumor (T) and No Tumor (NT)). To do that, each training set contains 2315 images, each test set contains 706 images, and each validation set contains 706 images.

Figure 3. Representation of MRI images showing different types of tumors in different planes. In the images, the tumor is marked with a red outline.



3.2. Preprocessing

In theory, image processing techniques are increasingly used as a way of diagnosing diseases, including brain tumor diseases. As we all know, data pre-processing is an integral part of deep learning. Moreover, there are many pre-processing techniques, which are applicable in different circumstances. The motivation behind image pre-processing is to improve the quality of visual information of each input image. So some preprocessing is required to remove unwanted noises and to improve the contrast of the MRI images.

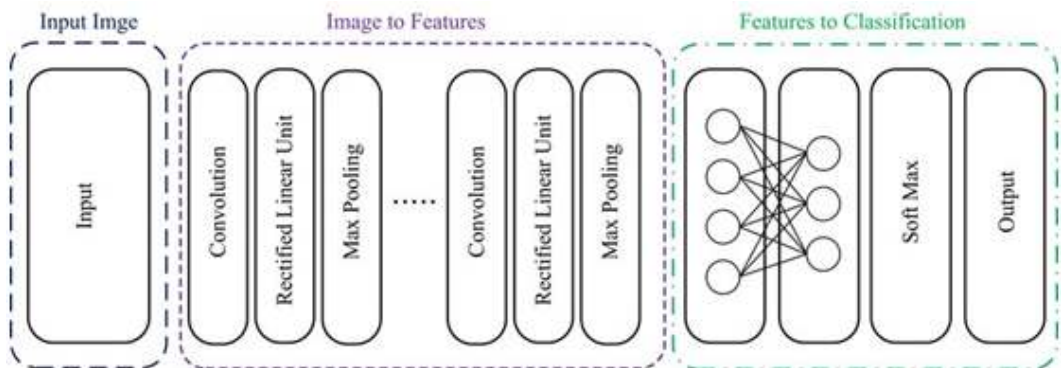
In this study, Magnetic Resonance Images (MRI) from the dataset were of different sizes and were provided in int16 format. These images represent the input layer of the network, so they were normalized and resized to 256×256 pixels. As per our models, we propose to import the OpenCV-Python package mainly used for image processing. OpenCV contains various tools to solve Computer Vision problems (Mahamkali & Ayyasamy, 2015). It contains low-level image processing functions and high-level algorithms for feature matching namely the Canny Edge Detection (CED) technique which is the most important feature in the application of image processing and computer vision. Canny Edge Detection (CED) is a multi-phase algorithm used to identify the edges of an object in an image (Selvakumar & Hariganesh, 2016; Deng et al. 2013). In this respect, we cropped the dark edges from the images and took only the brain portion from MRI images by using the Open source Computer Vision (CV) Canny Edge Detection technique.

3.3. Deep Convolutional Neural Networks (DCNNs)

Deep Learning (DL) is a part of an artificial neural network technique and a subclass of machine learning. Moreover, DL is part of a broader family of machine learning methods based on learning data representations (Brahami et al. 2020). In DL, multiple layers used for a higher level of the feature from the input dataset. Deep learning methodologies are becoming very common in the fields of medical image classification (Aledhari et al. 2019; Abdolmanafi et al. 2018). Many of the notable and most successful works in medical image classification involved implementing deep learning algorithms such as Convolutional Neural Networks (CNNs). In this field, Convolutional Neural Networks (CNNs or ConvNets), a branch of deep learning, have an impressive record for applications in image analysis and interpretation, including medical imaging (Pratt et al. 2016). For (Militante & Sibbaluca, 2020), it is very effective in a multi-layered structure when obtaining and assessing necessary features of graphical images. Furthermore, DCNN is a class of deep, feed-forward artificial neural networks that has successfully been applied to analyzing visual imagery. DCNNs use relatively minimal pre-processing compared to other image classification algorithms (Suganthi et al. 2020). According to earlier works, DCNN is a type of deep neural networks that learns features from the input data and uses two dimensional convolutional layers for the processing of two dimensional image data (Jyotiyan & Kesswani, 2020). In general, the deep convolutional neural network is composed of many layers in which many two-dimensional planes of feature mapping form (Wang et al. 2019). According to (Abdolmanafi et al. 2018), the popular network in this DCNN, which has a broad application in medical image analysis is Inception-v3 (Szegedy et al. 2015), VGG16 model (Litjens et al. 2017) and ResNet50 (Abdolmanafi et al. 2018) model is other network of this group. The architecture of CNN models, in any CCN model there are three types of main layer as convolutional layer which, pooling layer and dense layer.

Most of the layers in CNN convert an input image to features. Only the last few layers are used for classification (Gadekallu et al. 2020). Finally, Figure 4 graphically presents the general architecture of a CNN, with its main elements.

Figure 4. General Architecture of a CNN



In this light, we briefly discuss the parameters, architecture of deep CNNs and sub-networks of the three CNNs models (NASNet-A (Zoph et al. 2018), Xception (Chollet, 2017), DenseNet (Huang et al. 2017), and VGG16 & 19 (Simonyan & Zisserman, 2015)) for diseases brain tumor detection and classification in order to obtain high accuracy and reduce parameters. As well, the outstanding performance of CNN models inspires us to apply them on medical images.

3.3.1. VGG Network (VGG16 and VGG19) Architecture

The visual geometry group network (VGGNet) is a deep neural network with a multilayered operation. The VGGNet is based on the CNN model (Mateen et al. 2019). This deep learning method is one of the first attempts at adding depth to improve classification accuracy. The major characteristic of this architecture is instead of having a large number of hyperparameters, and they concentrated on simple 3×3 size kernels in convolutional layers and 2×2 size in max pooling layers (El Asnaoui & Chawki, 2020). During testing, in VGGNet, the test image is directly go through the VGGNet and obtain a class score map. This class score map is spatially averaged to be a fixed-size vector. For (Setiawan & Damayanti, 2020), VGGNet created the VGG16 (Simonyan & Zisserman, 2015) network architecture with 16 layers and VGG19 (Simonyan & Zisserman, 2015) with 19 layers. According to (Hieu & Hien, 2020), VGG16 is a CNN architecture that was used to win the ImageNet ILSVR competition 2014. It is as yet considered as one of the outstanding vision model architecture. Moreover, VGG-19 is useful due to its simplicity as 3×3 convolutional layers are mounted on the top to increase with depth level (Saikia et al. 2019; Mateen et al. 2019). For (Zhang et al. 2019), VGG-19 model has roughly 143 million parameters, where the parameters are learned from the ImageNet dataset containing 1.2 million general object images of 1,000 different object categories for training.

The use of uniform and smaller filter sizes on VGG can produce more complex features and lower computing when compared to AlexNet. In summary, we present across the Table 1, the difference between VGG16 and VGG19.

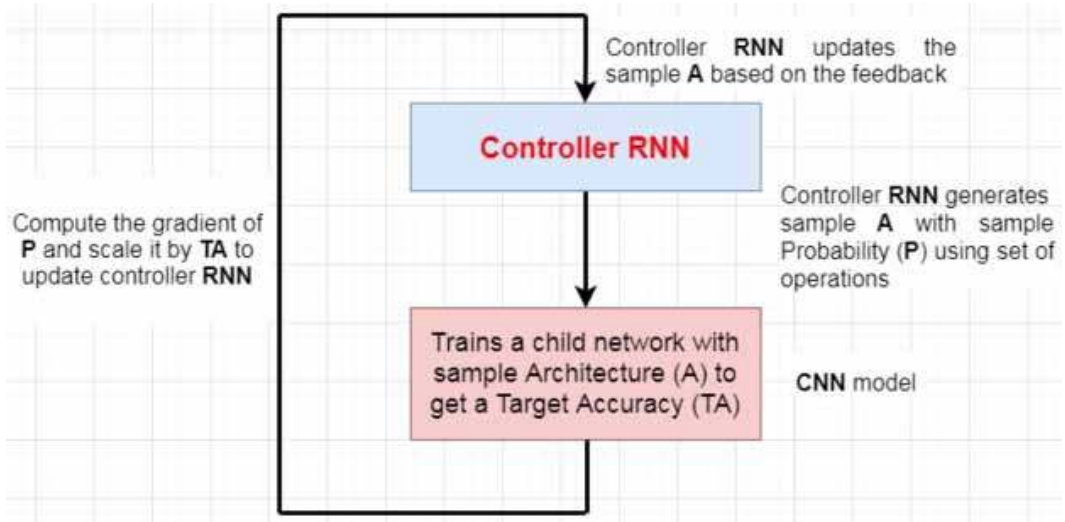
Table 1. Comparison of VGG16 and VGG19 Layers

Layer	VGG16	VGG19
Size of Layer	41	47
Image Input Size	244*244 pixel	224*244 pixel
Convolutional Layer	13	16
Filter Size	64 & 128	64,128,256, & 512
ReLU	5	18
Max Pooling	5	5
FCL	3	3
Drop Out	0.5	0.5
Softmax	1	1

3.3.2. NASNet Network Architecture

In theory, the network architecture for NasNet comes from a Neural Architecture Search (NAS) that uses a reinforcement learning approach to optimize architecture configurations. Moreover, the deep neural network has witnessed growth to the next generation by introducing the concept of optimized network which has been materialized through the concept of NAS by Google ML group (Radhika et al. 2019). Besides that, NASNet-A is a scalable CNN architecture that consists of basic building blocks (cells) that are optimized using reinforcement learning (Saxen et al. 2019). Specifically, several modifications was done based on number of layers, weights, regularization methods, etc., to improve efficiency of the network. According to (Cogan et al. 2019), the NAS uses a controller Recurrent Neural Network (RNN) to find the optimal neural architecture. According to (Zoph et al. 2018), the controller weights are updated with policy gradient. The whole end-to-end setup is shown in Figure 5.

Figure 5. NAS network architecture search



In Neural Architecture Search (NAS), a controller RNN predicts architecture (A) from a search space with probability P . A child network with architecture (A) is trained to convergence achieving accuracy (TA). Scale the gradients of P by A to update the RNN controller (Cogan et al. 2019).

As per our study, the model that we use for our experiments is the NasNet-A architecture, which was created based on the results of one of the best searches. Primarily, NASNet-A utilizes depthwise-separable convolutions, which will be described in Table 2.

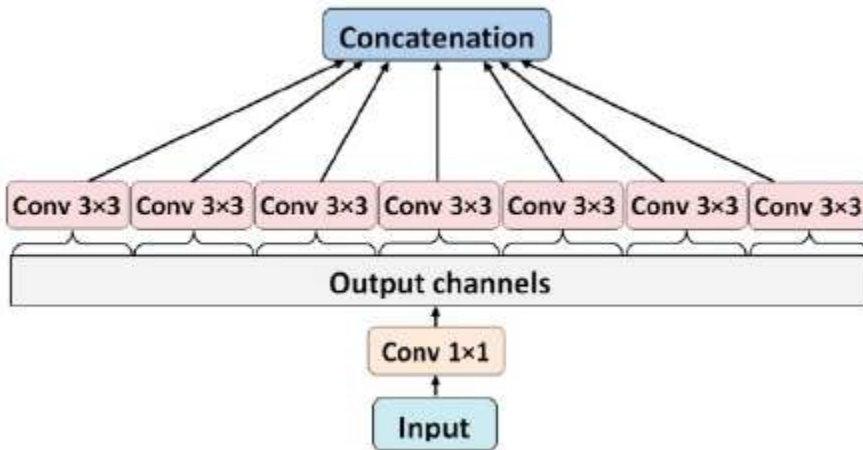
Table 2. Possible Operations for NasNet-A

Operation
identity
1x3 then 3x1 convolution
1x7 then 7x1 convolution
3x3 dilated convolution
3x3 average pooling
3x3 max pooling
5x5 max pooling
7x7 max pooling
1x1 convolution
3x3 convolution
3x3 depthwise-separable conv
5x5 depthwise-separable conv
7x7 depthwise-separable conv

3.3.3. Xception Network Architecture

Xception was presented in 2017 by Chollet (Chollet, 2017). As well, Xception is defined as a hypothesis based on the Inception module, which creates correlations of cross-channels and spatial relations within feature maps of CNN able to be completely decoupled. For (Leonardo et al. 2018), the Xception architecture is an extension of the Inception architecture which replaces the standard Inception modules with depthwise separable convolutions. The Xception model is 36 layers deep, not counting the fully connected layers in the end. The model contains depthwise separable layers like MobileNet, and it also contains “shortcuts” where the output of certain layers are summed with the output from previous layers. Besides that, the Xception model is robust, stronger than the Inception module, and can operate correlations of cross-channels and spatial relations with maps fully decoupled. According to (Jinsakul et al. 2019), after input, data using only one size of 1x1 convolution create separate convolution sizes of 3x3 without average pooling, which proceed in nonoverlapping sections of the output channels to then be fed forward for concatenation (see Figure 6).

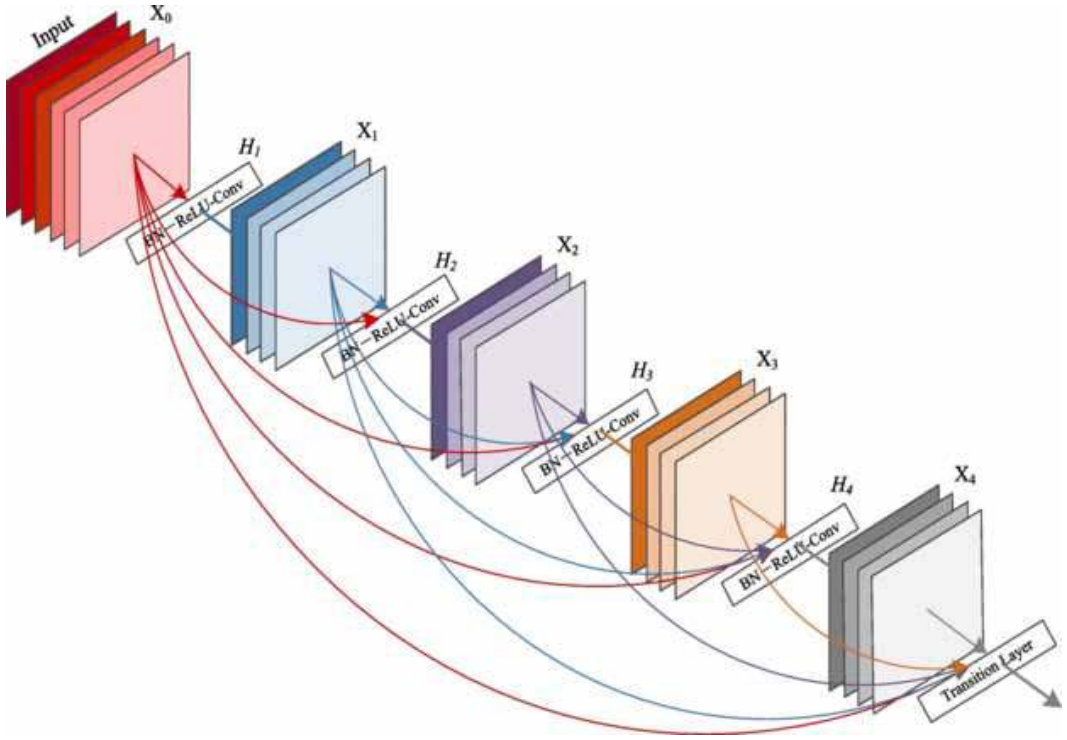
Figure 6. Xception Module Architecture



3.3.4. DenseNet Network Architecture

In theory, the Dense Convolutional Network (DenseNet) is one of the recently proposed neural network architecture, has achieved state-of-the-art performance in many visual tasks (Huang et al. 2017). The DenseNet exploits the condensed network providing easy-to-train and highly parametrically efficient models due to the possibility of feature reuse by different layers (Jaiswal et al. 2020). However, recent extensions of DenseNet with careful expert design, such as 23 Multi-scale DenseNet and CondenseNet (Huang et al., 2018), have shown that 24 there exists high redundancy in DenseNet. For (Chen et al. 2019; Chen et al. 2020), DenseNet a recently proposed CNN architecture has an interesting connectivity pattern: each layer is connected to all the others within a dense block. According to (Li et al. 2020), the Dense Block is an important part of the DenseNet for improving the information flow between layers. It is composed of BN, ReLu, and 3×3 Conv (see Figure 7).

Figure 7. DenseNet Architecture



4. EXPERIMENTAL RESULTS

In the literature, most of the research works that apply deep CNN models for brain tumor classification use hundreds of thousands of images to train the model. In this section, we presents the results of the performance on the MRI & CT scan images dataset.

4.1. System Requirements

The experimental environment of this paper is Windows 10 system, Python 3.6.2, Tensorflow 1.11.0, and Keras 2.2.4. In the hardware device section, the CPU is Intel Core i7 4300U @ 1.90 GHz 2.50 GHz specifications, GPU 1060 6 Gb D5 amp, Solid State Drive, Double Data Rate4 32 Gb, and MSI Z270 GAMING PRO CARBON Motherboard. The emulator is written in Python and uses the neural network library Keras and GPU.

4.2. Evaluation Criteria

The performance of a brain tumor classification approach is evaluated by various performance metrics. The accuracy metric, which determines the correctness of the identified instances in both classes of binary classification (Tumor (T) and No Tumor (NT)), must be supplemented by other metrics such as precision, recall, F1 score, and AUC. These popular parameters are defined as follows:

$$Sensitivity(Recall) = TP / TP + FN \quad (1)$$

Sensitivity (true positive fraction) is the probability that a detection test is positive, given that the person has the tumor disease.

The recall (Specificity) (true negative fraction) is the probability that a detection test is negative, given that the person does not have the disease:

$$\text{Recall (Specificity)} = TN / TN + FP \quad (2)$$

In general, sensitivity and specificity evaluates the effectiveness of the algorithm on a single class, positive and negative respectively:

$$\text{Accuracy} = TP + TN / TP + TN + FP + FN \quad (3)$$

$$\text{Precision} = TP / TP + FP \quad (4)$$

The precision metric will show the ratio of true positives over the total number of detected entities. In other words, this metric will help us understand how well a model is in returning only the true positives and not unrelated entities:

$$F - \text{score} = 2 * \frac{\text{Precision} * \text{Recall}}{\text{Precision} + \text{Recall}} \quad (5)$$

Commonly, accuracy is the most used metric to evaluate the classification performance. This metric calculates the percentage of samples that are correctly classified. As well, precision is how “precise” the model is out of those predicted positive and how many of them are actually positive. A high value of the metric (F-score) indicates that the model performs better on the positive class. Thus, F1 Score (also known as F-measure) might be a better measure when a balance between Precision and Recall is needed with an uneven class distribution (large number of Actual Negatives). This metric can be used to show the overall performance of a tool.

Likewise, a confusion matrix is commonly used to visualize the performance of a classification algorithm. Measurement of TP, FP, TN, and FN uses a confusion matrix of a classification with two classes. where TP, TN, FP, and FN stand for true positives, true negatives, false positives, and false negatives, respectively.

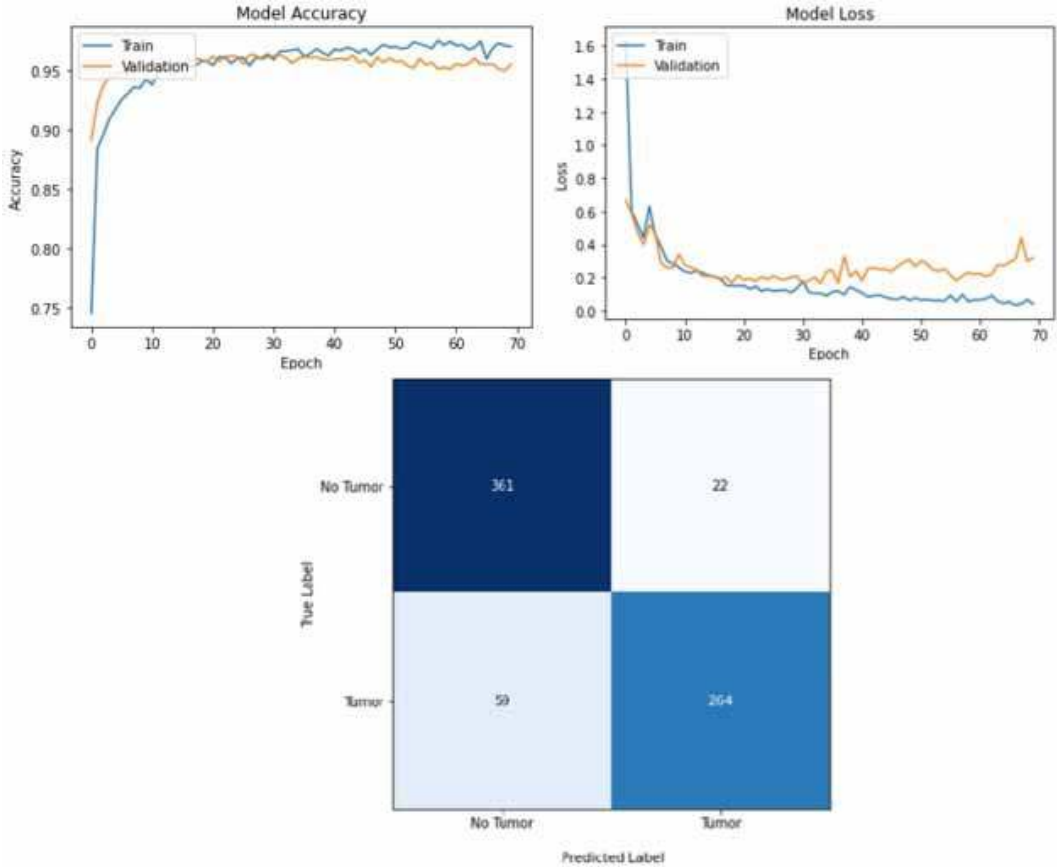
4.3. Results and Discussions

In this study, the most widely used MRI images dataset has been chosen to verify the proposed approach using Python programming language with Tensorflow framework. For this, we investigated the automatic binary classification of the cases of brain tumor disease using deeper and dense networks (Baseline CNN, Fine-tuning the top layers of DenseNet, Xception, NASNet-A, VGG16, and VGG19). This method can perform classification based on the various status of the T1-weighted contrast-enhanced MRI images (see Section 3.1). Multiple layered models have been designed for performing convolution and feature extraction. The Rectified Linear Unit (ReLU) activation function is used to define the output of internal layers. Moreover, the training curve is calculated from the training dataset that provides an idea of how well the model is learning. Similarly, the validation curve or test curve is calculated from a hold-out validation dataset that provides an idea of how well the model is generalizing. In theory, losses are the errors that occurred in the process of prediction while training the model. The optimum training process always reduces errors and increases accuracy. As per our approach, the lower the loss better is the model and the higher the accuracy more satisfactory

is the classification results. During the training process, the approach determines the graphs for the model's loss and accuracy for 70 epochs.

- Baseline CNN:** The graphical representation of training loss vs validation loss and training accuracy vs validation accuracy of baseline CNN model is displayed from Figure 8.

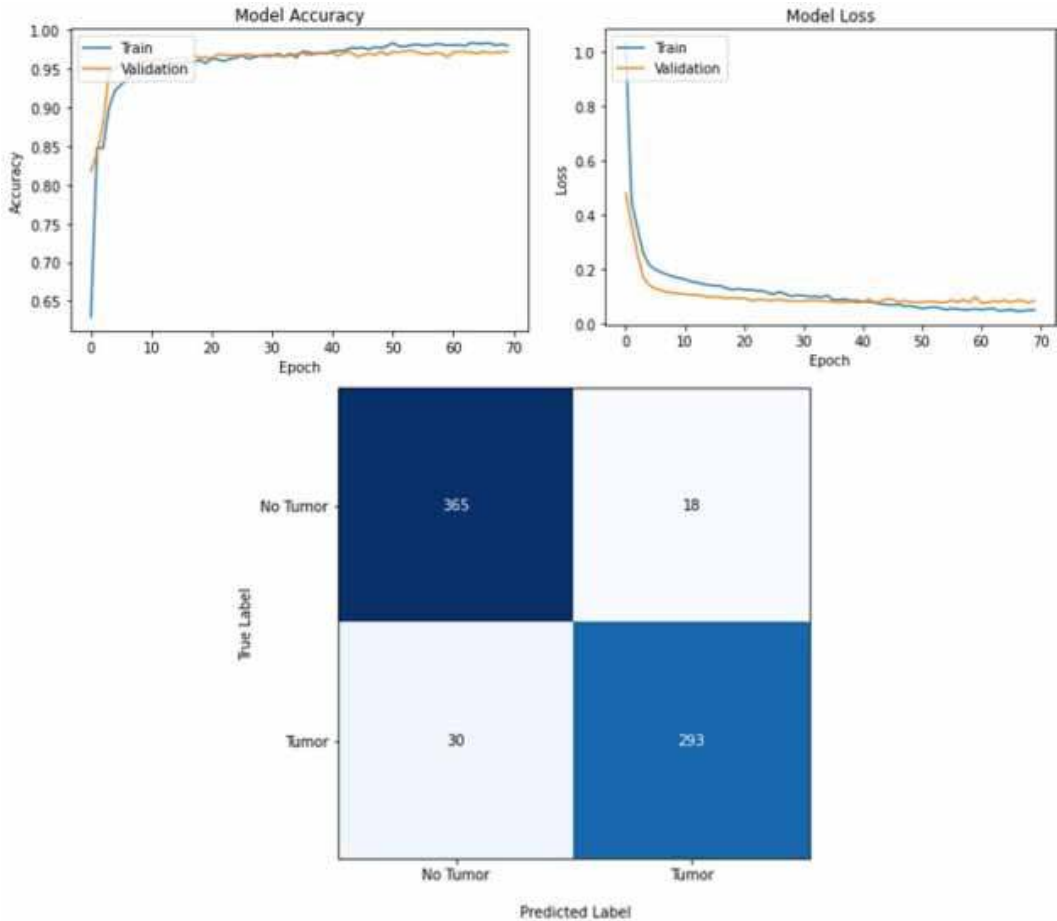
Figure 8. Result of Baseline CNN Model (Accuracy, loss curve and confusion matrix 'Actual and predicted labels are displayed on the y-axis and x-axis, respectively')



According to the figure above, there is an optimal convergence between the training data and the validation data in the accuracy model. As well, we are correctly monitoring the increase in precision and loss between train and validation in epoch this reflects that with each epoch the model is learning more information. For the loss model, the accuracy and loss start to deviate steadily, this could be a sign of stopping training at an earlier time. Likewise, we see that the global confusion matrix illustrated in Figure 8 giving a satisfactory result for the two classes such that the totality of the images well classified in the two classes “No Tumor” and “Tumor” is 361 and 264 with a precision of 0.94 and 0.86 respectively. Moreover, the totality of misclassified images is 82 images out of 706 test images with an accuracy curve of test data with 95.72%.

- VGG16:** The graphical representation shown in Figure 9 gives the percentage values of performance measures obtained for the VGG16 Model in a binary classification scenario.

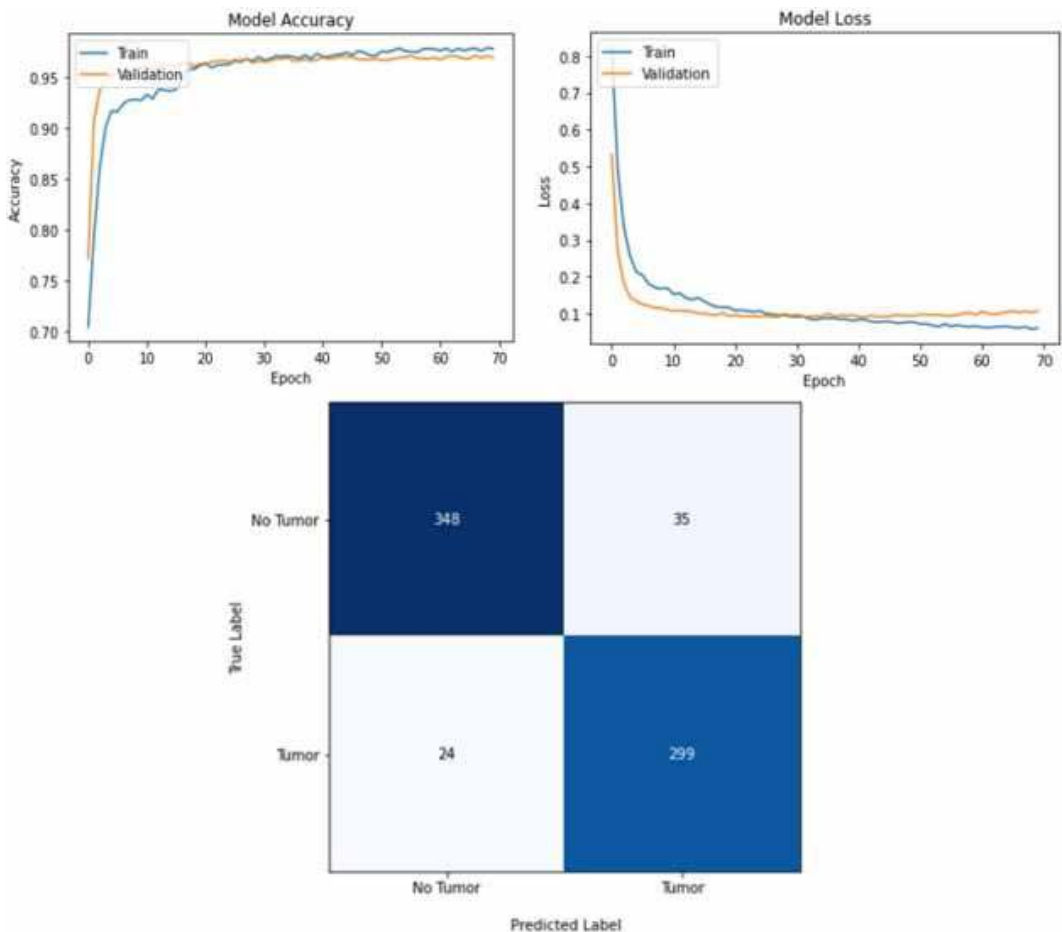
Figure 9. Result of VGG16 Model (Accuracy, loss curve and confusion matrix 'Actual and predicted labels are displayed on the y-axis and x-axis, respectively')



The results are given by VGG16 (see Figure 9) show that the Tumor class was detected with good sensitivity of 94.03% that is caused by the low sum of false negatives with reasonable precision of 95.54%. As it is observed, the accuracy value is 95.58%. From these graphs, we notice that the training and validation precision increases with the number of epochs. Likewise, the training and validation error decreases with the number of epochs. From the confusion matrix, we can observe for image class “No Tumor” the model was able to predict 365 images correctly in the no tumor class, but 18 were labeled as Tumor with an error rate of 9.04%. For the image’s class “Tumor”, the model was able to identify 293 images correctly, but 30 images were labeled as “No Tumor” with an error rate of 9.04%.

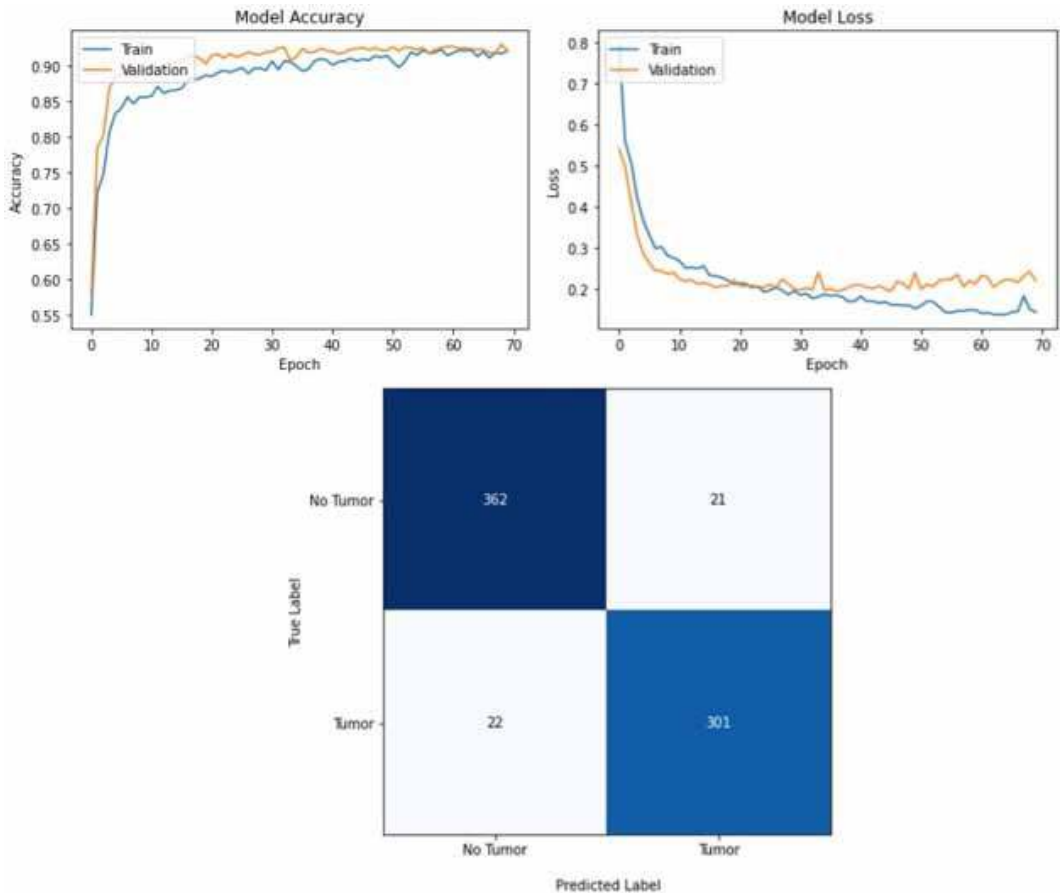
- VGG19:** As it is shown in the figure below (see Figure 10), it is observable that the VGG19 model provided an average accuracy of 96.27% that increases with the number of epochs in the curve of training data (validation data), this reflects that with each epoch the model learns more information. Likewise, we notice that the total misclassified images are 59 images, with an error rate of 4.46%, and the total well-classified images are 647 an accuracy rate of 96.27%. From the confusion matrix, we can observe for the image class “Tumor” the model was able to predict 299 images correctly in the tumor class, but 35 were labeled as no tumor. For the image’s class “No Tumor”, the model was able to identify 348 images correctly, but 24 images were labeled as Tumor.

Figure 10. Result of VGG19 Model (Accuracy, loss curve and confusion matrix ‘Actual and predicted labels are displayed on the y-axis and x-axis, respectively’)



- DenseNet:** Concerning the DenseNet model results (see Figure 11), we may notice that the Tumor class was detected with good precision, sensitivity, and specificity (95.55%, 95.51%, and 95.25% respectively). This can be explained by the sum of false positives and false negatives were low (precision and sensitivity). It also provides an accuracy rate of 95.53% and a loss of 19.62%. The confusion matrix indicates that, for images class “Tumor”, 285 images were predicted correctly

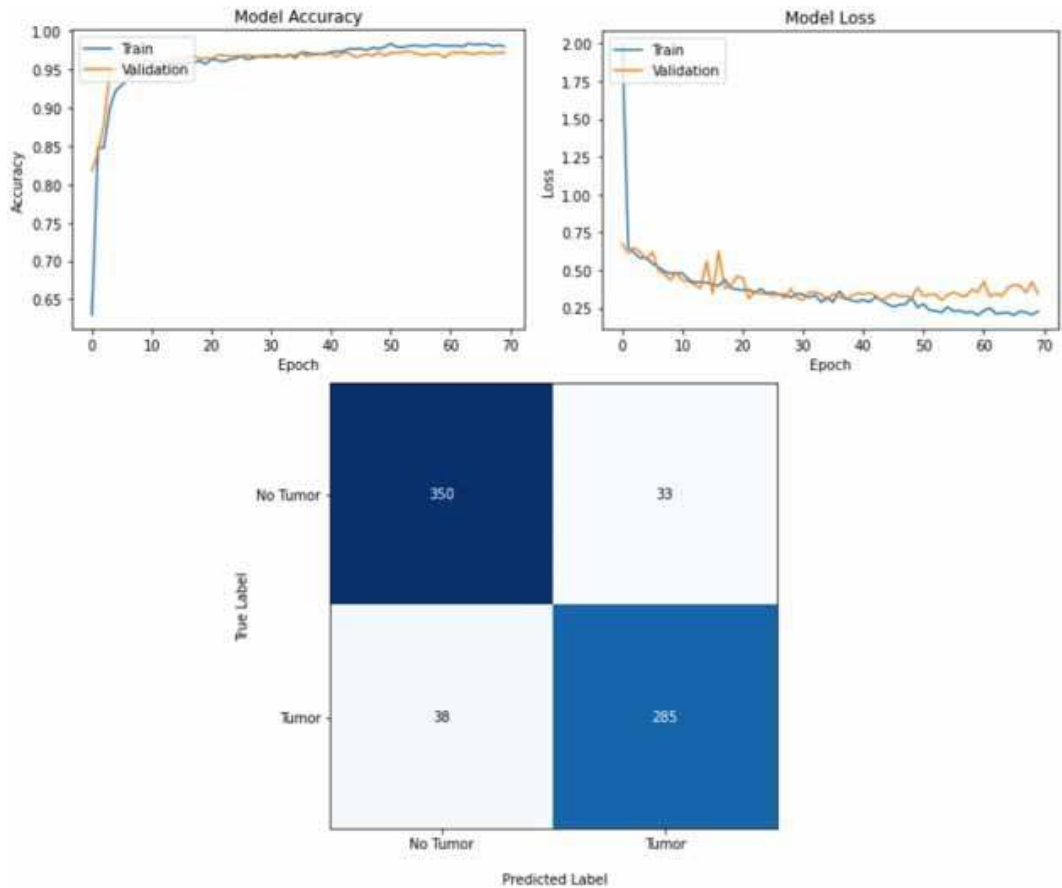
Figure 11. Result of DenseNet Model (Accuracy, loss curve and confusion matrix 'Actual and predicted labels are displayed on the y-axis and x-axis, respectively')



as Tumor, and 38 were labeled as “No Tumor”. In the second image’s class “No Tumor”, the DenseNet model was able to identify 350 images correctly, but 33 images were labeled as Tumor.

- **Xception:** For the Tumor class, the Xception model was able to identify 258 images correctly as Tumor and 38 images as No Tumor. On other hand, for the No Tumor class, 350 were correctly classified as No Tumor and 33 images as Tumor. The accuracy and loss curves in the training and validation phases are shown in Figure 12. The highest accuracy is observed at 94.93% and the loss is 20.45% at epoch 70. It is also noticeable that both training loss and validation values increased significantly at the primary epoch because of the number of Tumor data in that specific class. After training our model for 70 epochs, a good fit can be observed for the loss curve of train data in either the quick increasing interval.
- **NASNet-A:** The graphical representation shown in Figure 13 gives the percentage values of performance measures obtained for the NASNet-A Model in a binary classification scenario. The results are given by NASNet-A (see Figure 13) show that the Tumor class was detected with good sensitivity of 95.75% that is caused by the low sum of false negatives with reasonable precision of 96.93%. As it is observed, the accuracy value is 96.65% and the loss is 11.53% at epoch 70. From these graphs, we notice that the training and validation precision increases with the number of epochs. Likewise, the training and validation error decreases with the number of epochs. From the confusion matrix, we can observe for the image class “No Tumor” the

Figure 12. Result of Xception Model (Accuracy, loss curve and confusion matrix ‘Actual and predicted labels are displayed on the y-axis and x-axis, respectively’)



model was able to predict 358 images correctly in the “No tumor” class, but 25 were labeled as “Tumor”. For the image’s class “Tumor”, the model was able to identify 294 images correctly, but 29 images were labeled as “No Tumor”.

As per our objective, we investigated in this paper the binary classification (No Tumor and Tumor) based on MRI & CT scan images using deep convolutional neural networks architectures, in order to identify the best performing architecture based on the various performance metrics defined in evaluation criteria (see Section 4.2). Precision, sensitivity, and specificity are the key metrics for checking the accuracy of a model. Moreover, we evaluate the F1-score, which checks the accuracy of the test data in the form of harmonic average specifically for imbalance MRI & CT scan images dataset. Table 3 illustrates a comparison between our different deep learning models used in our experiment in terms of popular parameters.

Furthermore, based on Table 3, it can be seen that the table depicts in detail classification performances across multi-experiment classification, based on different fine-tuned versions of recent deep learning architectures. From the results, it’s notable that the accuracy when we use the baseline Xception is low compared with other DL architectures since these last models help to obtain respectively 94.93% of accuracy. In contrast, the highest accuracies are reported by CNN, VGGNet,

Figure 13. Result of NASNet-A Model (Accuracy, loss curve and confusion matrix 'Actual and predicted labels are displayed on the y-axis and x-axis, respectively')

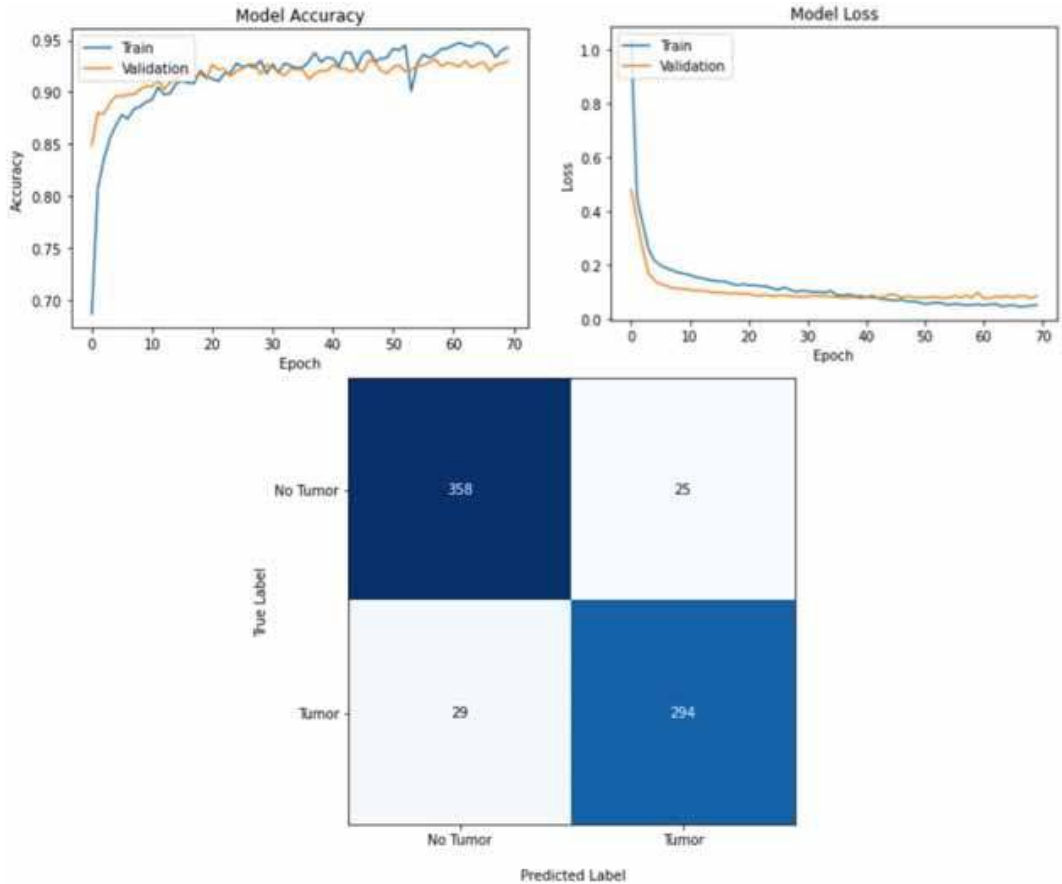


Table 3. Illustrates a report of evaluation metrics

	Precision	Recall (Sensitivity)	F1-score	Specificity	Accuracy	Loss	ROC-AUC Score
CNN	95.60%	94.26%	94.43%	94.01%	95.72%	19.77%	95.61%
VGG19	96.18%	95.33%	95.51%	95.26%	96.27%	11.66%	96.16%
VGG16	95.54%	94.03%	94.01%	93.78%	95.58%	14.14%	95.94%
DenseNet	95.55%	95.51%	95.62%	95.25%	95.53%	19.62%	96.03%
NASNet-A	96.63%	95.75%	95.63%	96.11%	96.65%	11.53%	97.89%
Xception	96.65%	95.86%	95.83%	96.90%	94.93%	20.45%	95.02%

NASNet-A, and DenseNet. Therefore, these models attain better classification accuracy since they respectively achieve 96.65%, 96.27%, 95.72%, 95.58%, and 95.53%.

Besides that, we conducted a comparative study of our proposed approach with other existing brain tumor detection models on grounds of the approach used, a number of MRI & CT Scan images

used in experimentation, methodology, features used for extraction and classification, and percentage accuracy achieved (see Table 4).

Due to the importance of the diagnosis given by the physician, we developed a platform for physicians to help in diagnosing the Brain Tumor (see Figure 14). Hence, timely and prompt disease detection and treatment plan leads to improved quality of life and increased life expectancy in these

Table 4. Comparison of proposed brain tumor detection and classification approach with existing classification methodologies

Author	Dataset	Methodology	Features	Accuracy
Paul et al. 2017	MRI (CE-MRI) images (Brain Tumor)	Fully connected and CNN structure	Deep Features Extraction and Classification	91.43%
Mohsen et al. 2018	MRI images & CT Scan images (Brain Tumor)	Deep Learning Techniques	Discrete Wavelet Transform (DWT) features	96.27%
Abiwinanda et al. 2018	T-1 Weighted CE-MRI images	CNN Technique	Model Based	84.19%
Sajjad et al. 2019	MRI images (Brain Tumor)	VGG-19 CNN Architecture	Model Based	90.67%
Sultan et al. 2019	MRI images (Brain Tumor)	CNN Architecture for multi-classification	Deep Features Extraction and Classification	96.13%
Suganthe et al. 2020	MRI images (Brain Tumor)	CNN and RNN models	Deep Features Extraction and Classification	90.00%
Jaiswal et al. 2020	CT Scan images of COVID-19	Deep transfer learning models (DTL) with DenseNet201	Features Extraction	96.25%
Proposed Approach	MRI and CT Scan images (Brain Tumor)	Deep CNNs Models (VGGNet, Xception and NASNet)	Deep Features Extraction and Classification	96.65%

Figure 14. Brain tumor medical analysis application



patients. By this, the physician will find it friendly to use. He can just log in and can enjoy the services with fast processing and immediate results with high security.

5. CONCLUSION

The medical field is the most sensitive of all the domains ever known, for the simple reason that it deals with humans. Likewise, deep learning was widely applied to several applications and proven to be a powerful machine learning tool for many complex problems as medical imaging. At the present time, detection of brain tumors from MRI & CT scan images is of vital importance for both doctors and patients to decrease the detection time and reduce financial costs. This paper presents an automated approach used to classify the T1-weighted contrast-enhanced MRI images into brain tumor and the no tumor class using five deep learning architectures (a baseline CNN, VGG16, VGG19, DenseNet, Xception, and NASNet-A). In the right context, the experiments were conducted using MRI images open dataset which contains 3,762 images acquired with three kinds of brain tumor, Meningioma, Glioma, and Pituitary tumor. All images were acquired from 285 patients in three planes: Sagittal (1259 images), Axial (1224 images), and Coronal (1279 images) plane, and performances were evaluated using various performance metrics. Likewise, the obtained results show that the CNN, VGGNet, NASNet-A, and DenseNet gave high performance (accuracy is more than 96%) against other architectures cited in this study (accuracy is around 94%). This automated approach can perform binary classification without manual feature extraction with an accuracy of 96.65%. Due to the high performance achieved by this model, we believe that these results help medical experts to make decisions pertinent. Moreover, our approach has been implemented as a simple supportive tool for medical doctors in the detection and classifying of brain tumors and in screening tumor patients in medical oncology services.

For future works, we aim to develop a full system for tumors via deep learning detection, segmentation, and classification with tumor research labs. In addition, the results may be improved using more datasets (big data) that can be added to improve the model performance, more experiments on hyperparameters settings in order to improve the approach, and more sophisticated feature extraction techniques based on deep learning that was developed for the biomedical image. As well, we aim to improve our approach for categorical classification problems such as identification of brain tumor types such as Glioma, Meningioma, and Pituitary or may be used to detect other brain abnormalities. Finally, we plan to improve the result visualization using class mind mapping (Brahami & Matta, 2015) in order to give a better understanding of the result.

REFERENCES

- Abdolmanafi, A., Duong, L., Dahdah, N., Adib, I. R., & Cheriet, F. (2018). Characterization of Coronary Artery Pathological Formations from OCT Imaging using Deep Learning. *Biomedical Optics Express*, 9(10), 4936–4960. doi:10.1364/BOE.9.004936 PMID:30319913
- Abiwinanda, N., Hanif, M., Hesaputra, S. T., Handayani, A., & Mengko, T. R. (2018). Brain Tumor Classification using Convolutional Neural Network. *World Congress on Medical Physics and Biomedical Engineering*, 68(1), 183–189. doi:10.1007/978-981-10-9035-6_33
- Aledhari, M., Joji, S., Hefeida, M., & Saeed, F. (2019). Optimized CNN-based Diagnosis System to Detect the Pneumonia from Chest Radiographs. *Proceeding of the IEEE International Conference on Bioinformatics and Biomedicine (BIBM'19)*, 2405–2412. doi:10.1109/BIBM47256.2019.8983114
- Ali Khan, H., Jue, W., Mushtaq, M., & Mushtaq, M. U. (2020). Brain Tumor Classification in MRI Image using Convolutional Neural Network. *Mathematical Biosciences and Engineering*, 17(5), 6203–6216. doi:10.3934/mbe.2020328 PMID:33120595
- Alqudah, A. M., Alquraan, H., Abu Qasmieh, I., Alqudah, A., & Al-Sharu, W. (2019). Brain Tumor Classification Using Deep Learning Technique - A Comparison between Cropped, Uncropped, and Segmented Lesion Images with Different Sizes. *International Journal of Advanced Trends in Computer Science and Engineering*, 8(6), 3684–3692. doi:10.30534/ijatcse/2019/155862019
- Alqudah, A. M., Alquraan, H., Qasmieh, I. A., Alqudah, A., & Al-Sharu, W. (2019). Brain Tumor Classification Using Deep Learning Technique - A Comparison between Cropped, Uncropped, and Segmented Lesion Images with Different Sizes. *International Journal of Advanced Trends in Computer Science and Engineering*, 8(6), 3684–3691. doi:10.30534/ijatcse/2019/155862019
- Amin, J., Sharif, M., Gul, N., Raza, M., Anjum, M. A., Nisar, M. W., & Bukhari, S. A. C. (2020). Brain Tumor Detection by Using Stacked Autoencoders in Deep Learning. *Journal of Medical Systems*, 44(2), 1–12. doi:10.1007/s10916-019-1483-2 PMID:31848728
- Anitha, R., & Raja, D. S. S. (2018). Development of Computer-Aided Approach for Brain Tumor Detection using Random Forest Classifier. *International Journal of Imaging Systems and Technology*, 28(1), 48–53. doi:10.1002/ima.22255
- Arunnehru, J., Kumar, A., & Verma, J. P. (2020). Early Prediction of Brain Tumor Classification Using Convolution Neural Networks. *Advances in Computational Intelligence, Security and Internet of Things*. doi:10.1007/978-981-15-3666-3_2
- Avşar, E., & Salçin, K. (2019). Detection and Classification of Brain Tumors from MRI Images Using Faster R-CNN. *Tehnički Glasnik*, 13(4), 337–342. doi:10.31803/tg-20190712095507
- Badža, M. M., & Barjaktarović, M. Č. (2020). Classification of Brain Tumors from MRI Images using a Convolutional Neural Network. *Applied Sciences (Basel, Switzerland)*, 10(6), 1–13. doi:10.3390/app10061999
- Brahami, M., & Matta, N. (2015). An Approach to Dynamic Fusion of the Knowledge Maps of an Activities Process: Application on Healthcare. *International Journal of Information Systems in the Service Sector*, 7(4), 1–25. doi:10.4018/IJISSS.2015100101
- Brahami, M., Sabri, M., & Matta, N. (2020). Towards a Model to Improve Boolean Knowledge Mapping by Using Text Mining and Its Applications: Case Study in Healthcare. *International Journal of Information Retrieval Research*, 10(3), 35–65. doi:10.4018/IJIRR.2020070103
- Chen, B., Wang, J., & Chi, Z. (2019). Improved DenseNet with Convolutional Attention Module for Brain Tumor Segmentation. *Proceedings of the Third International Symposium on Image Computing and Digital Medicine (ISICDM'19)*, 22–26. doi:10.1145/3364836.3364841
- Chen, B., Zhao, T., & Liu, J. (2020). Multipath Feature Recalibration DenseNet for Image Classification. *International Journal of Machine Learning and Cybernetics*, 11(9), 1–12. doi:10.1007/s13042-020-01194-4
- Chollet, F. (2017). Xception: Deep learning with Depthwise Separable Convolutions. *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, 1800–1807. doi:10.1109/CVPR.2017.195

- Choudhury, C. L., Mahanty, C., Kumar, R., & Mishra, B. K. (2020). Brain Tumor Detection and Classification Using Convolutional Neural Network and Deep Neural Network. *Proceeding of the International Conference on Computer Science, Engineering and Applications (ICCSEA'2020)*. doi:10.1109/ICCSEA49143.2020.9132874
- Cogan, T., Cogan, M., & Tamil, L. (2019). MAPGI: Accurate Identification of Anatomical Landmarks and Diseased Tissue in Gastrointestinal Tract using Deep Learning. *Computers in Biology and Medicine*, 111(103351), 1–8. doi:10.1016/j.combiomed.2019.103351 PMID:31325742
- Das, S., Aranya, O. F. M. R. R., & Labiba, N. N. (2019). Brain Tumor Classification Using Convolutional Neural Network. *Proceeding of the 1st International Conference on Advances in Science, Engineering and Robotics Technology (ICASERT'2019)*, 1–5. doi:10.1109/ICASERT.2019.8934603
- Deepak, S., & Ameer, P. M. (2019). Brain Tumor Classification using Deep CNN Features via Transfer Learning. *Computers in Biology and Medicine*, 111(103345), 1–9. doi:10.1016/j.combiomed.2019.103345 PMID:31279167
- Deng, C., Wang, G., & Yang, X. (2013). Image Edge Detection Algorithm based on Improved Canny Operator. *Proceeding of the International Conference on Wavelet Analysis and Pattern Recognition (ICWAPR'2013)*, 14–17. doi:10.1109/ICWAPR.2013.6599311
- El Asnaoui, K., & Chawki, Y. (2020). Using X-ray Images and Deep Learning for Automated Detection of Coronavirus Disease. *Journal of Biomolecular Structure & Dynamics*, 38, 1–22. doi:10.1080/07391102.2020.1767212 PMID:32397844
- El Kader Isselmou, A., Xu, G., Zhang, S., Saminu, S., & Javaid, I. (2019). Deep Learning Algorithm for Brain Tumor Detection and Analysis Using MR Brain Images. *Proceedings of the 2019 International Conference on Intelligent Medicine and Health - ICIMH 2019*, 1–10. doi:10.1145/3348416.3348421
- Gadekallu, T. R., Khare, N., Bhattacharya, S., Singh, S., Maddikunta, P. K. R., & Srivastava, G. (2020). Deep Neural Networks to Predict Diabetic Retinopathy. *Journal of Ambient Intelligence and Humanized Computing, Springer-Verlag*, 11(3), 1–14. doi:10.1007/s12652-020-01963-7
- Hieu, N. V., & Hien, N. (2020). Recognition of Plant Species using Deep Convolutional Feature Extraction. *International Journal on Emerging Technologies*, 11(3), 904–910.
- Huang, G., Liu, S., Van der Maaten, L., & Weinberger, K. Q. (2018). Condensenet: An Efficient DenseNet using Learned Group Convolutions. *Proceeding of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, 2752–2761. doi:10.1109/CVPR.2018.00291
- Huang, G., Liu, Z., Van Der Maaten, L., & Weinberger, K. Q. (2017). Densely Connected Convolutional Networks. *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, 4700–4708. doi:10.1109/CVPR.2017.243
- Ismael, M. R., & Abdel-Qader, I. (2018). Brain Tumor Classification via Statistical Features and Back-Propagation Neural Network. *Proceeding of the IEEE International Conference on Electro/Information Technology (EIT'18)*, 252–258. doi:10.1109/EIT.2018.8500308
- Jain, V., & Godara, S. (2017). Analysis of Brain MRI Tumor Detection and Classification using Hybrid Approach. *International Journal of Computer Science & Communication*, 8(2), 42–47.
- Jaiswal, A., Gianchandani, N., Singh, D., Kumar, V., & Kaur, M. (2020). Classification of the COVID-19 Infected Patients using DenseNet201 based Deep Transfer Learning. *Journal of Biomolecular Structure & Dynamics*, 38, 1–8. doi:10.1080/07391102.2020.1788642 PMID:32619398
- Jalali, V., & Kaur, D. (2020). A Study of Classification and Feature Extraction Techniques for Brain Tumor Detection. *International Journal of Multimedia Information Retrieval*, 9(4), 271–290. doi:10.1007/s13735-020-00199-7
- Jinsakul, N., Tsai, C.-F., Tsai, C.-E., & Wu, P. (2019). Enhancement of Deep Learning in Image Classification Performance Using Xception with the Swish Activation Function for Colorectal Polyp Preliminary Screening. *Mathematics*, 7(12), 1–21. doi:10.3390/math7121170
- Jyotiyana, M., & Kesswani, N. (2020). Deep Learning and the Future of Biomedical Image Analysis. *Studies in Big Data*, 68, 329–345. doi:10.1007/978-3-030-33966-1_15

- Kalaiselvi, T., Padmapriya, T., Sriramakrishnan, P., & Priyadharshini, V. (2020). Development of Automatic Glioma Brain Tumor Detection System using Deep Convolutional Neural Networks. *International Journal of Imaging Systems and Technology*, 30(3), 1–13. doi:10.1002/ima.22433
- Kaur, M., & Singh, D. (2020). Fusion of Medical Images using Deep Belief Networks. *Cluster Computing*, 23(2), 1439–1453. doi:10.1007/s10586-019-02999-x
- Khawaldeh, S., Pervaiz, U., Rafiq, A., & Alkhaldeh, R. S. (2018). Noninvasive Grading of Glioma Tumor using Magnetic Resonance Imaging with Convolutional Neural Networks. *Applied Sciences (Basel, Switzerland)*, 8(1), 1–27. doi:10.3390/app8010027
- Kumar, S., Dabas, C., & Godara, S. (2017). Classification of Brain MRI Tumor Images: A Hybrid Approach. *Procedia Computer Science*, 122, 510–517. doi:10.1016/j.procs.2017.11.400
- Leonardo, M. M., Carvalho, T. J., Rezende, E., Zucchi, R., & Faria, F. A. (2018). Deep Feature-Based Classifiers for Fruit Fly Identification (Diptera: Tephritidae). *Proceedings of the 31st SIBGRAPI Conference on Graphics, Patterns and Images (SIBGRAPI'2018)*, 41–47. doi:10.1109/SIBGRAPI.2018.00012
- Li, M., Kuang, L., Xu, S., & Sha, Z. (2019). Brain Tumor Detection Based on Multimodal Information Fusion and Convolutional Neural Network. *IEEE Access: Practical Innovations, Open Solutions*, 7, 180134–180146. doi:10.1109/ACCESS.2019.2958370
- Li, X., Shen, X., Zhou, Y., Wang, X., & Li, T-Q. (2020). Classification of Breast Cancer Histopathological Images Using Interleaved DenseNet with SENet (IDSNet). *PLoS One*, 15(5), 1–13. 10.1371/journal.pone.0232127
- Litjens, G., Kooi, T., Bejnordi, B. E., Setio, A. A. A., Ciompi, F., Ghafoorian, M., Van Der Laak, J. A., Van Ginneken, B., & Sánchez, C. I. (2017). A Survey on Deep Learning in Medical Image Analysis. *Medical Image Analysis*, 42, 60–88. doi:10.1016/j.media.2017.07.005 PMID:28778026
- Mahamkali, N., & Ayyasamy, V. (2015). OpenCV for Computer Vision Applications. *Proceeding of National Conference on Big Data and Cloud Computing (NCBDC'15)*, 52–56.
- Mateen, M., Wen, J., Song, S., & Huang, Z. (2019). Fundus Image Classification using VGG-19 Architecture with PCA and SVD. *Symmetry*, 11(1), 1–12. doi:10.3390/sym11010001
- Militante, S. V., & Sibbaluca, B. G. (2020). Pneumonia Detection Using Convolutional Neural Networks. *International Journal of Scientific & Technology Research*, 9(4), 1332–1337. doi:10.1109/ICSSIT48917.2020.9214289
- Mittal, A., & Kumar, D. (2019). AiCNNs (Artificially-integrated Convolutional Neural Networks) for Brain Tumor Prediction. *EAI Endorsed Transactions on Pervasive Health and Technology*, 5(17), 1–18. doi:10.4108/eai.12-2-2019.161976
- Mohsen, H., El-Dahshan, E. A., El-Horbaty, E. M., & Salem, A.-B. M. (2018). Classification using Deep Learning Neural Networks for Brain Tumors. *Future Computing and Informatics Journal*, 3(1), 68–71. doi:10.1016/j.fcij.2017.12.001
- Özyurt, F., Sert, E., Avci, E., & Dogantekin, E. (2019). Brain Tumor Detection based on Convolutional Neural Network with Neutrosophic Expert Maximum Fuzzy Sure Entropy. *Measurement*, 147(106830), 1–9. doi:10.1016/j.measurement.2019.07.058
- Paul, J. S., Plassard, A. J., Landman, B. A., & Fabbri, D. (2017). Deep learning for Brain Tumor Classification. *Proceedings of Medical Imaging 2017: Biomedical Applications in Molecular, Structural, and Functional Imaging*, 10137, 1–16. doi:10.1117/12.2254195
- Pratt, H., Coenen, F., Broadbent, D. M., Harding, S. P., & Zheng, C. Y. (2016). Convolutional Neural Networks for Diabetic Retinopathy. *Procedia Computer Science*, 90, 200–205. doi:10.1016/j.procs.2016.07.014
- Radhika, K., Devika, K., Aswathi, T., Sreevidya, P., Sowmya, V., & Soman, K. P. (2019). Performance Analysis of NASNet on Unconstrained Ear Recognition. In *Nature Inspired Computing for Data Science*. Springer. doi:10.1007/978-3-030-33820-6_3
- Ramadevi, R., Marshiana, D., Bestley, J. S., & Jamuna Rani, D. (2020). Recurrent Neural Network (RNN) Analysis for Brain Tumor Classification using Decision Tree Classifiers. *Journal of Critical Reviews*, 7(6), 2202–2206. doi:10.31838/jcr.07.6.344

- Al ayoubi, W., Shalash, W. M., & Abulkhair, M. F. (2020). Diabetic Retinopathy Detection Through Deep Learning Techniques: A Review. *Informatics in Medicine Unlocked*, 20, 1–11. doi:10.1016/j.imu.2020.100377
- Ruba, T., Tamilselvi, R., Beham, M. P., & Aparna, N. (2020). Accurate Classification and Detection of Brain Cancer Cells in MRI and CT Images using Nano Contrast Agents. *Biomedical & Pharmacology Journal*, 13(3), 1227–1237. doi:10.13005/bpj/1991
- Saikia, A. R., Bora, K., Mahanta, L. B., & Das, A. K. (2019). Comparative Assessment of CNN Architectures for Classification of Breast FNAC Images. *Tissue & Cell*, 57, 8–14. doi:10.1016/j.tice.2019.02.001 PMID:30947968
- Sajjad, M., Khan, S., Muhammad, K., Wu, W., Ullah, A., & Baik, S. W. (2019). Multi-Grade Brain Tumor Classification using Deep CNN with Extensive Data Augmentation. *Journal of Computational Science*, 30, 174–182. doi:10.1016/j.jocs.2018.12.003
- Samadi, F., Akbarizadeh, G., & Kaabi, H. (2019). Change Detection in SAR Images using Deep Belief Network: A New Training Approach based on Morphological Images. *IET Image Processing*, 13(12), 2255–2264. doi:10.1049/iet-ipr.2018.6248
- Sarhan, A. M. (2020). Detection and Classification of Brain Tumor in MRI Images Using Wavelet Transform and Convolutional Neural Network. *Journal of Advances in Medicine and Medical Research*, 32(12), 15–26. doi:10.9734/jammr/2020/v32i1230539
- Sasikala, M., & Kumaravel, N. (2008). A Wavelet-Based Optimal Texture Feature Set for Classification of Brain Tumors. *Journal of Medical Engineering & Technology*, 32(3), 198–205. doi:10.1080/03091900701455524 PMID:18432467
- Saxen, F., Werner, P., Handrich, S., Othman, E., Dinges, L., & Al-Hamadi, A. (2019). Face Attribute Detection with MobileNetV2 and NasNet-Mobile. *Proceeding of the 11th International Symposium on Image and Signal Processing and Analysis (ISPA)*, 176–180. doi:10.1109/ISPA.2019.8868585
- Seetha, J., & Raja, S. S. (2018). Brain Tumor Classification Using Convolutional Neural Networks. *Biomedical & Pharmacology Journal*, 11(3), 1457–1461. doi:10.13005/bpj/1511
- Selvakumar, P., & Hariganesh, S. (2016). The performance Analysis of Edge Detection Algorithms for Image Processing. *Proceeding of the International Conference on Computing Technologies and Intelligent Data Engineering (ICCTIDE'16)*, 1–5. doi:10.1109/ICCTIDE.2016.7725371
- Setiawan, W., & Damayanti, F. (2020). Layers Modification of Convolutional Neural Network for Pneumonia Detection. *Journal of Physics: Conference Series*, 1477(052055), 1–9. doi:10.1088/1742-6596/1477/5/052055
- Siar, M., & Teshnehlal, M. (2019). Brain Tumor Detection Using Deep Neural Network and Machine Learning Algorithm. *Proceeding of the 9th International Conference on Computer and Knowledge Engineering (ICCKE 2019)*, 1–7. doi:10.1109/ICCKE48569.2019.8964846
- Simonyan, K., & Zisserman, A. (2015). Very Deep Convolutional Networks for Large-Scale Image Recognition. *Proceedings of the International Conference on Learning Representations*, 1–14.
- Suganthe, R. C., Revathi, G., Monisha, S., & Pavithran, R. (2020). Deep Learning based Brain Tumor Classification using Magnetic Resonance Imaging. *Journal of Critical Reviews*, 7(9), 347–350. doi:10.31838/jcr.07.09.74
- Suganthi, S. R. L., Sneha, U. K., & Shwetha, S. (2020). Diabetic Retinopathy Classification Using Machine Learning Techniques. *International Journal of Engineering Trends and Technology*, 68(1), 51–56. doi:10.14445/22315381/IJETT-V68I1P207
- Sultan, H. H., Salem, N. M., & Al-Atabany, W. (2019). Multi-Classification of Brain Tumor Images Using Deep Neural Network. *IEEE Access (Special Section on Deep Learning for Computer-aided Medical Diagnosis)*, 7, 69215–69227. doi:10.1109/ACCESS.2019.2919122
- Szegedy, C., Liu, W., Jia, Y., Sermanet, P., Reed, S., & Anguelov, D. (2015). Going Deeper with Convolutions. *Proceedings of the IEEE conference on Computer Vision and Pattern Recognition*, 1–9. doi:10.1109/CVPR.2015.7298594

- Ucuzal, H., Yaşar, Ş., & Çolak, C. (2019). Classification of Brain Tumor Types by Deep Learning with Convolutional Neural Network on Magnetic Resonance Images using a Developed Web-Based Interface. *3rd International Symposium on Multidisciplinary Studies and Innovative Technologies (ISMSIT'19)*, 1–5. doi:10.1109/ISMSIT.2019.8932761
- Wang, C., Chen, D., Hao, L., Liu, X., Zeng, Y., Chen, J., & Zhang, G. (2019). Pulmonary Image Classification Based on Inception-v3 Transfer Learning Model. *IEEE Access: Practical Innovations, Open Solutions*, 7, 146533–146541. doi:10.1109/ACCESS.2019.2946000
- Zabalza, J., Ren, J., Zheng, J., Zhao, H., Qing, C., Yang, Z., Du, P., & Marshall, S. (2016). Novel Segmented Stacked Autoencoder for Effective Dimensionality Reduction and Feature Extraction in Hyperspectral Imaging. *Neurocomputing*, 185, 1–10. doi:10.1016/j.neucom.2015.11.044
- Zhang, Q., Wang, H., Yoon, S. W., Won, D., & Srihari, K. (2019). Lung Nodule Diagnosis on 3D Computed Tomography Images Using Deep Convolutional Neural Networks. *Procedia Manufacturing*, 39, 363–370. doi:10.1016/j.promfg.2020.01.375
- Zoph, B., Vasudevan, V., Shlens, J., & Le, Q. V. (2018). Learning Transferable Architectures for Scalable Image Recognition. *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR'2018)*, 1–14. doi:10.1109/CVPR.2018.00907