Brain Tumor Detection using MRI Images and Convolutional Neural Network

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***Abstract*—A brain tumor is the cause of abnormal growth of cells in the brain. Magnetic resonance imaging (MRI) is the most practical method for detecting brain tumors. Through these MRIs, doctors analyze and identify abnormal tissue growth and can confirm whether the brain is affected by a tumor or not. Today, with the emergence of artificial intelligence techniques, the detection of brain tumors is done by applying the techniques and algorithms of machine learning and deep learning. The advantages of the application of these algorithms are the quick prediction of brain tumors, fewer errors, and greater precision, which help in decision-making and in choosing the most appropriate treatment for patients. In the proposed work, a convolution neural network (CNN) is applied with the aim of detecting the presence of a brain tumor and its performance is analyzed. The main purpose of this article is to adopt the approach of convolutional neural networks as a machine learning technique to perform brain tumor detection and classification. Based on training and testing results, the pre-trained architecture model reaches 96% in precision and classification accuracy rates. For the given dataset, CNN proves to be the better technique for predicting the presence of brain tumors.**

***Keywords*—Brain tumor; machine learning; convolutional neural network; MRI images**

I. Introduction

A brain tumor is one of the major health problems related to human brain abnormalities [1]–[3]. It is a collection or a combination of unnatural tissue in the brain [4]. It usually occurs due to the fast growth of abnormal or damaged cells and created lamps of tissue in the brain. To find out whether the brain contains a tumor or not, MRI images are the first step in medical diagnosis [5], followed by manual analysis by an expert who looks for lesions in the brain. MRI is the most common and widely used technique for brain tumor detection and brain imaging as it proves better results especially when it It's about detecting differences between body tissues [6]. Compared to the computerized tomography (CT) scan and other techniques, MRI images are safer and can produce higher contrast images of brains [4]. Likewise, due to the high resolution of the images provided by MRI scans, a lot of information about the brain structure and the brain tissues are easily provided, this has considerable advantages in the field of image analysis [7], [8]. There are four standard sequences used in MRI scans modalities: The T1-weighted MRI (T1), T2-weighted MRI (T2), T1-weighted contrast-enhanced MRI (T1-CE), and FLAIR [9], [10]. In general, the T1W contrast-enhanced is the most commonly used modality, because it allows an easy annotation of the healthy tissues [11], [12].

Deep learning is a type of artificial intelligence derived from machine learning. Unlike programming where the content to execute the predetermined rules, here the machine can learn by itself, relying on a network of artificial neurons inspired by the human brain. Due to its higher performance in several fields as screening medical face mask [13], image description and a lot of challenges, the exploitation of DL technique in the medical image for classification, detection, and segmentation is highly encouraged [14]. In fact, various human diseases could be detected using such techniques, including COVID-19 [15]–[19], Parkinson's disease [20], breast cancer [21], diabetes diseases [22], medical image segmentation [23], and heart disease prediction [24]–[26]. A vast range of different scientific topics has developed because of advances in AI [27]–[35].

Convolutional neural networks (CNNs) are deep neural networks that have the capability to classify and segment images [36], [37]. CNN architectures for classification and segmentation include a variety of different layers with specific purposes, such as a convolutional layer, pooling layer, fully connected layers, dropout layers, etc. Recent studies on deep learning with convolutional neural networks have achieved excellent performance that is almost at the same level of performance of practicing radiologists [38], [39].

In recent years, CNN has been used in medical image segmentation. It has achieved great success in the field and auxiliary diagnosis. Compared to the traditional methods, network architecture gives to CNN algorithms the ability to learn complicated features from images [40], also CNNs are the top ranked and most popular algorithms used in computer vision, and actively contribute in this specific area of imaging due to their capability of detecting significant features, more particularly when it comes to medical imaging in which to processing difficult images with several details is needed, indeed CNN-based approaches are placed in the well-used leader board of the many image understanding challenges, especially Brain Tumor segmentation (BRATS), the biomedical challenge of Image Computing and Computer Assisted Intervention (MICCAI), ISBI (International Symposium on Biomedical Imaging), and IPMI (Information Processing in Medical Imaging) [41]. In this context, an application of a machine learning algorithm based on convolutional neural networks for the detection and classification of brain tumors is proposed.

The remainder of this paper is organized as follows: Section II presents a brief review of related works. Section III explains our proposed methodology and the machine learning algorithms implementation. Some performance evaluation techniques are presented in Section IV. Results and discussion are given in Section V. Section VI presents a conclusion with a discussion regarding the future works.

II. Related Work

In the research published in recent years relating to the segmentation of brain tumors, there is two branches of machine learning methods: Supervised learning and unsupervised learning .The difference between these models is simple, in supervised learning human intervention is needed at least to label the data appropriately, the machine learning model learns through iterating the operations of prediction of the labeled data communicated as input and improves the results by adjusting the response each time [42].

In unsupervised method-based segmentation, the human touch always needed for validating output variables [43], among its techniques there is the support vector machine (SVM) method and the fuzzy clustering approach are used. These methods have achieved the best performance when it comes to predicting or detecting a tumor, on the other hand the performance obtained is a little weak when the border between the normal tissue and the tumor area is blurred. Also, the extraction process usually takes time because the extraction algorithms have to extract a lot of information and details related to these edges and a lot of essential features.

Segmentation is the process of separating the image into distinct regions and is one of the most vital and demanding aspects of computer-aided clinical diagnostic tools. Although brain tumor segmentation is primarily done manually, it is very time consuming and the segmentation is subject to variations both between observers [44]. Therefore, an automatic and robust brain tumor segmentation will have a significant impact on brain tumor diagnosis and treatment.

Convolutional neural networks (CNN) differ from other machine learning techniques in the fact that the segmentation is done automatically and does not require the intervention of an expert as well as the feature extraction which is done with precision, on the other hand there are several parameters to be learned by a neural network (CNN) which results in expensive computation time and requires process graphics units (GPU) to train the model [45]. The role of a CNN network consists of two main tasks: feature extraction and data classification, the convolution and pooling layer are responsible for feature extraction, fully connected layers help to achieve the classification task [46]. In [47], the authors presented a convolutional neural network for brain tumor detection, 2 CNNs models were made as a comparison to find the best model for classification. The first model includes one convolution layer, the second includes two layers. This study showed that increasing convolutional layers improves the model performances and resulted in accuracy of 93% and a loss value of 0,23.

Among the techniques for using artificial neural networks, there is also transfer learning, the principle is simple, instead of designing a new CNN model and training it from scratch, existing architectures which are well trained on large dataset and which have demonstrated their performance are used, this makes it possible to use each transfer learning model and adapt it to the desired stain according to the nature of the task and the characteristic to be detected or classified [48].

Due to their ability to self-learn without the intervention of an expert, CNN models based on Transfer learning techniques have achieved excellent performance, the use of the weight sharing technique provides an adequate network and allows to automatically detect the tumor through the MRI images [49].

A research published in [50], Aimed boosting accuracy by the use of transfer learning strategy they implemented three transfer learning approaches using pre-trained CNN models, namely: VGG19 ,Inception V3 and MobileNet V2, They obtained respectively an accuracy rate of 88,22%, 91% and 92%. The authors concluded that the MobilnetV2 is the most efficient Model compared to the other models.

Using the ANN approach, Authors in [51],worked on two classes named benign tumors and malignant tumors, they started by preprocessing the images with the filters, then applied the average color moment technique on the images to extract the characteristics. After the transmission of these characteristic maps to the ANN, the classification was made with an accuracy rate of 91.8%.

A study published in [52], the model uses the histogram statistical equalization technique which consists in applying a transformation to each pixel of the image by calculating several statistical characteristics such as the average sum, the variance, the entropy, the dissimilarity, this model is therefore used for low-grade and high-grade class images of cervical glioma. The results obtained from the proposed method of accuracy, sensitivity and specificity reached 83.6% accuracy, 80.88% sensitivity and 86.84% specificity.

One of the techniques used in the detection of characteristics and classification of images consists in combining the concept of deep learning, CNNs, with other methods of preprocessing, these techniques include data augmentation, edge detection, genetic algorithm (GA), discrete wavelet transform (DWT) and principal component analysis (PCA). Authors in [53] have combined the two techniques of data augmentation and edge detection, data augmentation makes it possible to increase the amount of data artificially, other images are generated from the first images provided. The edge detection will allow finding the region of interest (ROI), the extraction of the characteristics is done thanks to a simple CNN model. They obtained 89% classification accuracy.

The results of these searches are classified in Table I, highlighting the classification model with a description of the chosen preprocessing technique, as well as the scores obtained based on the metrics used in each work.

TABLE I. SUMMURY OF SOME RELATED WORKS

Study	Dataset	Processing technique	Classifier	Result
[47]	Kaggle Dataset	Data Augmentation	CNN	Ac=93% Loss = 0,23
[50]	Brain Tumor Dataset	Transfer learning	VGG19	Ac=88% F1score=88.18%
			Inception V3	Ac=91% F1score=90.98%
			MobileNetV2	Ac=88% F1score=88.18%
[51]	Harvard Medical School Website Dataset	Noise Filtering Average color Moment	ANN	Ac=91.8%
[52]	LGG Flair MRI images	ROI feature extraction	Random forest	Ac=83.6% Sensitivity=80.88% Specificity=86.84%

III. MATERIALS AND METHODOLOGY

A. Global Overview on Proposed Detection Model

To complete the image classification task using machine leaning techniques such as conventional neural networks, these steps must be followed in sequential order: data extraction, data preprocessing, Feature selection, learning and classification Considering the common standard process of machine learning, our first step concerned the collection of data, the data is retrieved from Kaggle datasets of Brain MRI Images [54] The data folder concerns a set of 3000 MRI data images classified according to the presence or not of the tumor and labelled (Yes tumor and No tumor). In the development of our CNN architecture, we took into consideration several criteria to avoid limitations that are not suitable for our case study. One of the major limitations is the limited data, medical images are difficult to retrieve for privacy reasons and other several reasons, to have a robust model a large number of medical images is needed; there is currently some techniques which can limit this problem like Data augmentation. Several technical considerations are also considered. For example, the use of complicated transforms which can disturb the learning process is avoided, according to some research results, it was found that complicated transforms are not always better than simple ones because they can introduce some noise in the features and disturbs the learning process.

For the data pre-processing step, image partitioning techniques as well as the normalization of their size are involved. After this stage, the CNN is defined and implemented model as an algorithm for brain tumor detection. Then the input data is divided into training, validation, and test data. Having defined and compiled the model, evaluation metrics algorithm is defined in order to evaluate the model performance, then some predictions are made by executing the model on some MRI images. Fig. 1, describes the CNN architecture model implemented in our work, Layers definitions and roles are described in Subsection D.

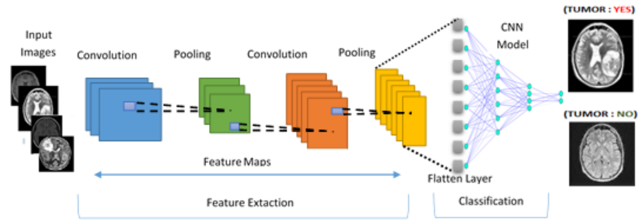

Fig. 1. Architecture of the Proposed Model.

B. Dataset Collection and Preprocessing

This section present some information about the database used, in fact a publicly accessible Kaggle database [54] is used . This database is composed of three folders, the first folder contains 1500 MRI scans presenting a brain tumor, the second folder contains 1500 MRI of healthy brains, in addition there is a folder containing some unlabeled MRI scans for testing purpose, the latter is not used, because another approach for the test data is planned. Thus, the final database obtained is built on the first 2 files and consists of 3000 images as input data distributed as follows: 1500 images with tumor and 1500 images without tumor. Fig. 2 illustrates the sample images of the dataset.

MRI images are not necessarily clear, sometimes visualization defects the quality of the image, these defects result from poor quality of image distortion and resolution, and could lead to a false analysis, and affect patient treatment options. Therefore, several preprocessing techniques can be introduced to make the images more robust and more usable by the neural network, the most common techniques concern the aspect ratio: uniform image size, dimensionality reduction, and data augmentation. The images have been resized to (224, 224, 3) = (image width, image height, number of channels) to facilitate the learning process.

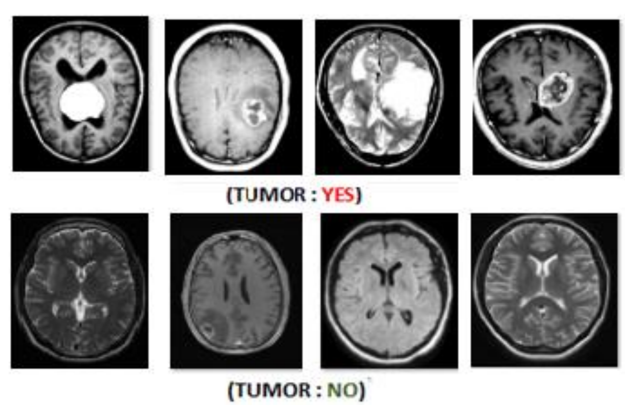

Fig. 2. Samples Images for Brain Tumor Dataset.

Input image will be processed into the first pre-process which is the process of wrapping and cropping, it consists of the removal of unwanted outer areas and some of the peripheral areas from a photographic or illustrated image, after that the database is divided into training, testing, and validation sets with an 80:10:10 ratio. The 3000 images dataset is split into training, testing, and validation sets of 2398, 300, and 300 images respectively, and then all the images are processed in the collection into an array. The last step is the coding when the tagged data are transformed into a numerical label so that they may be interpreted and analyzed. Fig. 3 describes the flowchart followed by the model from input images and preprocessing to the CNN model algorithm and the prediction of healthy and unhealthy brains.

C. Machine Learning Algorithm for Classification

Classification algorithms classify brain tumors into respective categories. It has an essential task in interpreting, extracting features, analyzing, and interpreting images in many applications. The CNN model must first extract features from each image before learning how to distinguish between the images provided to it. In this research, a CNN model with several layers is proposed; four convolution layers, three Maxpooling layers, one flatten layer, and six dense layers. In general, the core building blocks of convolutional neural networks are convolutional layers, activation functions, pooling, and fully connected layers. To improve the results in the output of the CNN network, the input data must go through several stages. The main objective is to correct the adjustments, allowing the CNN to recognize the inaccurate features in the images. The over-fitting correction is done through four techniques: data augmentation, dropout, batch normalization, and pooling. These process steps represent the hidden layers of the neural network and are used to perform the CNN model. Some definitions and roles of these layers are described below.

To build our proposed model, the first required Conv2D parameter is the number of filters that the convolutional layer will learn. In the proposed architecture, the input is an image of (224*224*3) size, 20 filters are implemented with a kernel size of (4*4). The same parameters are kept for the other two convolution layers with a reduction in kernel size to (2*2). After each convolution operation, the Maxpooling layers with successive calls to the dense layers and the RELU activation function are introduced. In the dense layers, the unit's values are respectively (1024, 512, 256, 128, 64). Finally, the Softmax function is used as the activation function in the output layer. There are 14 547 134 parameters in total. All these details are described in Fig. 4, which illustrates the architecture of our proposed model.

- Convolutional layer Is the main layer of a convolutional neural network, and composed of a filter for the input data, a feature map and a feature detector known as the CNN core whose role is the detection and the extracting of the features in the image, such as edges and colors [55].

- The Pooling layer Thanks to the spatial variance property, Maxpooling teaches the neural network that it is the same characteristic to be detected despite the differences that may exist between the images of the same object, namely the way in which the images are presented, dimensions, textures. This can only be done after having a ready features map.

- Flatten Layer represents the input layer for the artificial neural network, this phase consists of grouping an entity map in a column, and hence the name "Flattening", this allows to have a large data vector compatible with the neural network input.

- Max-Pooling Layer: Maxpooling is used to extract the most relevant features in the images, in the original entity map, the end is always the maximum value, and unnecessary details in each image have are removed to allow network of neurons to do the job efficiently.

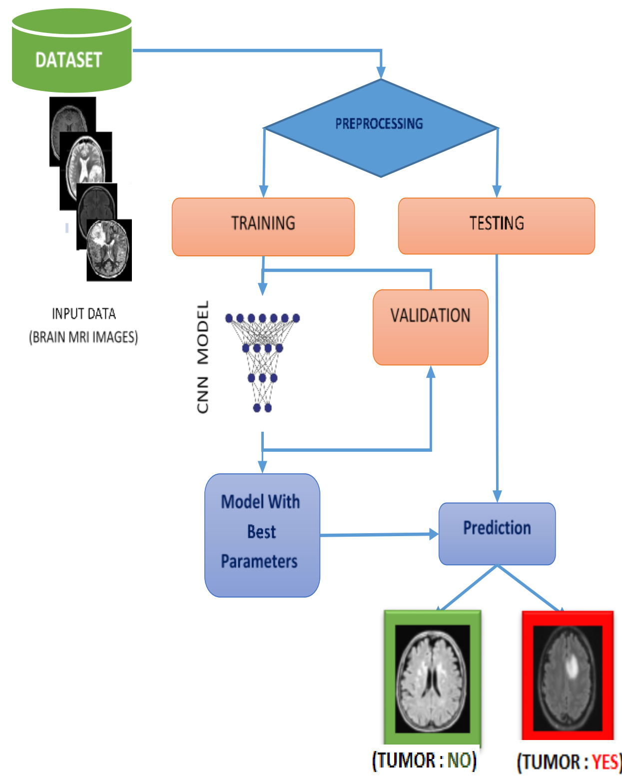

Fig. 3. The Flowchart to Implementation of the CNN Model.

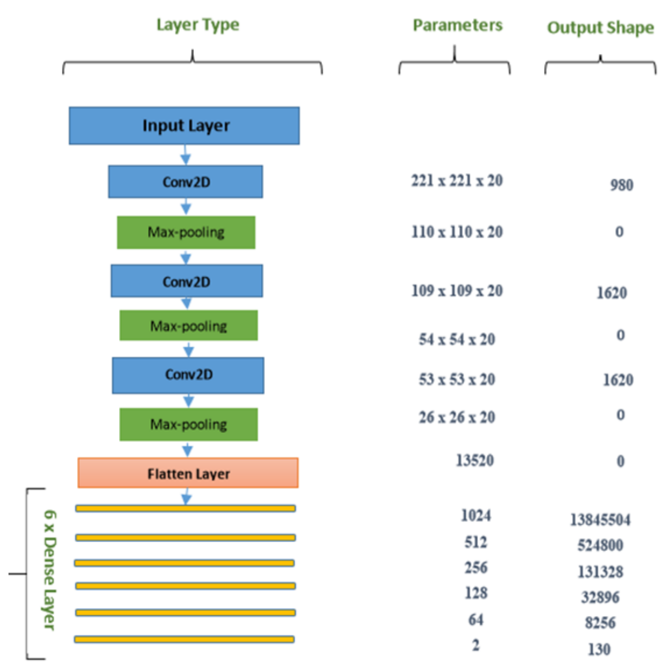

Fig. 4. The Proposed Architecture for CNN Model.

IV. Performance Evaluation Metrics

Several standard evaluation metrics are generally introduced to evaluate the performance of the system, among these metrics there is Accuracy, Precision, Recall, AUC, F1_score, confusion matrix and Receiver Operating Characteristic curve (ROC). The principle of metrics and their mathematical calculation formula is detailed below.

- Confusion Matrix

A confusion matrix is represented by a two-dimensional table which summarizes the results of the predictions of the classification carried out and allows to compare between the correct and false results of the prediction, which allows to see at what point a model can be confused in its predictions and to measure these performances. In a confounding matrix the results are classified into four main categories: true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN). The four elements of the confusion matrix are shown in Table II.

TABLE II. Elements of the Confusion Matrix

Element	**Description**
TP	Images containing the tumor and correctly classified.
NP	Images not containing the tumor and correctly classified.
FP	CNN classifies images as containing tumors but that does not contain any tumor.
FN	CNN classifies images as not containing any tumor but are containing a tumor.

- Loss Function

Loss function is a function that evaluates the difference between the predictions made by the neural network and the actual values of the observations used during learning. The more the result of this function is minimized, the more the neural network performs. Its minimization, reducing to a minimum the difference between the predicted value and the actual value for a given observation, is done by adjusting the different weights of the neural network.

V. Results and Discussion

Several standard evaluation metrics are generally introduced to evaluate the performance of the system, among these metrics there is Accuracy, Precision, Recall, AUC, F1_score, confusion matrix and Receiver Operating Characteristic curve (ROC).

A. Training Results

The CNN model is trained using a notebook from the open Google Colab platform which allows to take full advantage of popular Python libraries like TensorFlow and Keras. Colab notebooks run this code on Google's cloud servers and put in our service the power of Tesla K80 GPU with 12 GB of GDDR5 VRAM, increasing performance and reducing training time considering the large number of parameters to train with the proposed CNN model .in addition this platform had an Intel Xeon Processor with two cores running at 2.20 GHz, and 13 GB of RAM. Fig. 5 and Fig. 6 show the evolution of the accuracy and loss curve during the two training and validation periods.

From the plot of Accuracy curves in Fig. 5 which represents the graph evolution during the training period and the validation period, it is clearly seen that the training accuracy is higher than the validation accuracy; the same for the loss curve in Fig. 6, the training curve is above the validation curve which leads to the conclusion that the proposed CNN model has no overfitting issue.

B. Testing Results

The performance of the proposed methodology was evaluated by the measures of precision, specificity, accuracy and, above all, the ROC curve for two classes (normal and abnormal brains) and compared to the performance of other classifiers, the metrics mathematical equations are detailed below.

$$Specificity = \frac{TN}{TN+FP} \tag{1}$$

$$Sensivity = \frac{TP}{FN+TP} \tag{2}$$

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{3}$$

$$Precision = \frac{TP}{TP+FP} \tag{4}$$

$$F1-Score = 2 * \frac{Precision * Sensivity}{Precision+Sensivity} \tag{5}$$

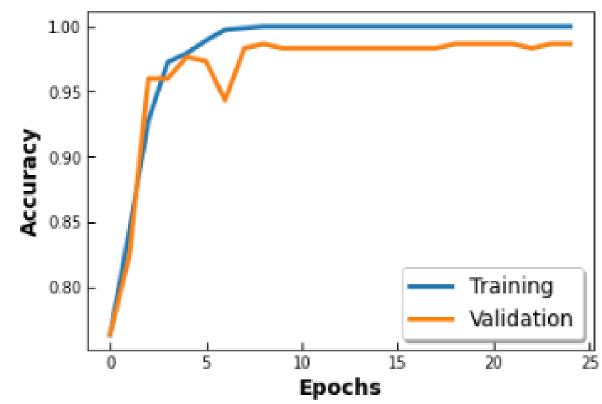

Fig. 5. Accuracy Curve of the Proposed Model.

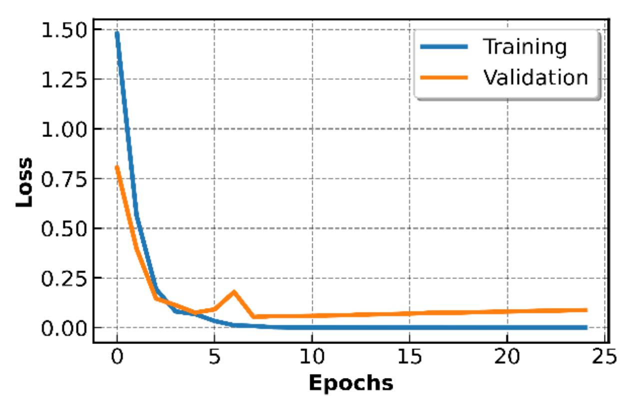

Fig. 6. Loss Curve of the Proposed Model.

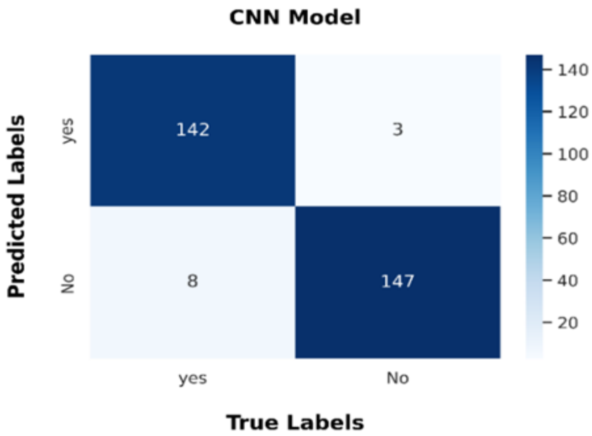

Fig. 7. Confusion Matrix of the Proposed Model.

According to the results of the values obtained by the confusion matrix in Fig. 7, it's shown that 142 positive cases of brain tumors from 300 were correctly classified by the model and 147 Non-tumorous brain images were correctly classified as belonging to the negative class by the model. The TP, TN, FP and FN values emerged by the confusion matrix are then used by the code for the calculations of the Loss Metrics accuracy, as well as the precision values and sensitivity. The results of the evaluation metrics are provided in Table II.

Another way to visualize the sensitivity and specificity of the model is by creating a ROC curve, which is a plot that displays the sensitivity and specificity of a logistic regression model. The AUC ROC equals the probability of having a randomly chosen "true" rating greater than a randomly chosen "false" rating. In the case of an ideal classification, the AUC ROC value is equal to 1, for a value of 0.5 (case of the diagonal line on the curve) this explains that the classifier only guesses [56].The plot of the ROC curve in Fig. 8 indicates that the highest area is under the curve with a percentage of 96%, which means that the CNN model correctly classifies the images into their categories. Table III report all the performance evaluation metrics of the proposed model.

C. Discussion

Our experimental results demonstrate that the proposed CNN model converges better than the ANN approach, the Random Forest classifier, Transfer learning algorithms, and other CNN models. As shown in Table IV, the proposed model achieved the best accuracy rate of 96% and the best F1-Score of 96.5% with a precision of 98%. These values are high and well ranked compared to the results obtained by the other models already mentioned. Table IV compares the different models and allows us to conclude that our model is the best ranked in terms of accuracy.

Through the analysis of the accuracy and loss curves during the two periods of training and validation, the graph proves that the model has no overfitting issues and returns an average loss value of 0.28, which means that the model is doing well in predicting tumor health and unhealthy brains. The ROC curves show that our proposed CNN model is a reliable system for the detection and classification of brain tumors.

TABLE III. PERFORMANCE EVALUATION OF THE PROPOSED MODEL BASED ON SCORING METRICS

Evaluating Metrics	**Performance Score**
Loss	0,2896
Accuracy	96.33%
Precision	97.93%
Sensitivity	95%
F1–Score	96.44%
Specificity	75.72%

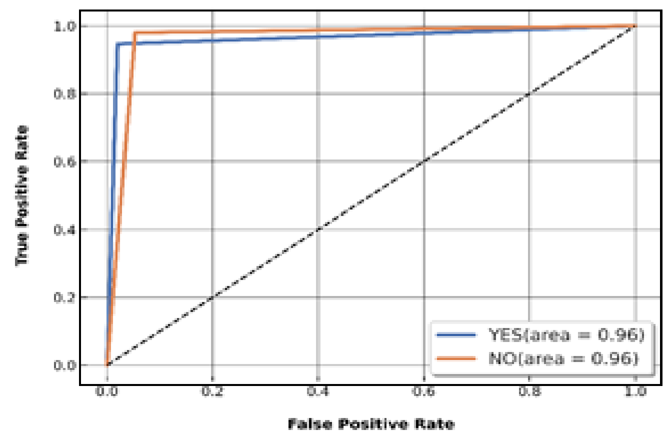

Fig. 8. ROC Curve of the Proposed Model.

In addition to the research work, the performance of the proposed model has been compared with the results obtained by other studies focused on the same case study of brain tumors. For example, the authors in [57] proposed a 7-layered 2 CNN; they obtained an accuracy of 95%. Another technique proposed in [58] using cascaded CNN for segmentation, Vgg19 and data augmentation approach, obtained an accuracy value of 86.7%, 78.9%, and 95.6% for AD, lesion, and normal class. Authors in [59] used the support vector machine and 82% accuracy was obtained. Compared to these models, our proposed CNN model remains the best ranked in terms of accuracy, whether for those adopting the same convolutional neural network architectures or those using other segmentation techniques.

TABLE IV. COMPARATIVE SUMMURY OF DIFFFERENT CLASSIFIERS FOR SEGMENTATION ACCURACY

Study	**Method/Classifier**	**Accuracy Rate**
[47]	CNN	93%
[50]	MobileNet V2	92%
	Inception V3	91%
	VGG19	88%
[51]	ANN	91,8%
[52]	Radom forest with ROI process	83,6%
	Radom forest without ROI process	87,6%
Proposed Study	**CNN Model**	**96%**

VI. Conclusion and Persepectives

In this paper, a CNN model for the segmentation of MRI images of brain tumors into two classes with tumors and without tumors is proposed. The proposed method for detection and classification of MRI images provided the best accuracy achieved by other neural network models. These medical images have undergone preprocessing and resizing before being processed by the convolutional neural network. Training and validation were performed on 3,000 high-resolution MRI images. The performance of the CNN model is evaluated using several evaluation metrics. Through this experiment, the proposed model is found to outperform other CNN models in several performance aspects, including 96% overall accuracy and 98% accuracy. Finally, for the given dataset, CNN proves to be the best technique to predict the presence of brain tumors. Based on performance evaluation metrics and curve analysis, this work demonstrates the ability of a CNN network to detect and classify tumors in the brain with a higher accuracy rate. This work has presented the architecture of convolutional neural networks and has demonstrated their performance when applied to an adjusted database of brain images. In future work, the architecture of the proposed model could be perfected, and its reliability and performance will be evaluated with a large database.

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