Deep Learning Approach to Classify Brain Tumors from Magnetic Resonance Imaging Images

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Abstract—**Brain tumor is one of the primary causes of mortality all over the globe, and it poses as one of the most complicated tasks in contemporary medicine when it comes to its proper diagnosis and classification into its many different types. Both benign and malignant tumors affect the lives of their respective patients as they may lead to mortality, or in the least many related difficulties and sicknesses. Typically, MRI (Magnetic Resonance Imaging) is used as a diagnostic technique where experts manually analyze the images to detect tumors. On the other hand, advanced technologies such as deep learning can step into the light and aid in the diagnosis and classification procedures in a much more time-efficient and precise manner. MRI images are an effective input that can be used in deep learning technologies such as CNN in order to accurately detect brain tumors. In this study, VGG-16, ResNet50, and Xception were trained on a Kaggle dataset consisting of brain tumor MRI images. The performance of the models was evaluated where it was found that brain tumors can be efficiently detected from MRI images with high accuracy and precision using VGG-16, ResNet50, and Xception. The highest performing model was the proposed XCeption model with perfect scores.**

Keywords—Deep learning; brain tumor; MRI images; Convolutional Neural Networks (CNN); Xception; VGG-16; ResNet50

I. Introduction

In the last few decades, as science and technology prospered, several groundbreaking inventions and essential algorithms have been developed with the help of machine and deep learning techniques and computer science systems. Essentially, deep learning is now involved in all the major aspects of human life such as marketing, banks, education, as well as other smart technologies such as drones and self-driving cars, thus it is only normal for it to be also integrated into the healthcare section, especially for identifying human morbidities [1].

The brain is one of the most complicated organs in the human body and it basically controls the most important tasks that would keep the human alive. For instance, the brain is responsible for vision, controlling emotions, breathing, memory, regulating temperature, and motor skills, among many other roles [2]. One of the diseases that interfere with the proper functions of the brain is brain tumor. Brain tumor is a group of cells in the brain that have uncontrolled division and thus increase in size and number and possess altered functions rather than having their normal physiological functioning [3]. Among the numerous types of cancer, two categories arise distinguishing them into benign brain tumors and malignant brain tumors [4].

In either case, whether the brain tumor is benign or malignant, its presence must be identified as it directly affects the wellbeing of the individual and his quality of life [5]. Physicians utilize Magnetic Resonance Imaging (MRI) to detect brain cancers, where they look for contrast between the different tissues shown in the scans. Nonetheless, in order for the tumor to be properly identified, it requires highly trained medical experts [6].

Fortunately, advanced computer vision techniques and the deep learning and machine learning development made it possible to efficiently identify brain tumors from MRI images, more precisely and faster than physicians can. These technologies provide early diagnosis which can save a patient's life, and further categorization of the brain tumor which would facilitate the selection of future treatment options [7].

Artificial Neural Networks ANNs can perform the task of identifying brain tumors through analyzing the MRI images since it can perform image processing and is able to recognize complex patterns and identify correlations between nonlinear relationships which are often present in the medical field [8]. In fact, ANNs are computer models that aim to mimic how the actual brain works in thought processing. An interesting feature in ANNs is that they are flexible and can alter their architecture relative to the information that they keep learning while processing the data [9].

CNN is a form of ANN and it similarly consists of an input layer, hidden layers, and an output layer. CNNs can generate an output as a result of analyzing the input, which can be MRI images in the case of brain tumors. In addition, CNNs can be trained to perform future outcomes depending on the information that it learned during training [10]. Training the CNN network is thus essential, where it is fed with MRI input images that are labeled with the proper classification "tumor" or "healthy" through which the network will learn to distinguish between them and generate an accurate result to distinguish the presence or absence of tumor in a new input accordingly.

In this study, the VGG-16 network, along with ResNet50 and Xception, are implemented with the objective of detecting tumor presence or absence in MRI images. The purpose is to achieve the highest possible accuracy, ensuring fast and reliable results while maintaining affordability for clinics that may be interested in automated detection of brain tumor.

The following are the study's contributions:

1) Implementation of VGG-16, ResNet50, and Xception: The study involves the implementation of three widely recognized neural network architectures.

2) Detection of Tumor Presence: The primary objective of the study is to accurately detect the presence of tumors in MRI images.

3) Fast and Reliable Results: Another contribution of this study is the focus on obtaining fast and reliable results. By leveraging advanced neural network architectures, the aim is creating a system which can rapidly and accurately identify tumors in MRI images, aiding in timely medical diagnoses.

4) Affordable Solution for Clinics: This study aims to develop an efficient and effective system that can be implemented in clinical settings without excessive costs, making it accessible to a broader range of healthcare facilities.

The rest of the paper takes into consideration an overview of some important studies and methodologies in Section II and Section III respectively. The details of implementation of the study including descriptions of the dataset and the proposed models. When the models are implemented, their results are viewed in Section IV. Finally, Section V concludes the paper.

II. Literature Review

Since brain tumor detection and classification is important, developing tools to properly identify it is equally important. Several machine learning algorithms have been implemented for this purpose, of which a variety of algorithms have been reviewed to show the diversity of possible algorithms as well as their relative performances in previous studies.

Two machine learning algorithms, namely Naïve Bayes and K-Nearest Neighbor algorithms have been implemented in several studies to classify brain tumors. For instance, Mirkov and Gavrovska [11] implemented a system relying on these two classifiers. The study involved a total of 253 MRI images of health brains and brains with tumors. The preprocessing of these images was done through image intensity adjustments, Guassian high pass filtering, and image binarization. In addition, the solidity was calculated in order to get an estimation of the regions that might be containing tumor. Correlation value, homogeneity, contrast, and energy are the features extracted by the GLCM process which are used by the Naïve Bayes (NB) and the KNN classifiers to determine the presence of tumor in a given MRI image. Mirkov and Gavrovska reported that the KNN algorithm achieves better sensitivity than NB which indicates the proper identification of tumor in all positive samples. KNN achieves an accuracy of 77% that can be increased to 98% if the number of selected features was increased.

Linear Discriminant Analysis LDA is also often used in classification problems. Usha.B.L et al. [12] proposed a system divided into several steps. The preprocessing step involves denoising of images and K-means based segmentation. Decomposing through DWT and Haar based basis function. The different features are extracted through GLCM such as entropy, variance, energy, and contrast. After that, the classification is carried out via LDA algorithm, which is an unsupervised machine learning algorithm that describes different observations and differentiates them into categories. In their case, Usha et al. found linearity between the features, which means LDA might be a good choice for classification of brain tumors. As a result, LDA was able to achieve only 70% accuracy, which is considered among the least accurate possibilities.

Another supervised machine learning algorithm can be used for brain tumor classification is the random forest classifier. In their study, Thayumanavan and Ramasamy [13] used 253 MRI images of the brain and applied median filter to them in order to remove unnecessary noise, and to make sure that the images are smoothed without interfering with the edges. Features like contrast, homogeneity, correlation, and energy were extracted by histogram of oriented gradients HoG and discrete wavelet transform DWT. Finally, these features were used for classification by Random Forest, Decision Tree, and Support Vector Machine algorithms. Upon testing, it was revealed that the Random Forest classifier achieves the highest accuracy at 98% compared to the other classifiers. Its relative sensitivity was 96% and the specificity was 99%.

AdaBoost is an ensemble machine learning model that has been used by Minz and Mahobiya [14] to classify brain tumors from MRI images. Noise elimination was performed through the median filter and segmentation was performed through thresholding technique. For feature extraction, GLCM was used where a total of 22 features were extracted including contrast and correlation. In their study, only 50 MRI images were used in order to compare the results of AdaBoost to those of neural machine learning algorithm. In terms of accuracy, AdaBoost was superior, achieving 89% accuracy and a higher specificity (62%). However, the sensitivity of the neural algorithm was 94% greater than that of AdaBoost (88%). Therefore, the accuracy of AdaBoost is not very high compared to other classification algorithms used for brain tumor detection.

Fuzzy Interference System FIS was utilized by Kumar et al. [15] to classify brain tumors. After the MRI brain images were acquired, noise was removed by Speckle noise removal technique. After that, improved Roughly Fuzzy C-Means Clustering RFCM was used to perform the feature extraction, where variance, entropy, energy, correlation, and contrast were extracted. Optimized Fuzzy Interference System OFIS was then used for brain tumor classification, whereas Generalized Framework of Grasshopper Optimization Algorithm EGOA was finally used for optimization. This system is capable of differentiating the parts of input images into different categories that are: white matter, grey matter, background, tumor tissue, and cerebral spinal fluid. When using the improved RFCM method, it was noticed that the average accuracy, sensitivity, and specificity were improved, such that the model achieved 97% accuracy, 98% specificity, and 93% sensitivity.

Convolutional Neural Networks are also among the algorithms that are used to achieve good accuracy in classifying brain tumors. Badža and Barjaktarovic [16] used around three thousand MRI images between axial, sagittal, and coronal planes. After preprocessing, normalization, and resizing, augmentation was done such that the new number of images became 9192 images. The CNN architecture was made up of an input, two blocks with ReLu activation, classification block with SoftMax function, and an output. To evaluate the performance of the provided architecture, a ten-fold cross-validation approach was used. In both the original dataset and the augmented dataset, performing validation once resulted in better results than when performing 10-fold validation. In the end, the CNN architecture scored an overall of 97% accuracy, 97% precision, 97% recall, and 97% f1-score.

TABLE I. SUMMARY OF RELATED WORK

Study	Classification Algorithm	Accuracy	Sensitivity and other metrics
Mirkov and Gavrovska	KNN	77%	89% sensitivity 65% specificity
Usha.B.L et al.	LDA	70%	Not available
Thayumanavan and Ramasamy	Random Forest	98%	96% sensitivity 99% specificity
Minz and Mahobiya	AdaBoost	89%	62% specificity
Kumar et al.	Fuzzy Interference System FIS	97%	98% specificity 93% sensitivity
Badža and Barjaktarovic	CNN	97%	97% precision

From the collection of studies that were described in the literature review and Table I, it has become obvious that there are a range of possibilities when it comes to the different algorithms that can be used in brain tumors classification depending on MRI images. The results conveyed by each study suggest that some algorithms perform much better in terms of accuracy and sensitivity than others. For instance, KNN, LDA, and AdaBoost are among the less-fit algorithms for identifying brain tumors, whereas algorithms such as Random Forest and FIS perform much better. However, the performance of CNN is comparable to that of RF and FIS while using a much larger dataset for training and testing. Thus, CNN poses as one of the best options for classifying brain tumors.

III. METHODOLOGY

In this study, the methodology encompasses many aspects, initially starting from data preprocessing, moving into the developmental stages of the model, then to training the developed model before it can be evaluated in comparison with other models as described in Fig. 1. In order for the study to proceed some data must be collected to be used for training and testing. The next step would be to process the collected data to optimize its quality before building the deep learning models. in this study, XCeption, ResNet50, and VGG16 are the selected deep learning models. The purpose of these models is to extract patterns and distinctive features from the processed data to identify brain tumor. After the models are developed, trained and tested, they are compared to several different models to assess their accuracy for brain tumor classification and analysis.

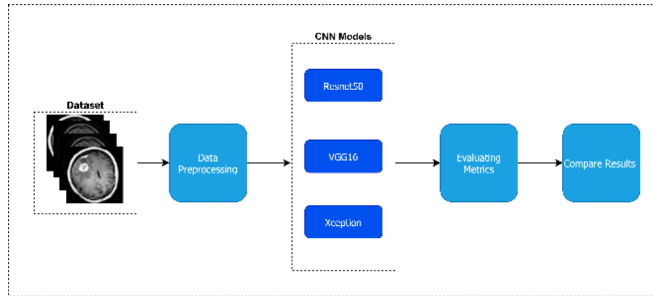

Fig. 1. Visual representation of the proposed architecture.

A. Dataset

For the purpose of training and testing our proposed model to properly identify brain tumors based on data from MRI images, a Kaggle dataset for MRI brain tumor was selected. This dataset is publicly available and accessible. Furthermore, the selected dataset comprises MRI images that have binary classifications to whether the image contains a healthy brain scan or a scan showing brain tumor. Fig. 2 illustrates some of the statistics that are related to the used dataset, such that it contains 1500 brain tumor images and 1500 healthy brain images.

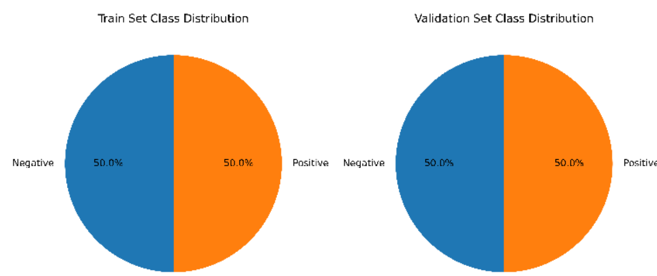

Fig. 2. Distribution of dataset into Positive and Negative images.

Fig. 3 shows a few samples from our used dataset showing MRI scans of healthy brain and brain tumor.

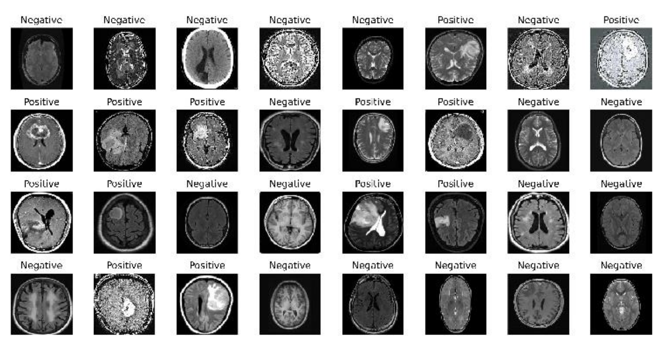

Fig. 3. A sample of the data in our dataset.

B. Data Preprocessing

Before the deep learning models are trained, some data pre-processing steps must be put into action on the MRI brain tumor dataset. The purpose of data pre-processing is to achieve better quality of the data and to make sure that the data is compatible with each of the chosen deep learning models, otherwise the data would not be used for training nor testing. The pre-processing steps start with normalization of the MRI images in order to obtain a dataset with consistent intensity values. Through normalization, the pixel values were scaled to a common range between [0, 1]. This way, the brightness and contrast variations are also avoided which allows the deep learning models to focus on the actual features of the tumors. Then, data augmentation was performed as a means of improving the model convergence. Data augmentations leads to an increase in the images within the dataset. In this study, data augmentation was done by performing flips. Following that, as shown in Fig. 2, the dataset was partitioned into validation and training sets. As the name suggests, the training set was used to train the network, and parameters were learned through backpropagation. On the other hand, the loss values were learned through forward propagation. Finally, the validation dataset was used as an evaluation for the model's performance. It was also used to fine-tune hyperparameters, and select the best-fit model [17].

C. Implementation

The properties of the CNN structure including the replicated layers and the fact that the weights are shared makes the learning process of this model much easier. The inputs of CNN can be videos, images, or even audio files. However, the innovations based on CNNs can be most evident in computer vision tasks, where CNNs are implemented for object tracking, image segmentation, and image classification [18]. In short, a Neural network is a full structure that connects an input layer through multiple layers in between to an output layer.

In CNN, there are usually three building-block layers that are used in its design; these layers are the fully connected “FC” layer preceded by pooling layer and convolutional layers. In simpler terms, the CNN is arranged as an input layer, convolutions, pooling, and fully connected layers as described in Fig. 4. In general, the input of a CNN network is either a one grey scale image or an RBG image that has three colors and different intensity values [19].

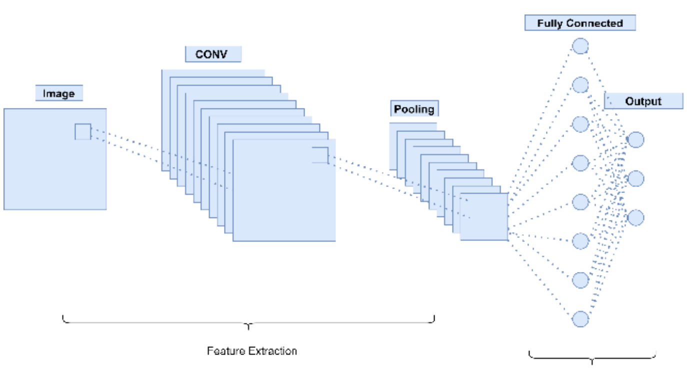

Fig. 4. General architecture of a CNN.

Extensive work on CNN lead to the creation of different architectures in CNN such as Lenet, Faster R-CNN, ResNet, and VGGs [20].

D. Transfer Learning

In transfer learning, there are mainly two approaches when it comes to deep learning, these approaches are fine-tuning and feature extraction. In feature extraction, the architecture of a pretrained model, often trained on ImageNet, is used except for its top layer. This architecture is used for feature extraction, and is augmented with another classifier on top. Fine-tuning, on the other hand, uses the pre-trained model's weights as beginning values for training, which are updated and altered as the training progresses. This approach aims to adapt general features to a specific job without erasing general learning.

ImageNet pre-trained weights were employed in this study as a part of transfer learning since the dataset is small. Consequently, the models will be able to avoid overfitting. The three deep learning models to be used in this study, VGG16, ResNet50, and Xception, were adjusted such that their last layers were fine-tuned, and a pre-trained classifier was utilized for feature extraction. A flatten layer was sued in place of the last set of layers in the three models in order to transform the data from the previous layer into one-dimensional tensor. As a result, a dense layer was introduced with sigmoid activation being applied to the previous layers, producing a single output. The output represents probabilities for positive and negative classes. In the upcoming section, a concise explanation of the models' structure and their utilization in this binary classification task will be presented.

E. VGG-16

The VGG-16 neural network [21] became popular for demonstrating that deeper networks may outperform shallower networks by using smaller convolutional filters. One notable feature of VGG-16 is its simplified architecture, which minimizes the number of hyper-parameters. The model consists of convolutional layers with 3x3 filters and a stride of 1, along with same padding. The pooling layers utilize 2x2 filters with a stride of 2.

As shown in Fig. 5, the initial two layers of VGG-16 include 64 convolutional filters, resulting in a volume of 224x224x64. The next pooling reduces the volume to 112x112x64. Additional convolutional layers are added with 128 filters, resulting in a dimension of 112x112x128. Another pooling layer reduces the volume to 56x56x128. Additional convolutional layers with 256 and 512 filters are incorporated, followed by pooling, ultimately leading to a final volume of 7x7x512. The model concludes with a fully connected layer consisting of 1024 units. The term "VGG-16" refers to the model's 16 layers that include little weights.

Throughout the architecture, VGG-16 consistently employs a pattern of convolutional layers followed by pooling layers, progressively reducing the volume. The number of filters doubles across each stack of convolutional layers, reflecting the underlying principle that guides the network's design.

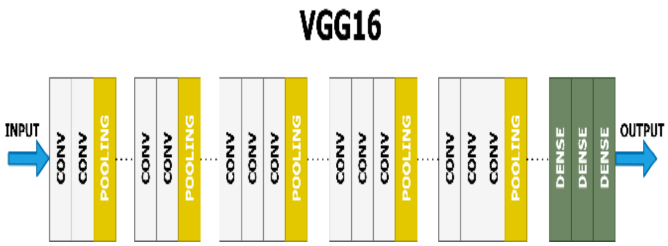

Fig. 5. Visual Representation of the Proposed VGG-16.

F. *ResNet-50*

Residual networks or ResNet, is a widely adopted neural network architecture which serves as a fundamental structure for numerous computer vision applications. Its design enables the effective training of deep neural networks, even with up to 50 layers. ResNet-50 [22] specifically addresses the challenge of vanishing gradients by incorporating skip connections between layers. This architectural choice enhances both the efficiency and accuracy of training. The ImageNet dataset is used to train the ResNet-50 model at first. The ResNet-50's fully connected layers are deleted in this study, and a new layer is built depending on the dataset utilized as shown in Fig. 6. Since this study focuses on only two classes, modifications are made to the output layers to accommodate the desired classification task. The model includes a dense layer with 1024 neurons, utilizing the rectified linear unit (ReLU) [23] activation function.

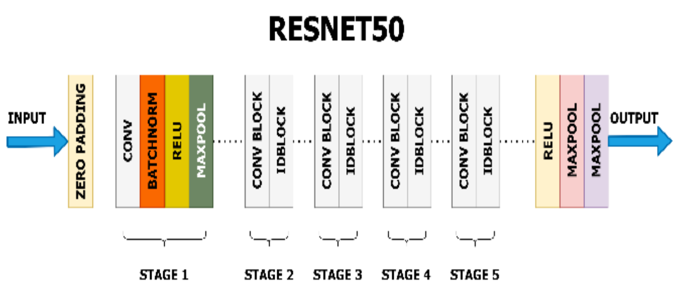

Fig. 6. Visual Representation of the Proposed ResNet-50.

G. *Xception*

Xception was created in 2016 by François Chollet, the developer of the Keras library, as an adaption of the Inception architectures. Xception varies from the classic InceptionV3 model in that the Inception modules have been replaced by depth-wise separable convolutions. This modification leads to enhanced performance compared to InceptionV3. Xception exhibits superior accuracy in terms of "Top-1" and "Top-5" accuracy on the ImageNet dataset. Despite these improvements, the number of parameters in Xception remains similar to InceptionV3, approximately 23 million. Fig. 7 shows the architecture of the proposed XCeption model.

Typically, the system begins its operation by receiving input images. A data pre-processing step is carried out to optimize the compatibility of the images with the chosen model. Subsequently, the dataset is divided into training and testing subsets, sometimes with the inclusion of a validation subset. The model is then fitted and trained to carry out the prediction task. Following testing, the model's performance is assessed and evaluated using the confusion matrix. Finally, the overall accuracy of the model is determined.

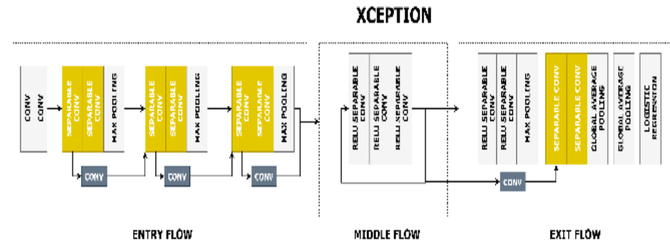

Fig. 7. Visual Representation of the Proposed Xception.

H. *Environment*

Various tools and environments were used for the development of this system, including TensorFlow, NumPy, seaborn, and matplotlib. The Colab environment was utilized to generate the computational power necessary for training complex models. Specifically, the T4 GPU with 16 GB of GPU RAM, available in Colab, was utilized. The training process was accelerated by this powerful GPU, resulting in faster iterations and improved model performance. Additionally, Colab provided 12 GB of RAM, enabling the handling of large datasets and efficient loading of data into memory.

IV. Results

A set of evaluation metrics are usually used to evaluated the performance of machine learning models. The models are often evaluated according to precision, recall, f1-score, loss, and accuracy. The performance of our models in identifying brain tumors from MRI images was evaluated using the metrics described. The assessment involved the utilization of various statistical techniques, including the confusion matrix, which compares the expected results with the actual results. The confusion matrix incorporates terms such as true positive, true negative, false positive, and false negative, which serve as the basis for calculating evaluation metrics. The true values signify that the results achieved by the model match with the actual results, whereas the false values signify that the model failed to achieve results that are identical to the actual ones [24]. Accuracy is basically a measure of the amount of accurate predictions with respect to all of the predictions, and thus it can be calculated as in Eq. (1):

$$Accuracy = \frac{True\ Positive + True\ Negative}{True\ Positive + True\ Negative + False\ Positive + False\ Negative} \quad (1)$$

Precision on the other hand is used to determine how good is the model in determining if a sample is positive. Precision is measured by the proportion of true positive with respect to all the positive results whether they were correct or not, as shown in Eq. (2).

$$Precision = \frac{True\ Positive}{True\ Positive + False\ Positive} \quad (2)$$

Recall value increases proportionally to the positive values and it is measured by dividing true positive values over the actual positive values (True positive and False negative) as shown in Eq. (3).

$$Recall = \frac{True\ Positive}{True\ Positive + False\ Negative} \quad (3)$$

A metric that takes into consideration both accuracy and recall is termed the F1-score.

The performance of the three proposed models "ResNet-50, VGg-16, and Xception" was recorded and assessed after they were properly trained. 600 MRI images were used for this purpose, where tumor-absent and tumor-present classes were obtained.

The results obtained from the VGG-16 model demonstrated a high level of accuracy and precision, with an accuracy score of 0.99. The precision values for both the "negative" and "positive" classes were 0.98 and 1.00, respectively. Additionally, the recall rates were impressive, with a recall of 0.98 for the "positive" class and a perfect recall of 1.00 for the "negative" class. The F1-score, which consider both recall and precision, achieved a value of 0.9882. Furthermore, the area under the curve (AUC) was calculated to be 0.9967, indicating excellent differentiation between the classes.

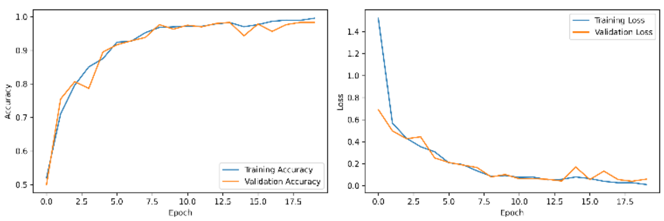

Fig. 8. Accuracy and Loss: VGG16.

Fig. 8 illustrates the VGG16 model's training progress as a function of loss and accuracy.

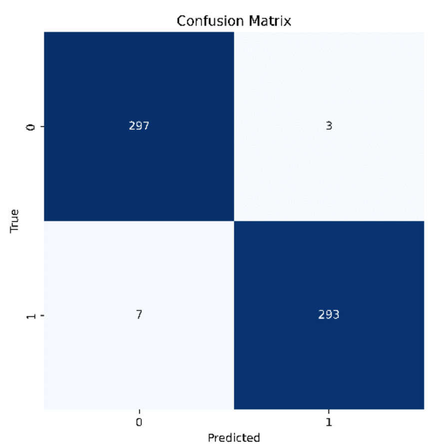

Fig. 9. Confusion Matrix: VGG16

By displaying the distribution of predicted and actual class labels, the confusion matrix gives an extensive evaluation of the VGG16 model's performance, as shown in Fig. 9.

Outstanding performance was observed in the Xception model across all evaluation metrics. The accuracy, F1-score, recall, and precision all achieved perfect values of 1.00. Additionally, the AUC was calculated as 1.0000, providing further confirmation of the model's capability to accurately classify brain tumors.

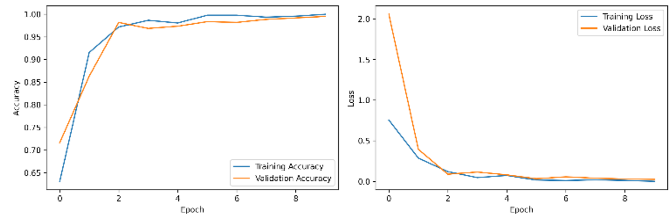

Fig. 10. Accuracy and Loss: Xception.

Fig. 10 illustrates the Xception model's training progress as a function of loss and accuracy.

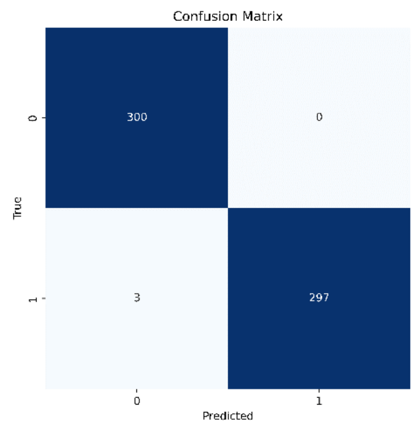

Fig. 11. Confusion Matrix: Xception.

By displaying the distribution of predicted and actual class labels, the confusion matrix gives an extensive evaluation of the Xception model's performance, as shown in Fig. 11.

Likewise, exceptional performance was demonstrated by the ResNet-50 model. The accuracy reached 0.99, with a 0.99 precision for the "negative" class and 1.00 for the "positive" class. The recall rates were 0.99 for the "negative" class and 0.99 for the "positive" class. The F1-score achieved a value of 0.9950, indicating a strong balance between precision and recall. Furthermore, the AUC was calculated as 1.0000, underscoring the model's ability to effectively distinguish between cases with and without tumors.

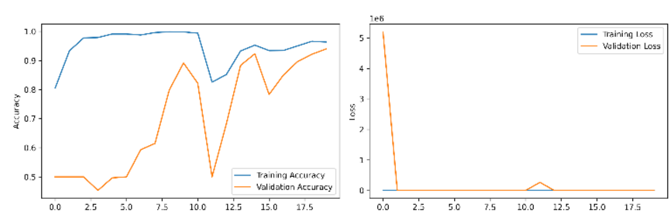

Fig. 12. Accuracy and Loss: Resnet50.

Fig. 12 illustrates the training progress of the Resnet50model in terms of accuracy and loss.

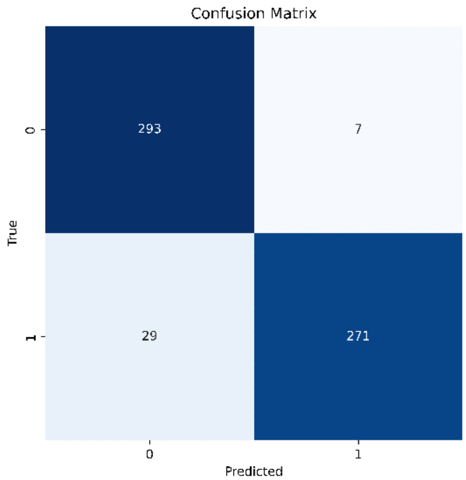

Fig. 13. Confusion Matrix: Resnet50.

By displaying the distribution of predicted and actual class labels, the confusion matrix gives an extensive evaluation of the Resnet50 model's performance, as shown in Fig. 13.

In comparison to each other, all of the proposed model achieved high accuracies and were able to score high performance on the front of classifying brain tumors. On the other hand, it was evident that Xception model was superior in terms of results since it achieved perfect values in all of the evaluation metrics while ResNet-50 and VGG-16 scored slightly less, regardless of achieving very high accuracies, and proving their competence in differentiating between brain tumors and normal images.

The accuracy, recall, precision, and F1-score for each algorithm are summarized in Table II.

TABLE II. COMPARISON BETWEEN ALL METRICS FOR EVERY ALGORITHM

Algorithm	Accuracy	Precision	Recall	F1-Score
VGG-16	0.99	0.9966	0.9800	0.9882
Xception	1.00	0.9967	0.9967	0.9967
ResNet-50	0.99	0.9967	0.9933	0.9950

All of the proposed models achieved outstanding performances demonstrating their high effectiveness in distinguishing brain tumors. These achieved results indicate that deep learning approaches have powerful capabilities in analyzing medical images.

A. Discussion

When compared to the performances to other models in the studies in the literature review shown in TABLE III. and Fig. 14, the performances of the proposed models suggest significant advancements. To illustrate, the Xception model achieved perfect results such as perfect accuracy of 100%. This shows that the model has an exceptional ability to distinguish brain tumors from normal images. This result surpasses the accuracies reported in other papers, highlighting the effectiveness of the Xception architecture for this brain tumor classification task. Additionally, the proposed ResNet50 and VGG16 models also demonstrated exceptional accuracy, both achieving a remarkable 99%. The results of VGG-16 and ResNet-50 are comparable to the results mentioned in the literature, enforcing the ability of deep learning to be used for this task. When comparing the performances reported in various papers, it becomes apparent that there is a range of accuracy values. The Random Forest classifier achieved 86% accuracy [24], whereas a CNN model reached 98.80% accuracy [33]. It is evident that deep learning approaches, specifically CNN-based architectures, consistently outperformed traditional machine learning algorithms. The findings in this study align with this trend, since the proposed models surpassed the accuracies reported in the other papers, achieving an impressive accuracy of 99%.

TABLE III. TRAINING IMAGES, TESTING IMAGES AND ACCURACY FOR EACH MODEL

Model	Training Images	Testing Images	Accuracy
Random Forest[23]	372	93	86%
CNN [25]	2451	613	91.30%
R-CNN [26]	2451	613	91.66%
ANN [27]	160	40	92.14%
CNN [28]	222	56	93.90%
CNN [29]	400	100	96.08%
CNN [30]	2451	613	96.13%
SVM [31]	372	93	97.10%
Deep CNN [32]	372	93	98.07%
CNN [33]	510	1265	98.80%
Proposed ResNet50	2400	600	99.00%
Proposed VGG16	2400	600	99.00%
Proposed Xception	2400	600	100.00%

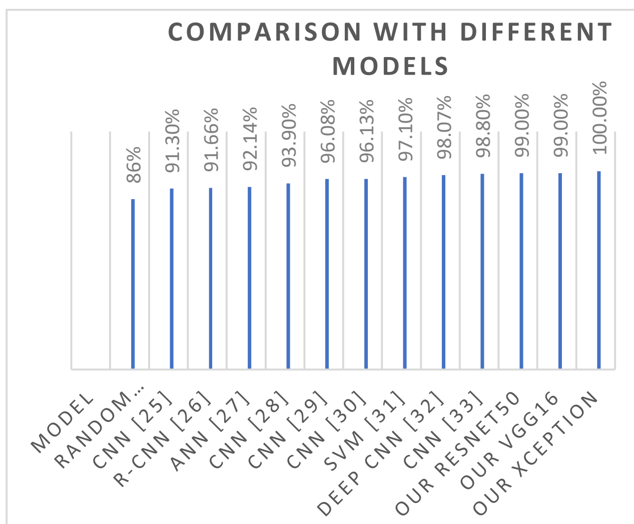

Fig. 14. Comparison between the performance of the proposed models and the other models.

V. Conclusion

The physical and psychological effects of tumors, including brain tumors, are significant and can be life-altering, impacting the patient's quality of life and life expectancy. Timely diagnosis of such tumors can greatly improve the patient's prognosis by enabling early intervention, potentially saving lives. Artificial intelligence, specifically deep learning, has shown important advancements in many sectors, including the medical field. This has led to numerous studies implementing these technologies for the automatic detection of brain tumors.

In this study, we aimed to develop an affordable, fast, and reliable system based on deep learning to accurately detect brain tumors from MRI images. We implemented, trained, and tested three algorithms for this purpose. The evaluation results demonstrate that the models can accurately and precisely identify the presence of tumors.

In the future work, we should aim to collect and use larger and more diverse datasets of brain MRI images which leads to the enhancement of the models' ability to generalize to new data, allowing the model to deal with real world complexities in brain tumor diagnosis. Additionally, efforts should be made to optimize the models for various platforms, enabling deployment across multiple devices to assist its adoption and utilization by doctors more effectively.

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