DOI: 10.15849/IJASCA.230720.22

Int. J. Advance Soft Compu. Appl, Vol. 15, No. 2, July 2023
Print ISSN: 2710-1274, Online ISSN: 2074-8523

Detection Brain Tumor Disease Using a Combination of Xception and NASNetMobile

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Abstract

Among Artificial Neural Networks (ANNs), Deep Convolutional Neural Networks (CNNs) have emerged as the most effective architecture for solving complex image-driven pattern recognition tasks. With the availability of large datasets and improvements in hardware technology, research on CNNs has accelerated, and several interesting deep CNN architectures have been proposed. In this study, we propose a novel CNN model based on transfer learning, which combines two state-of-the-art architectures, Xception and NASNetMobile, for image classification. The model takes images of specific dimensions or called "best windowing of images" as input and uses Xception and NASNetMobile to classify them into two categories. The outputs of these architectures are then concatenated using a concatenate layer, and a dropout layer is added to prevent overfitting problems in CNN. We evaluated the suggested model for a challenging MRI brain tumor dataset consisting of 3000 images, with 1500 images classified as normal and 1500 images classified as abnormal. Our results show that the suggested model produced excellent accuracy, demonstrating its effectiveness in enhancing the performance of CNNs for image classification tasks.

Keywords: *Convolutional Neural Network, Transfer Learning, Image Classification, Xception, NASNetMobile.*

1. Introduction

Artificial Intelligence (AI) has become an integral part of our daily lives, from speech recognition and image processing to natural language processing and autonomous systems. Among the various branches of AI, deep learning has emerged as the most promising and widely used technique for solving complex problems such as object recognition, speech recognition, natural language processing, and many others. Deep learning algorithms are composed of ANNs that are trained on large datasets to learn patterns and make accurate predictions [1].
Convolutional neural networks (CNNs), in particular, have lately attained leading-edge performance in a number of computer vision applications, including image classification, object identification, and segmentation. CNNs have been shown to be effective in extracting high-level features from raw input data, making them a popular choice for various applications. However, the promised results that CNN produce, there is need for more accurate ones. Interesting concepts have been explored to enhance CNN, including different activation and loss functions, regularization, parameter optimization, and architectural advancements. Where, the deep CNN's representational capability has significantly improved because of architectural advancements [2], [3].

Received 3 April 2023; Accepted 6 July 2023

Deep learning is a machine learning approach that uses non-linear transformations to extract features from large datasets. It has become a widely used method for supervised learning in various fields. Specifically, Convolutional Neural Networks (CNN) have proven to be highly effective for image classification since 2012[4]. Additionally, one of the most striking examples of ANN architecture is CNN. With their precise yet straightforward architecture, CNNs offer a brief introduction to ANNs and are frequently used to solve difficult image-driven pattern recognition issues. Due to the dimensions of the input data, convolutional neural networks (CNNs) can take the 1-D, 2-D, or 3-D forms. 1-D CNNs, which are a variant of 2-D CNNs, is used with two data dimensions of the sort used in 2-D CNNs, such as movies and photos. Different one-dimensional applications of 1-D CNNs, particularly with signal processing, include structural damage detection and structural health monitoring, and early-stage detection of arrhythmia in ECG beats [5].

Image classification is a critical component of computer vision, serving an important role in our studies, work, and everyday lives. The image classification process involves various steps, such as picture preparation, segmentation, extraction of essential features, and matching identification. Recent advancements in image classification techniques have enabled faster and more accurate retrieval of image information. With the advent of deep learning, feature extraction and classification have been integrated into a single learning framework, overcoming the traditional challenges associated with feature selection. One key ingredient of deep learning in image classification is the use of convolutional architectures [6].

The study of convolutional neural networks has recently emerged quickly and produced relevant results on a variety of tasks due to the significant rise in the quantity of annotated data and the excellent improvements inside the capabilities of picture processing devices [7]. There are a number of sophisticated pre-trained CNNs out there that can transfer learning. It only needs the training and testing datasets at its input layer, then. In terms of internal layers and procedures, the network architecture varies [8]. Deep CNN's multi-layered, hierarchical structure allows it to extract low-level, middle-level, and high-level information. High-level features are a combination of lower and mid-level features. CNN's ability to extract features in a hierarchical manner is what mostly accounts for its appeal [2], [9].

Recent advancements in information technology and e-healthcare have made it possible for healthcare workers to treat patients more effectively [10]. A brain tumor is a lump that develops inside the brain from the skull's or the brain's surrounding tissues and has a negative impact on people's quality of life. This mass is divided into two kinds: benign or malignant [11]. Hence, our study aims to improve the accuracy of classifying brain tumor images using CNNs, which is of utmost importance as brain tumors can have a significant impact on a person's quality of life, and early detection is crucial for successful treatment. In pursuit of our goal, our study presents several important contributions, including:

- Introducing a new architecture or modification to the standard CNN architecture that improves performance, based on transfer learning.
- We illustrate the utility of transfer learning for image classification using the Xception and NASNet models.
- Training CNN with different parts of the image and finding the best part that gives high accuracy and less error.
- Providing insights into the inner workings of CNNs and explaining why certain modifications or techniques lead to improved performance, potentially leading to better understanding and interpretability of these complex models.

The layout of this paper is as follows: Section 2. related work, Section 3. Motivation, Section 4. Material and methodology brief discussion proposed method, Section 5. presents results and discussions, and Section 6. presents the conclusion and future work.

2. Related Works

Several scholars have worked on processing brain MRIs using diverse approaches at various stages.

Toğaçar M. and et.al [11] proposed the BrainMRNet CNN model. This architecture contains a residual network and was constructed using hypercolumn technology and attention modules. pre-trained models for convolutional neural networks (AlexNet, GoogleNet, and VGG16) were employed in their investigation, but the BrainMRNet model outperforms them. The BrainMRNet model's classification success rate was 96.05%.

Priyanka Modiya and et.al [12] suggested a new method for detecting brain tumors that makes use of a convolutional neural network, a transfer learning approach, and a dimensionality reduction technique. EfficientNetB7 models for transfer learning are utilized for feature extraction, while the PCA approach is used for feature reduction. 3000 MRIs, including 1500 normal and the remaining abnormal images, make up its experiments on the Kaggle dataset. Accuracy is increased by combining features from PCA and the CNN Efficient Net model. precision and validation were attained (80.00%).

Sobhangi Sarkar and et. al [13] conducted a study that makes use of axial slices from MRI scans to identify the type of brain tumors. The glioma, meningioma, and pituitary tumors, the three most often diagnosed brain tumors, were represented in the dataset used for the study. A 2D CNN was created for classification purposes with, overall accuracy of 91.3% and it attained recalls of 88%, 81%, and 99% for the diagnosis of meningioma, glioma, and pituitary cancers, respectively.

Milica M. Badza and et.al [14] provide a novel CNN architecture for separating the three different tumor forms that can appear in brain tumors. In T1, the constructed network outscored the already-existing, previously-trained networks. Magnetic resonance imaging is weighted for contrast. The performance of the network was evaluated using four method combinations of two 10-fold cross-validation approaches and two databases. Subject-wise cross-validation, one of the 10 ways, was utilized to gauge the network's ability to generalize, and an improved picture database was used to gauge the network's advancement. The best result for the 10-fold cross-validation method was obtained for the record-wise cross-validation for the augmented data set, and, in that case, the accuracy was 96.56%.

Mohamed Arbane and et.al [15] used a transfer learning-based convolutional neural network (CNN) to suggest a deep learning model for diagnosing brain cancers from MRI data. The implemented system examines three CNN architectures: ResNet, Xception, and MobilNet-V2. The latter produced the best results, scoring 98.24% accuracy and 98.42% F1-score, respectively.

Zar Nawab and et. al [16] suggested a block-wise transfer learning-based fine-tuning technique and used a deep CNN model that had already been trained. The benchmark dataset for T1-weighted contrast-enhanced magnetic resonance imaging (CE-MRI) was used to assess the proposed approach. Unlike traditional methods that require handcrafted features and extensive reprocessing, The suggested approach is more general and, when five cross-validations are made, the average accuracy is 94.82%. The authors not only compared their results with conventional machine learning techniques, as well as deep learning techniques utilizing CNNs. The findings of the experiment show that the suggested method uses recent classification algorithms on the CE-MRI dataset the most effectively.

Xizhi Wu and et.al [17] proposed a transfer learning approach based on Xception and compared its performance with the Inception-V3 model. Their experimental outcomes based on the dataset from the Intel Image Classification Challenge, demonstrate that the Xception-based transfer learning significantly outperforms Inception-V3 and shows greater robustness with fewer overfitting problems. While the accuracy of transfer learning on Inception-V3 reached 91.81%, the Xception-based transfer learning achieved an accuracy of 91.20%. Overall, these findings suggest that the proposed Xception-based transfer learning approach is a promising technique for improving image classification tasks.

Mavra Mehmood and et.al [18] proposed an automated method for intracranial tumor MRI was presented, featuring colored images of the tumor region to enhance discrimination between tumor and non-tumor areas. The generated images achieved an average Structure Similarity Index (SSIM) score of 0.92 and an average Peak Signal to Noise Ratio (PSNR) value of 28%, outperforming existing techniques. Moreover, The use of NASNet-Large resulted in quantitative improvements in Classification Accuracy (CA) in both the pre-and post-colorization phases, with scores of 88.5% and 92.4%, respectively, as well as other measures.

Dhurgham Hassan and et.al [19] Data sharing is prohibited under the proposed federated learning (FL) model due to patient privacy concerns. they have suggested two techniques of aggregation using the FL approach: the first involves rating the weight % of each client, and the second uses average weights. the performance of the ranking weights percentage approach with the average weights of proposed CNN and pre-training (VGG-16) in the FL environment, in addition to SVM and VGG-16, has been compared in order to assess the suggested model. The experiments' findings show that their model's accuracy result is quite effective when using the ranking weight percentage approach, reaching accuracy (98%) on datasets (BT_large-1c), in comparison to other methods.

Table1: Summary of related work

References	Years	Technology	Dataset	Accuracy
Toğaçar M. and et.al [11]	2020	BrainMRNet CNN model	MRI Image dataset	96.05%
Priyanka Modiya and et.al [12]	2022	EfficientNet-B7 with PCA	BT-large-1c	80.00%
Sobhangi Sarkar and et. al [13]	2020	2D CNN model	MRI dataset	91.3%
Milica M. Badza and et. al [14]	2020	T1-weighted contrast-enhanced	MRI image database	96.56%.
Mohamed Arbane and et. al [15]	2022	CNN based on transfer learning, ResNet, Xception and MobilNet-V2	MRI dataset	98.24% ,98.42%
Zar Nawab and et. al [16]	2019	T1-weighted contrast	CE-MRI dataset	94.82%
Xizhi Wu and et.al [17]	2020	Xception based transfer learning	Intel Image Classification dataset	91.20%.
Mavra Mehmood and et. al [18]	2022	Adversarial Neural Networks (Pix2Pix-cGANs)	MRI dataset	88.5%, 92.4%,
Dhurgham Hassan and et.al [19]	2022	Proposed federated learning (FL)	BT-large-1c	98.00%

3. Motivation

The motivation behind this paper is to push the boundaries of severity classification from images using transfer learning, with a specific focus on medical images of MRI brain tumor images. Our ultimate goal is to achieve remarkable accuracy while mitigating the issue of overfitting. Early detection of brain tumor diseases holds immense significance in improving human lives. Thus, to address these crucial objectives, we introduce a pioneering model that harnesses the power of both the Xception architecture and the NASNETMobile architecture. This unique fusion optimizes the model's performance by capitalizing on transfer learning through pre-trained deep CNNs, accompanied by meticulous hyperparameter tuning. Extensively proven in the realm of medical image analysis, these techniques yield superior outcomes when compared to models trained with randomly initialized weights. Overall, our proposed classification model proudly establishes its superiority over conventional deep CNN models, excelling in both accuracy and performance.

4. Material and Methodology

This section offers a deep learning model based on transfer learning for CNN that can classify brain cancers from MRI images. The model is described in depth along with the architecture model. The proposed model has two architectures network (Xception and NASNetMobile) training respectively.

4.1Transfer Learning

One important downstream use of learned image classification algorithms is Transfer Learning [20]. The field of artificial intelligence has given considerable attention to Transfer Learning (TL). When faced with difficult machine learning issues like insufficient training data or shifting learning objectives, TL can handle them successfully. A significant development in TL has occurred over the previous ten years [21]. Instead of beginning with a massive quantity of data and working from scratch, the fundamental objective of TL is to complete the target job utilizing the knowledge acquired via completing source tasks in several domains. [22]. The following are more advantages of using one of the pre-trained architectures that are available. More processing power is first required in order to train large models on large datasets. Second, it can take many weeks to properly train the network. By using pre-trained weights to train the new network, the learning process can be accelerated [23].

4.2Xception Network

The Inception architecture, which takes advantage of the concept of depthwise separable convolution, can be thought of as a modified version of Xception [24]. The size of the initial conception block was enlarged, the various spatial dimensions (1x1, 5x5, 3x3) were replaced with only one dimension (3x3), and a 1x1 convolution was introduced to lower the computational complexity. By separating spatial and feature-map (channel) correlation, which is theoretically stated in equations (1 & 2), Xception improves the network's processing efficiency. It operates by first employing 1x1 convolutions to translate the output of the convolution to low-dimensional embeddings. It then undergoes n spatial transformations, where n is a cardinality specifying the width and represents the number of transformations.

$$f_{l+1}^{k}(p,q) = \sum_{x,y} f_l^k(x,y).\, e_l^k(u,v) \quad (1)$$
$$F_{l+2}^{k} = g_c\left(F_{l+1}^{k}, K_{l+1}\right) \quad (2)$$

In equation (2), kl is a kth kernel of a layer with a depth of one that is spatially convolved across a kth feature-map Fkl. The spatial indices of the feature-map and kernel are (x,y) and (u,v), respectively. The number of kernels K in depth-wise separable convolution is equal to the number of input feature-maps, in contrast to standard convolutional layers where the number of kernels is independent of preceding layer feature maps. Whereas k_{l+1} is k^{th} kernel of (1x1) spatial dimension for $l+1^{th}$ layer, which performs depthwise convolution across output feature-maps $[F^1_{l+1},\ldots,F^k_{l+1},\ldots,F^K_{l+1}]$ of l^{th} layer, used as input of $l+1^{th}$ layer. feature-maps from the lth layer's output are used as the l+1th layer's input. In Xception, each feature-map is independently convolved across spatial axes, followed by pointwise (1x1) convolutions that provide cross-channel correlation. Xception uses a transformation technique that uses the same number of segments as feature-maps, in contrast to traditional CNN architectures that use three for the inception block and just one for the convolutional operation. This strategy increases learning efficacy and performance without reducing the number of factors [2].

4.3NASNetMobile Network

NASNet (Neural Architecture Search Network) and NASNetMobile are both deep learning architectures that were developed using Neural Architecture Search (NAS) techniques. NAS is a process that automates the design of neural networks, allowing the development of architectures that perform better than those created by human experts. While NASNetMobile is a smaller and more efficient version of NASNet that was developed to run on mobile devices with limited computational resources [25]. It has fewer parameters than NASNet, at around 4.2 million, and uses fewer layers. It also incorporates depth-wise separable convolutions to reduce computational complexity. According to [26], NASNetMobile achieved an accuracy of 74.0% on the ImageNet classification task, which is still impressive considering its smaller size.

Both NASNet and NASNetMobile have been shown to outperform other state-of-the-art neural network architectures on the ImageNet classification task. They are also highly modular, which allows them to be easily adapted to other computer vision tasks [25].

4.4Proposed Model

In this study, we build a model as shown in Fig (1) by using keras that combines the Xception and NASNetMobile respectively, which defines a neural network with two pre-trained models, parallel Xception and NASNetMobile. These models are combined to improve the performance of the final model. At first, the input image, resize to (224,224) pixels with 3 color channels, then crops each image is based on the coordinates (x, y) and dimensions (w, h) and normalize images by dividing the intensities by 255, then creates an input layer that takes in the image data, then creates an instance of the Xception model without the top layer, which is the final fully connected layer. After that, create an instance of the NASNetMobile model without the top layer. Pass the input layer through the Xception and NASNetMobile models, respectively. Then concatenates the output of the two models using a global average pooling layer. Then the output of two models adds as input to the dropout layer with the rate of 0.5 to prevent overfitting.

4.5Dataset

The proposed model has been trained and evaluated based on the dataset of MRI brain tumors. The dataset Brain Tumor Detection 2020 dataset, as BT-large-1c, consists of 3000 images obtained from the Kaggle website (https://www.kaggle.com/ahmedhamada0/brain-tumor-detection). It contains two parts: 1500 normal for healthy ones and 1500 abnormal for unhealthy that are shown in Fig (2).

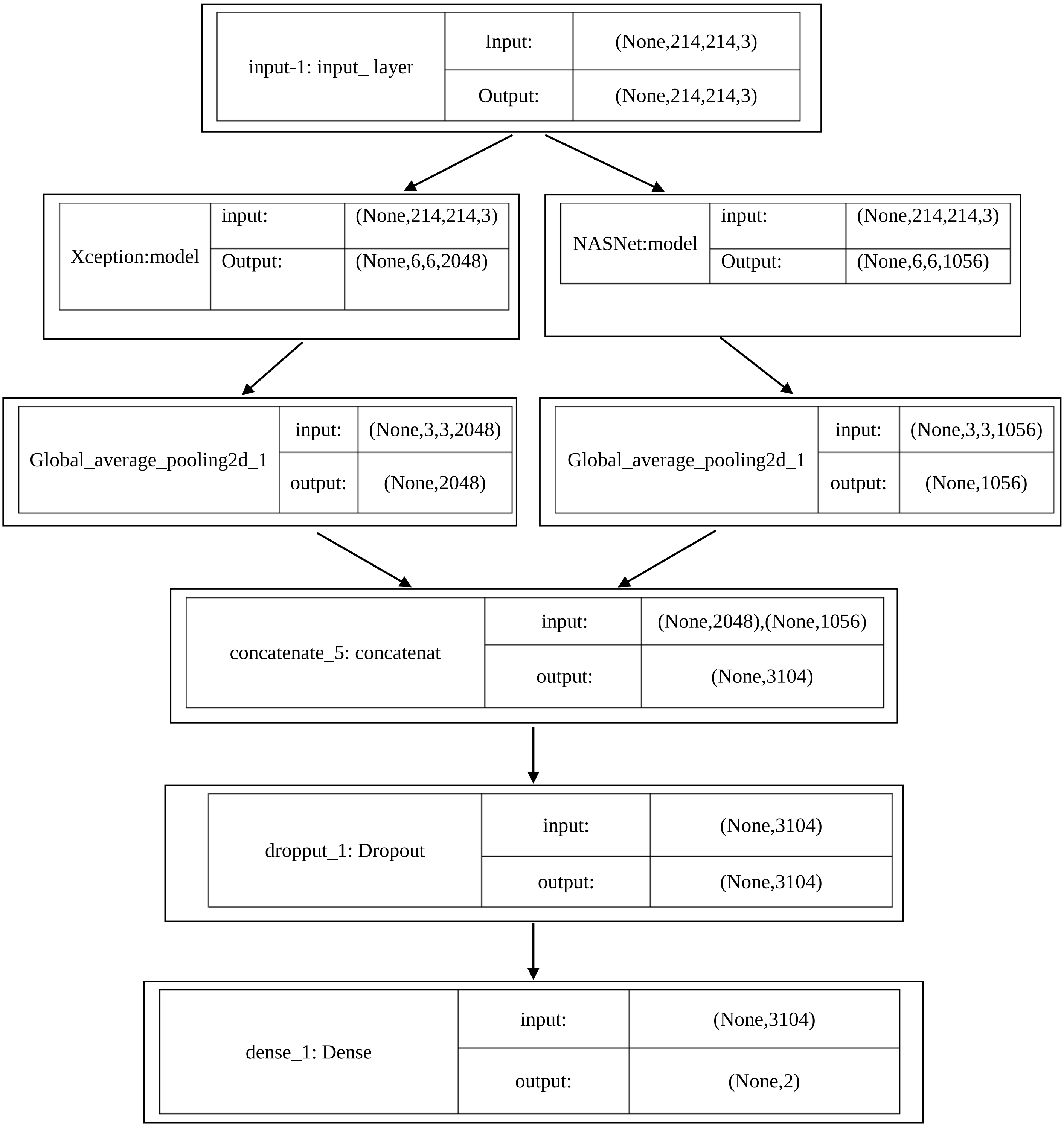
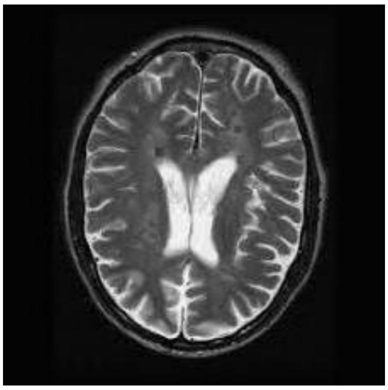


Fig. 1: Model structure layers (Xception and NASNetMobile)

(a)



(b)

Fig. 2: example of (a) image of unhealthy brain (b) image of healthy brain

5. Experimental Results and Discussions:

The objective of this study was to enhance the performance of the classification model-based Brain TUMRS data sets, so it can diagnosis the patients accurately. The experiments were initiated by dividing the data sets into two groups; training data (80%) and testing data*20%). Also, the training dataset would be (training 80% and validation 20%). The model is developed using Keras library and supported by Tensor Flow as a backend with Python, with the optimized hyperparameter values as the learning rate is 0.0001, the batch size is 32 and the maximum number of epochs is 50. The proposed model would be tested with different windows of the input image in in order to explore the impact of this parameter on the results and the training process. These different experiments were compared with the control case. So, there are different results were produced as shown in Table (2). The examining of the results, demonstrated the effectiveness of the proposed model according to the achieved accuracies with different cases, the accuracies about (0.9366 to 0.9983) and a low loss value(from 0.35 to 0.0059). Also there is a good impact of using windowing approach on the results, the accuracies were varied according to the size of windows. The best accuracy was achieved (0.9983) and loss value(0.0059) with the window size (214,214). While the training performance would be explained through Fig (3), overfitting problem came down with the proposed work.

Table2: explain different performances for different windows from images

Dimension of the image window	Accuracy	Loss
Original image (224,224)	0.9800	0.08
Window (214,214)	0.9983	0.005
Window (200,200)	0.9800	0.04
Window (195,195)	0.9916	0.01
Window (185,185)	0.9966	0.02
Window (165,165)	0.9366	0.35

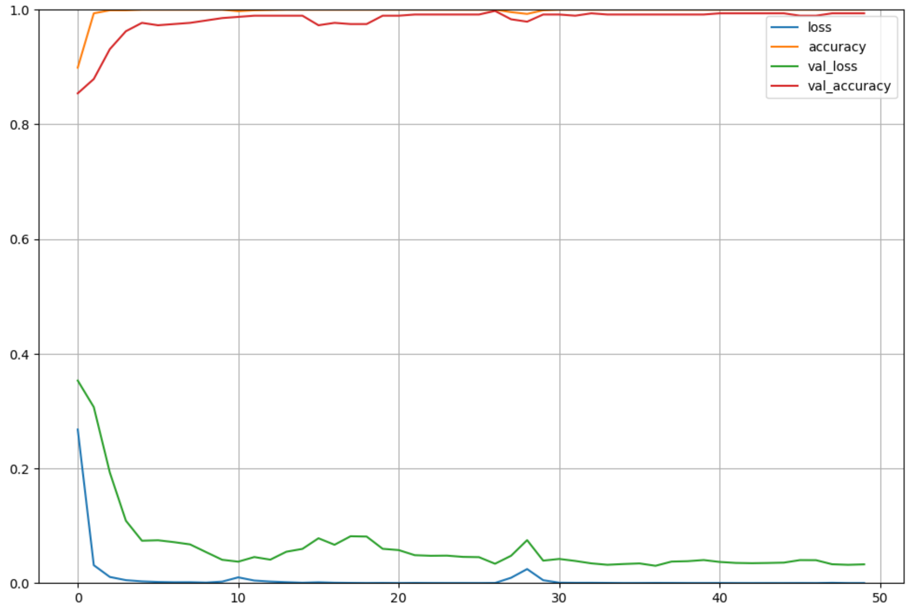


Fig.3: performance of proposed model through training process

Tracing the diagram in Fig (3), it can be noticed the perfect training process that is represented by accuracy lines (training and validation), indicating no overfitting problem. After the construction of the model, it would be tested with testing data, and the results are shown in Fig (4). These findings indicate the model's ability to accurately.

```
Classification Report:
               precision    recall  f1-score   support

           0       1.00      1.00      1.00       300
           1       1.00      1.00      1.00       300

    accuracy                           1.00       600
   macro avg       1.00      1.00      1.00       600
weighted avg       1.00      1.00      1.00       600
```

Fig. 4: performance testing process

This study highlights the remarkable impact of transfer learning on network performance and the reduction of misclassification rates in medical image analysis. The accurate classification of medical images holds immense significance in the timely and accurate diagnosis of diseases in patients. Moreover, our innovative model, which combines the robust Xception and NASNETMobile network architectures, effectively addresses the often-neglected issue of overfitting prevalent in existing networks, ensuring enhanced reliability and generalization.

In addition, we conducted comprehensive experiments involving five distinct window configurations in the image processing phase, where the dimensions of height and width were meticulously determined. Our findings unequivocally demonstrate that each window configuration exerts a profound influence on both the accuracy and error rate of the network. Notably, after careful evaluation, we identified the specific window configuration of (214, 214) as the optimal choice, resulting in the highest accuracy and the lowest error rate for our model. This crucial insight enables us to fine-tune our approach and maximize the performance of our model, ensuring the utmost precision and reliability in medical image classification. We compared our model with other studies as shown in table (3).

Table 3: Comparison results with other studies.

References	Years	Technique	Dataset	Accuracy
Priyanka Modiya and et.al [12]	2022	EfficientNet-B7 with PCA	BT-large-1c	80.00%
Dhurgham Hassan and et.al [19]	2022	Proposed federated learning (FL)	BT-large-1c	98.00%
Proposed model	**2023**	**-**	**BT-large-1c**	**99.83%**

6. Conclusions

In this study, a new CNN architecture has been proposed based on transfer learning for classifying images of Brain TUMRS. A model was built by combining two pre-trained models, Xception and NASNetMobile, to create a neural network with parallel models. The input image is resized and cropped in different dimensions to arrive at a suitable part of the image to enhance the classification process, then an input layer is created to take in the image data. Instances of the Xception and NASNetMobile models are created without their top layers and the input layer is passed through each model. The outputs of both models are concatenated using a global average pooling layer and added as an input to a dropout layer to prevent overfitting. The combination of the two pre-trained models improves the performance of the final model. The success of our model demonstrates the potential of deep learning algorithms in improving the accuracy and reliability of medical image analysis.

Our findings have important implications for the diagnosis of Brain TUMRS. Accurate and timely diagnosis is critical for improving patient outcomes, and our model offers a promising solution for achieving this goal. By automating the image analysis process, our model can provide faster and more accurate diagnoses, which may ultimately lead to improved patient outcomes and quality of life. Additionally, CNN's block-based design promotes modular learning, which simplifies and improves the comprehension of architecture. The idea of the block as a structural unit will endure and help CNN work more effectively.

While our study has demonstrated the effectiveness of our proposed CNN architecture, further research is needed to fully explore the potential of deep learning algorithms for medical image analysis. Future studies should investigate the use of larger datasets, different imaging modalities, the use of specific optimization algorithms to enhance image classification, and the impact of different high-level features on model performance.

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Notes on Contributors

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