Abdalla *et al.*
Journal of Electrical Systems and Inf Technol (2023) 10:51
https://doi.org/10.1186/s43067-023-00119-9

Journal of Electrical Systems and Information Technology

RESEARCH **Open Access**

The impact of image augmentation techniques of MRI patients in deep transfer learning networks for brain tumor detection

Peshraw Ahmed Abdalla[1*], Bashdar Abdalrahman Mohammed[1] and Ari M. Saeed[1]

*Correspondence: peshraw.abdalla@uoh.edu.iq

[1] Computer Science Department, College of Science, University of Halabja, Halabja 46018, Kurdistan Region, Iraq

Abstract

The exponential growth of deep learning networks has enabled us to handle difficult tasks, even in the complex field of medicine. Nevertheless, for these models to be extremely generalizable and perform well, they need to be applied to a vast corpus of data. In order to train transfer learning networks with limited datasets, data augmentation techniques are frequently used due to the difficulties in getting data. The use of these methods is crucial in the medical industry in order to enhance the number of cancer-related magnetic resonance imaging pathology scans. This study evaluates the results of data augmentation methods on three deep transfer learning networks, such as InceptionV3, VGG16, and DenseNet169, for brain tumor identification. To demonstrate how data augmentation approaches affect the performance of the models, networks were trained both before and after the application of these methods. The outcomes revealed that the image augmentation strategies have a big impact on the networks before and after using techniques, such as the accuracy of VGG16 is 77.33% enhanced to 96.88%, and InceptionV3 changed from 86.66 to 98.44%, and DenseNet169 changed from 85.33 to 96.88% the accuracy percentage increase of the models are 19.55%, 11.78%, and 11.55%, respectively.

Keywords: Artificial intelligence, Image augmentation, Deep learning, Cancer detection, Medical diagnostic imaging

Introduction

Even though medical research is quite sophisticated nowadays, it remains a challenge for doctors to identify some diseases early [1]. To identify a brain tumor, doctors employ magnetic resonance imaging (MRI) and brain tomography pictures, utilizing artificial intelligence for the early detection of head tumors is of paramount significance in safeguarding patients' health. AI-driven tools and algorithms have the potential to offer rapid and precise diagnoses, enabling timely medical interventions that can greatly enhance treatment efficacy and increase the likelihood of successful recovery. This underscores the importance of employing AI-based techniques and diagnostic solutions for the early identification of head tumors, ultimately advancing healthcare and elevating the quality of life for individuals grappling with this serious medical condition. Brain tumors are an exceptionally severe and potentially deadly category of cancer. Their location and potential for aggressive growth make timely detection and treatment absolutely vital. Thus, there is a pressing need for continued research, advanced treatment modalities, and vigilant medical attention to enhance the prospects of individuals grappling with this formidable ailment. The two types of glioma, the most prevalent type of brain tumor, are commonly known as low-grade (LGG) and high-grade (HGG). Nearly three-fifths of people are diagnosed with HGG, which has a high mortality rate and an accelerated development rate. HGG tumors are typically malignant [2]. The average lifespan of HGG patients is 14 months after diagnosis. There are various disease-treating options, including radiotherapy and chemotherapy [3].

The usual treatment method for this condition is surgery. The presence and growth of brain tumors within the skull can exert pressure on adjacent brain tissues, leading to a range of neurological symptoms and complications. The specific effects can vary widely depending on the tumor's size, location, and rate of growth. Such pressure changes can result in symptoms like headaches, cognitive impairment, changes in personality, and even severe neurological deficits. Understanding the dynamics of these pressure-related effects is crucial for diagnosing and managing brain tumors effectively, as it helps healthcare professionals make informed decisions about treatment and patient care. Patients with the condition may occasionally experience problems with their circulatory systems and may even become paralyzed. In addition, the symptoms vary according to the part of the brain that is afflicted. These include speech problems, numbness, vision and hearing loss, abnormal gait, and a variety of other symptoms. The specific cause of brain tumors is unknown. Nowadays, machine and deep learning approaches are applied in various fields.

However, it is undeniable that brain tumors can occur in people of various ages [4]. Because the condition is so serious, research into brain tumor diagnostics is a very active area of study [5]. In this research, a technique for aiding medical professionals in disease diagnosis was created utilizing a dataset of MRI images which publicly accessible [6]. The main issue with deep learning and machine learning models is the need for huge amounts of data [7], but in some situations, this amount of data is not available. Additionally, building a trustworthy model to aid in the early diagnosis of brain tumor sickness is the goal of this work, which combines image augmentation and transfer learning approaches in individuals when only a limited amount of data is available for creating a specific model for head tumor detection. The reduction of doctors' workload is another advantage of this study as well as it is imperative to establish safeguards that protect both doctors and patients from the risk of incorrect diagnoses, which can occur when healthcare providers are fatigued and burdened with excessive workloads. By addressing the issue of exhaustion among medical professionals and implementing measures to alleviate their workload, we not only enhance the accuracy of diagnoses but also promote the overall well-being of healthcare practitioners, leading to a more robust and reliable healthcare system. This research endeavor brings forth a range of innovative contributions that warrant a closer examination. These groundbreaking elements are not only noteworthy but also serve as the focal points of this study. The following points delve into the distinctive contributions of this research with comprehensive detail:

- A methodology for comparing the effectiveness of various models after applying data augmentation techniques is provided.
- Convolutional neural networks' efficiency, such as Inception V3, VGG16, and DenseNet169, is compared to see how transfer learning and image enhancement methods affect it.

In this study, the performance of three transfer learning models is evaluated before and after applying image augmentation techniques using MRI imaging to find brain tumors. Several measures, including accuracy, recall, precision, and f1 score, were used to assess the models.

Literature review

There is various research for the detection of brain cancer in the literature. A trustworthy segmentation technique for the automatic segmentation of brain tumors was introduced by Dong et al., in their research they made use of the BRATS2015 dataset. They said that the approach they suggested produced positive outcomes [8]. Amin et al. presented an automatic system that can tell from MRI scans if the brain contains a tumor or not. The studies used the Harvard, Rider, and local databases, and the greatest degree of accuracy was 97.1% [9]. Wu et al. recommended a technique for recognizing brain tumors by color-based segmentation. The method employed in this strategy is K-means clustering. They claimed that the technique could effectively segment MRI brain tumor pictures, assisting pathologists in accurately identifying the size and location of lesions [10]. Based on a genetic algorithm a prototype for finding brain tumors was developed by Chandra et al., and their model was applied to detect tumor pixels on MRI scans [11], The results of recent research are encouraging for diagnosing and treating brain tumors, and offer a wide range of uses. Nevertheless, despite the positive outcomes that the authors mention, due to considerable limitations, only a small number of studies are valid in the actual clinical situation. The authors emphasize that the results cannot be generalized since the models are trained on a tiny amount and restricted access to data.

In a study by Xu et al. [12], a comprehensive examination of image augmentation techniques was conducted, introducing an innovative taxonomy that categorizes these techniques into three distinct groups: model-free, model-based, and optimizing policy-based methods. The investigation delved into the underlying goals of image augmentation, analyzing the complexities associated with implementing deep learning models in computer vision tasks. It also embraced the concept of vicinity distribution to gain deeper insights. The study's findings underscore the substantial enhancements that image augmentation brings to task performance. A review paper by Chen et al. [13] presented a comprehensive examination of deep learning techniques applied to post-processing MR images, encompassing tasks such as artifact reduction, noise suppression, and resolution enhancement. They demonstrated that deep learning methods yield enhanced image quality compared to traditional approaches. Nevertheless, the existing challenges and prospects for the availability of data, generalization capabilities, and clinical validation of deep learning algorithms underscore the need for continued and collaborative research efforts in this rapidly advancing field. Another research by Zhou et al. [14] introduced an innovative approach for enhancing underwater images, referred to as the Multi-Feature Embedded Fusion (MFEF) method. Given the common challenges of low contrast, color distortion, and blurred details in underwater images, They leveraged input processing techniques like White Balance (WB) and Contrast Limited Adaptive Histogram Equalization (CLAHE) to acquire high-quality input. The core of their method involves the Multi-Feature Fusion (MFF) module, which facilitates comprehensive interaction among diverse image features, preserving fine details effectively.

Trabucco et al. [15] tackled the issue of limited diversity in data augmentation by introducing a novel approach involving image-to-image transformations driven by pre-trained text-to-image diffusion models. Their technique involves altering images to modify their meaning, leveraging readily available diffusion models. Notably, their method exhibits versatility in adapting to new visual concepts with only a small number of labeled examples. To assess the effectiveness of their approach, they conducted evaluations on few-shot image classification challenges and a practical weed recognition task, where they observed enhanced accuracy in the tested scenarios. Alomar et al. [16] surveyed the data augmentation techniques, particularly recent research in image classification and segmentation employing data augmentation techniques, which are critical for deep learning models to overcome the overfitting issue and achieve better performance. In addition, they proposed a geometric augmentation technique, i.e., RLR (random local rotation), focusing on manipulating local information within images without adding non-original pixel values.

Anaya-Isaza and Mera-Jiménez [17] by using the ResNet50 network to detect brain tumors, contrasted the effects of different conventional data augmentation strategies. With the help of transfer learning and a network built using only zeros, the ImageNet dataset was used for the training. With the help of their investigation, the researchers were successful in obtaining a 92.34 percent F1 detection score with the ResNet50 network. Abdalla et al. [18] investigated typical data augmentation methods' effects on three deep learning networks, namely MobileNetV2, VGG19, and DenseNet201, to detect brain tumors. The results demonstrated that picture augmentation schemes had a significant impact on the networks both before and after using approaches. Kumar et al. [19] determined a classification scheme to reduce the tumor's severity via MRI images while taking into account AlexNet, ResNet 50, and Inception V3's prediction accuracy. The three-convolution neural network (CNN) models receive data from the database that has been enhanced. Based on the accuracy and performance between the three models, a comparison line is made with AlexNet achieving the best accuracy of 96.2%.

Shoaib et al. [20] by using four deep convolutional neural networks, including BRAIN-TUMOR-net, transfer learning, inceptionv3, and inceptionresnetv2, attempted to identify between normal cases versus pituitary tumors, meningioma tumors, and glioma tumors. They employ the augmentation approach in order to increase the dataset size due to the small number of photos. The results of the research showed that the best performance with the augmented images is achieved by the DL model that was built from scratch. A study by [21] was conducted to determine the most practical adjustment by applying five different modifications to five different well-known CNNs. To create a novel CNN architecture for brain tumor identification, each structure is modified with five layers and parameter tuning.

Olin et al., assert that the models were developed using small datasets for neck and head diseases and included only one research with a maximum of 800 images [22]. However, only 775 people with glioblastoma are represented by Jayachandran et al. study [23]. Similarly, Amemiya et al. claim that the evidence from their research of 127 patients is restricted and more data would result in improved results [24]. The number of brain tumor patients in the Tandel et al. study is restricted to 130, but they get around this problem by utilizing picture scale, rotation, transfer learning, and data augmentation [25]. The number of images is also increased by Jiang et al. by flipping, resizing, and smoothing the images [26]. In a similar vein, Wang et al. employ flipping, Gamma function color (contrast) change, rotation, and image warping [27]. In fact, writers executed the applications using a modest amount of data, but they didn't use any learning transfer or data augmentation techniques. These include, for example, Al-Saffar and Menze [28, 29]. According to the research that has been given it is quite evident that more training data are required to enhance the performance of the models.

Materials and methods

This section explains the applied networks, image augmentation techniques, and the used dataset for this research. The type of the tumor, its location, size, and extent of damage to the brain and nerves are all crucial information for determining the best course of action. For the early detection of the tumor, it is essential to reveal the information concealed in the MRI pictures.

Dataset

The used Dataset for the experiments was obtained from the Kaggle platform, which is publicly available [6]. There are 253 MRI images in the entire original dataset. Two classes make up this set of data. In first-class data, there are 98 MRI images of no tumor. Images of the tumor-bearing patient make up the second class of data with 155 images; the extension type of the images is (JPG). MRI scan of a person with a brain tumor is shown in Fig. 1 on the right side. A healthy person is depicted on the left in Fig. 1's MRI pictures. The dataset is split into two different folders for the purpose of taring and testing the models, The first folder includes *(%75) of the images for the taring, and the remaining part (%25) is used to validate the models with and without applying the suggested image augmentation method, for achieve the most reliable results the models tested with the same images before and after applying images augmentations to the dataset.*

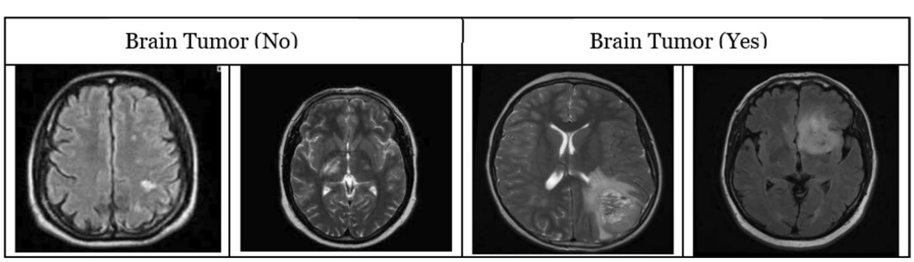


Fig. 1 Sample images of brain MRIs form the dataset

Image augmentation techniques

Deep learning networks' intrinsic demand for vast amounts of data has prompted the creation of a variety of techniques, from straightforward changes like geometric transformations to intricate mosaic-based graphics. The following fundamental methods are some of the most often used methods; This study used a combination of the following techniques:

- Rescale
- Width Shift
- Height Shift
- Shear
- Zoom
- Rotation
- Horizontal Flip
- Brightness

For this purpose, a method in Python was created and applied to the training folder of the dataset, as demonstrated in Fig. 2.

In the domain of deep learning applied to medical imaging, it's important to note that a substantial majority, approximately 86 percent, of data augmentation methods

```
def augmentataion_generator(height,width):

    datagen = ImageDataGenerator(
            rescale=1./255.,
            width_shift_range=0.1,
            height_shift_range=0.1,
            shear_range=0.1,
            zoom_range=0.1,
            rotation_range=30,
            horizontal_flip=True,
            brightness_range=(0.5, 1.0)
            )
    aug_train_ds = datagen.flow_from_directory(
            data_dir,
            batch_size=64,
            shuffle=True,
            class_mode='binary',
            target_size=(height, width),
            classes={'no': 0., 'yes': 1.}
            )
    return aug_train_ds
aug_train_ds = augmentataion_generator(height,width)
```

Fig. 2 The Python augmentataion_generator method utilized can be categorized as either "fundamental" or "deformable" techniques. These techniques play a fundamental role in augmenting medical image data to enhance the performance and adaptability of models.

- *Fundamental techniques*: Fundamental data augmentation approaches encompass core transformations of the original image data. These transformations encompass actions like rotation, scaling, flipping, and cropping. These modifications enable the model to learn and recognize features from diverse angles, orientations, and scales, thus increasing its resilience to variations in patient positioning and scanner settings.
- *Deformable techniques*: Deformable augmentation strategies introduce controlled spatial deformations into the images. These deformations can mimic anatomical variations or distortions encountered in clinical imaging. By exposing the model to such variations, it becomes more proficient at handling real-world data where subtle anatomical variances exist among patients.

These augmentation methodologies are pivotal in training deep-learning models for the analysis of medical images. They not only assist in diversifying the training dataset but also contribute significantly to the model's generalization ability and its capacity to adapt to variations encountered in real-world clinical contexts. Recognizing the prevalence and effectiveness of these techniques underscores their importance in advancing the performance and reliability of deep learning models applied in medical imaging tasks [17].

Figure 3 demonstrates some examples after applying the suggested *augmentataion_generator* method to the train folder of the dataset. The augmentation strategy resulted in an increase of 506 images in the dataset size.

Deep learning architectures

In recent years, the field of medical imaging has witnessed a significant transformation due to the rapid advancements in deep learning techniques. Deep learning, a subset of

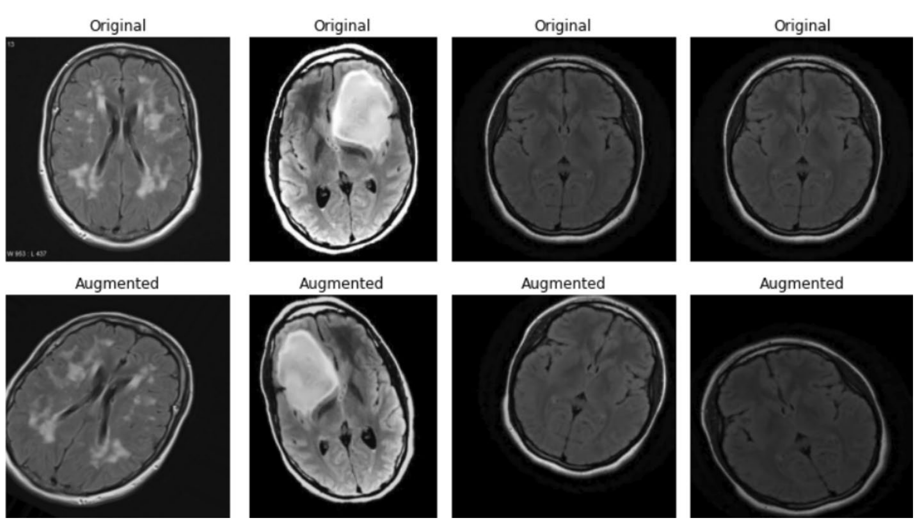


Fig. 3 MRI images before and after applying the augmentataion_generator method

machine learning, has emerged as a powerful tool in various domains, including medical diagnostics. One of the compelling applications is the detection of brain tumors using deep learning models. Brain tumors, which can have life-altering consequences, necessitate accurate and timely diagnosis to facilitate effective treatment. Traditional methods of tumor detection often rely on manual analysis of medical images, which can be time-consuming and prone to human error. However, deep learning approaches offer a promising solution to this challenge by enabling automated and accurate detection of brain tumors. For feature conversion and extraction, deep learning employs numerous layers. Each layer inputs the output of the preceding layer [30]. There are many deep learning architectures; this research used the following networks:

InceptionV3

The InceptionV3 model, a pioneering convolutional neural network (CNN) architecture developed by Google researchers, introduces inception modules to efficiently capture intricate image features. Through parallel convolutional operations of different filter sizes and pooling, the model adeptly extracts diverse features, aided by 1×1 convolutions for dimensionality reduction. To counter vanishing gradient issues, batch normalization and ReLU activations are employed, promoting efficient gradient propagation during training. Factorization techniques and dimensionality reduction further enhance the model's capacity to learn complex features while managing computational demands. With a balance between complexity and efficiency, InceptionV3 excels in image classification tasks, boasting superior performance on benchmark datasets and establishing itself as a pivotal advancement in the deep learning landscape. Figure 4 illustrates the InceptionV3's architecture [31].

VGG16

The VGG16 model, developed by the Visual Geometry Group at the University of Oxford in 2014, is celebrated for its uncomplicated architecture. Rather than depending on pre-designed attributes, VGG16's key breakthrough was its substantial depth, encompassing 16 layers in total. Within these layers, 13 are dedicated to convolutions, while the remaining 3 are fully connected. The convolutional layers are organized into sets of two to three consecutive layers, accompanied by max-pooling stages for spatial dimension reduction. A distinguishing feature of VGG16 is its consistent employment of 3×3 convolutional kernels across all layers. This strategic homogenization of

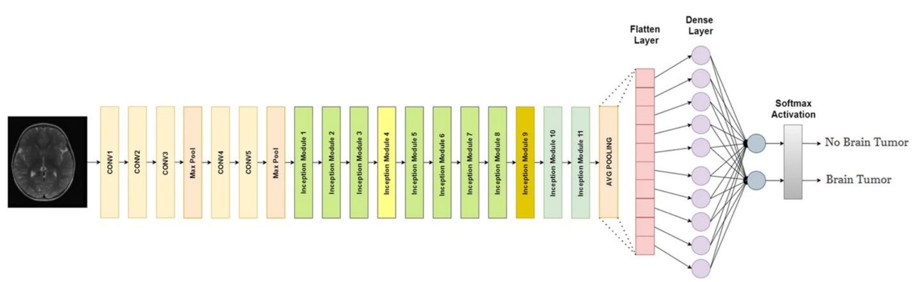


Fig. 4 The InceptionV3 network's architecture [32]

parameters played a crucial role in the model's success. The systematic arrangement of convolutional layers alternated with max-pooling layers facilitated the acquisition of hierarchical features at different levels of intricacy. Although VGG16 is relatively less complex than subsequent architectures, its exceptional performance across standard datasets underscored its aptitude for learning intricate feature hierarchies [33]. There are 16 layers with different values, as indicated by the number 16 in the VGG16 algorithm. An estimated 138 million elements make up this system [34]. Figure 5 illustrates the architectural design of VGG16 [35].

DenseNet169

The DenseNet169 architecture represents a notable progression in the realm of convolutional neural networks, particularly in addressing challenges linked to information flow and feature reuse. Presented by Huang et al. in their "Densely Connected Convolutional Networks" paper, DenseNet169 builds on the concept of dense connectivity, where each layer gains input from all prior layers. This novel approach improves gradient propagation, promoting the reuse of features, which in turn aids learning efficiency and mitigates issues like vanishing gradients. The architecture is marked by its significant depth, encompassing 169 layers, and its incorporation of densely connected blocks, contributing to more intricate feature representations. DenseNet169 has displayed remarkable performance across diverse image classification benchmarks, underscoring its proficiency in capturing complex patterns and data hierarchies. This model's influence is evident in subsequent network designs that embrace the principles of dense connectivity to achieve improved training dynamics and resilience.

DenseNet169 is the name of a 169-layer convolutional neural network. The ImageNet database contains a pre-trained version of the network that was developed using more than one million images. The pre-trained network can recognize 1000 different object types in images. As a result, the network has amassed substantial feature representations for a variety of pictures. Up to 224 by 224-pixel images can be sent over the network [27]. Figure 6 presents the architectural layout of DenseNet169.

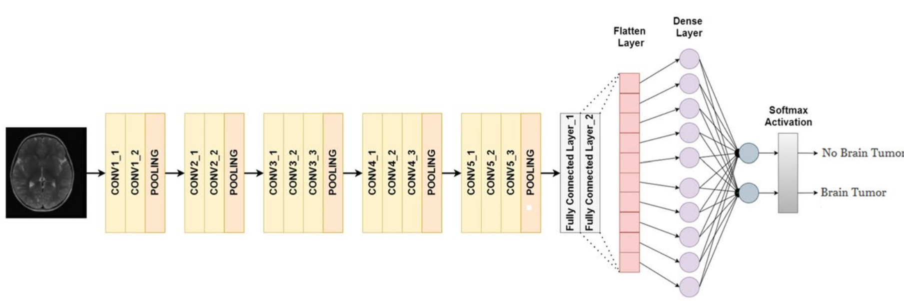


Fig. 5 The VGG16 architecture

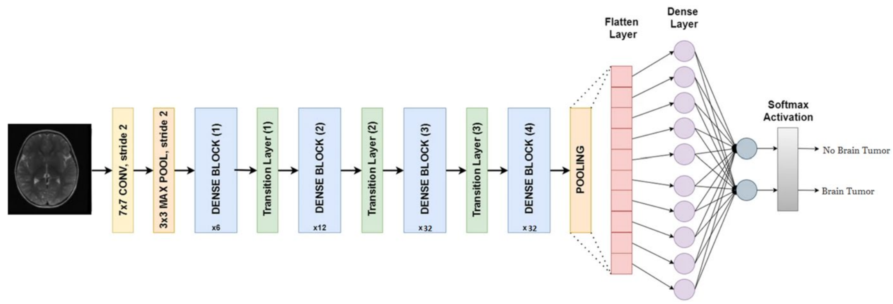


Fig. 6 The architecture of DenseNet169

		Predicted Class		
		Positive	**Negative**	
Actual Class	**Positive**	True Positive (TP)	False Negative (FN) Type II Error	**Sensitivity** $\frac{TP}{(TP+FN)}$
	Negative	False Positive (FP) Type I Error	True Negative (TN)	**Specificity** $\frac{TN}{(TN+FP)}$
		Precision $\frac{TP}{(TP+FP)}$	**Negative Predictive Value** $\frac{TN}{(TN+FN)}$	**Accuracy** $\frac{TP+TN}{(TP+TN+FP+FN)}$

Fig. 7 A Confusion matrix

Experimental results

Images of brain tumors were categorized using deep learning architectures. The effectiveness of the models in deep learning is expressed by a set of criteria. A confusion Matrix was used to determine each of these performance measures. In Fig. 7, a straightforward Confusion matrix example is shown. Because of its well-known libraries, Python is used to execute these models as a programming language. Libraries like Matplotlib and Pandas are used to present statistical analysis and produce visual graphs. Kaggle has functioned as an IDE for these computers using the NVidia K80 GPU.

A confusion matrix is a typical visual representation of the efficiency of categorization systems. The matrix (table) shows the percentage of events in the test data that were correctly and incorrectly recognized in contrast to the actual outcomes (target value A confusion matrix serves as a valuable tool to evaluate the performance of a classification model. It presents a comprehensive breakdown of the model's predictions, organizing them into four distinct categories:

- Instances correctly predicted as positive: True Positives (TP).
- Instances correctly predicted as negative: True Negatives (TN).

- Instances inaccurately predicted as positive when they are actually negative: False Positives (FP).
- Instances inaccurately predicted as negative when they are actually positive: False Negatives (FN).

By structuring these outcomes in a matrix format, the confusion matrix offers a clear and detailed picture of how the model is performing across different prediction scenarios. This breakdown aids in assessing the model's strengths and weaknesses, facilitating targeted improvements [36].

This research employed a number of metrics to provide more context, including:

- *Accuracy*: Accuracy can be evaluated by using CM parameters. In this scenario, the total number of forecasts is divided by the total number of accurate predictions, as explained in Eq. 1.

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{(\text{TP} + \text{TN} + \text{FP} + \text{FN})} \tag{1}$$

- *Precision*: Precision, in the context of classification or recognition tasks, refers to the measure of accuracy that quantifies the ratio of correctly identified positive instances to the total number of instances labeled as positive. In other words, precision evaluates the extent to which the positive predictions made by a model are actually accurate. It focuses on minimizing the occurrence of false positives, ensuring that the identified positive cases are genuinely relevant and reliable. Equation 2 shows a precision formula.

$$\text{Precision} = \text{TP}/(\text{TP} + \text{FP}) \tag{2}$$

- *Recall (sensitivity)*: is a metric that measures the proportion of actual positive instances correctly identified by a model among all the true positive instances. Its formula is demonstrated in Eq. 3.

$$\text{Recall} = \text{TP}/(\text{TP} + \text{FN}) \tag{3}$$

- *F_1 score*: is a metric that measures the proportion of actual positive instances correctly identified by a model among all the true positive instances. Equation 4 shows the F1 score formula.

$$F_1\ \text{Score} = 2 \times (\text{Precision} \times \text{Recall})/(\text{Precision} + \text{Recall}) \tag{4}$$

- *Negative predictive value*

$$\text{NPV} = \text{TN}/(\text{TN} + \text{FN}) \tag{5}$$

- *False discovery rate*

$$\text{FDR} = \text{FP}/(\text{FP} + \text{TP}) \tag{6}$$

- *False negative rate*

$$\mathrm{FNR} = \mathrm{FN}/(\mathrm{FN} + \mathrm{TP}) \tag{7}$$

- *False positive rate*

$$\mathrm{FPR} = \mathrm{FP}/(\mathrm{FP}\ + \mathrm{TN}) \tag{8}$$

- *Matthews correlation coefficient*

$$\mathrm{MCC} = \mathrm{TP} \times \mathrm{TN} -\ \mathrm{FP} \times \mathrm{FN}/\mathrm{sqrt}((\mathrm{TP} + \mathrm{FP}) \times (\mathrm{TP} + \mathrm{FN}) \times (\mathrm{TN} + \mathrm{FP}) \times (\mathrm{TN} + \mathrm{FN})) \tag{9}$$

- *Specificity*
  It is a fundamental metric in binary classification tasks such as medical diagnosis or machine learning classification models, playing a crucial role in assessing the performance of classification models, especially in scenarios where correctly identifying negative cases holds significant importance.
  Specificity is calculated using the following formula:

$$\mathrm{Specificity} = \frac{\mathrm{TN}}{(\mathrm{TN} + \mathrm{FP})} \tag{10}$$

  In this formula:
  True Negatives (TN) are the cases where the model correctly identifies them as negative.
  False Positives (FP) represent instances where the model incorrectly classifies negative cases as positive.

VGG16

Figure 8 illustrates plots of accuracy and loss obtained using the VGG16 architecture. 64 picture test data were used to evaluate the VGG16 architecture; the images were randomly selected for each model, but to achieve the most reliable result each model was tested on the same data with and without applying the suggested image augmentation method to the training data folder. 62 of these data were successfully categorized; 25 images were used in the testing phase for the normal case (no brain tumors). The model accurately detected 23 of them, and all the total images for brain tumors were 39; in other words, all of them were correctly detected by the model. The 2 remaining test data were wrongly categorized. The confusion matrix of the VGG16 architecture is exposed in Fig. 9.

InceptionV3

Figure 10 illustrates accuracy and loss charts obtained using the InceptinV3 architecture. 64 picture test data were used to evaluate the InceptinV3 model. 63 of these data were successfully categorized; 28 images were used in the testing phase for the normal cases; the model accurately detected 27 of them, and all the total images for brain tumors was 36, which all of them correctly detected by the model. The remaining test data were wrongly categorized. The confusion matrix of the InceptinV3 architecture is illustrated in Fig. 11.

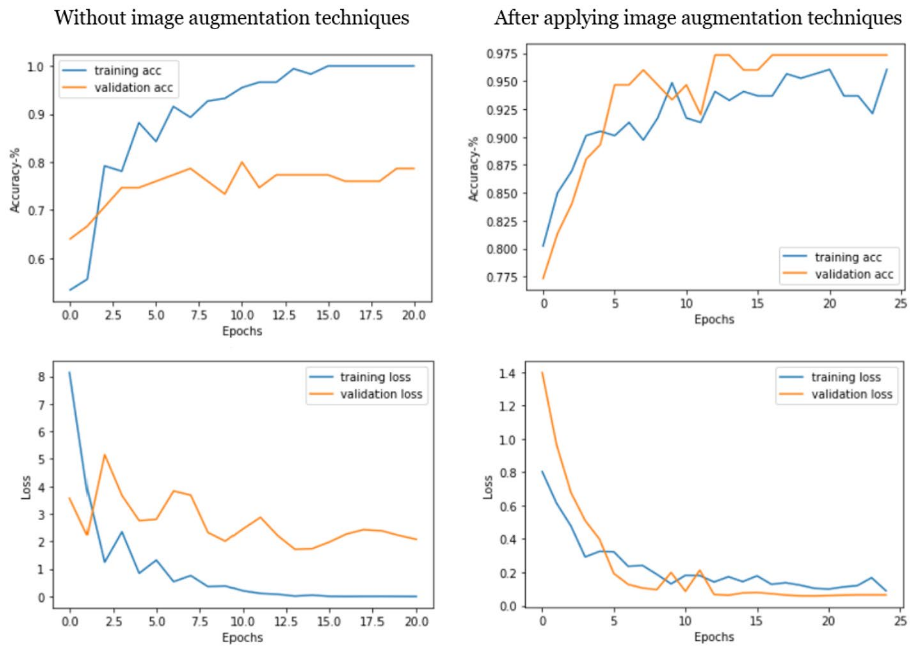


Fig. 8 The outcomes of VGG16 with and without applying the proposed method

		No Brain Tumor	Brain Tumor
True Classes	No Brain Tumor	**23**	2
	Brain Tumor	0	**39**
		Predicted Classes	

Fig. 9 VGG16 confusion matrix after applying the proposed method

DenseNet169

In Fig. 12, accuracy and loss plots achieved using the DenseNet169 architecture are shown. 64 picture test data were used to evaluate the DenseNet169 architecture. 62 of these data were successfully categorized; the normal class includes 24 images in the testing phase; the model accurately detected 22 of them, and all the total images for brain tumors was 40, which all of them correctly detected by the model. The 2 remaining test data were wrongly categorized. The confusion matrix of the DenseNet169 architecture is demonstrated in Fig. 13.

Discussion

The influence of employing image augmentation methods on MRI patient images reveals that the outcomes after implementing these techniques demonstrate an upsurge. The impact of integrating image augmentation techniques into the processing of MRI patient images is noteworthy. The obtained results, subsequent to the application of these techniques, indicate a noticeable enhancement.

The impact of image augmentations for detecting and diagnosing brain tumors is explained in Fig. 14. The overall comparison for the models (VGG16, InceptionV3, and

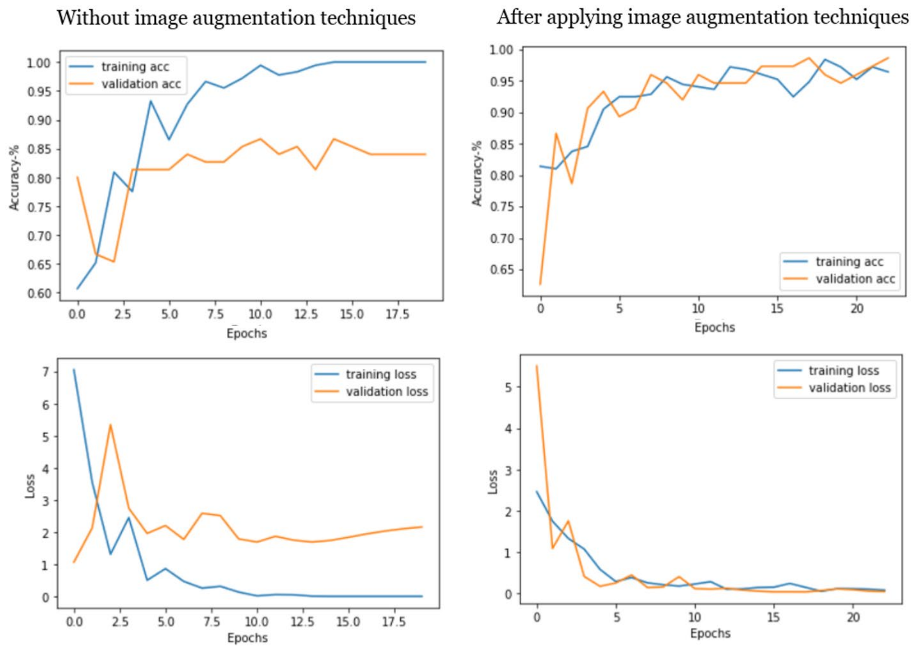


Fig. 10 The outcomes of InceptinV3 with and without applying the proposed method

		No Brain Tumor	Brain Tumor
True Classes	No Brain Tumor	**27**	1
	Brain Tumor	0	**36**
	Predicted Classes		

Fig. 11 InceptionV3 confusion matrix after applying the proposed method

DenseneNet169) after applying the techniques for MRI patients is demonstrated in Fig. 15 via several metrics.

In addition, the outcomes of the suggested models are contrasted with previous and state-of-the-art works, as shown in Table 1. When compared to other related works, the results demonstrated the best accuracy for predicting brain tumors was provided by the suggested models with applied data augmentation. Since InceptionV3 has a significant and relative accuracy scale, it performs better than other models among the suggested models. With the help of MRI images, this technique was developed to identify brain tumors.

Conclusion

In conclusion, the utilization of image augmentation techniques on MRI patient images holds substantial promise in the realm of medical imaging. The evident improvements in results underscore the potential of these methods to augment the

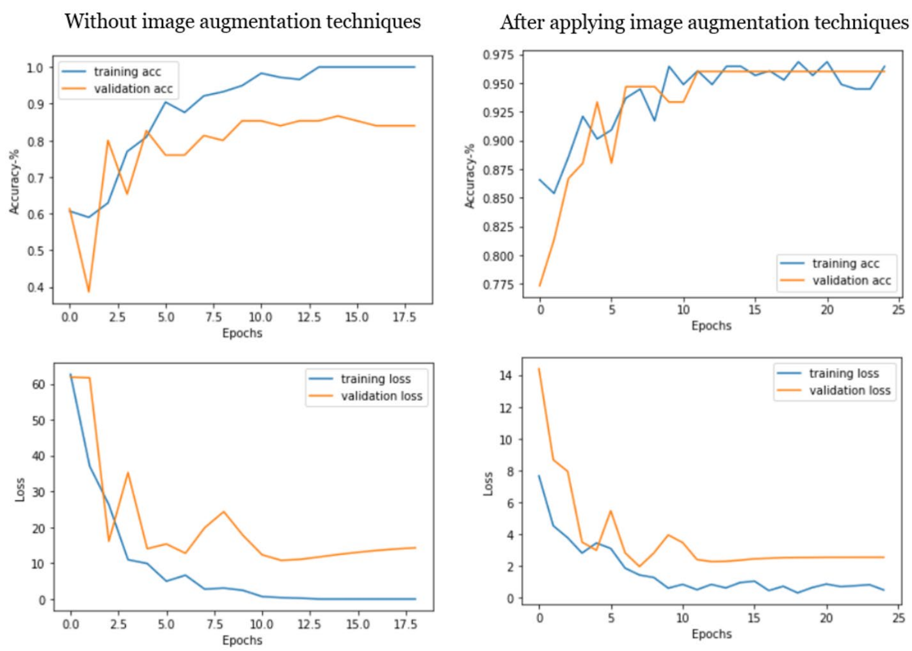
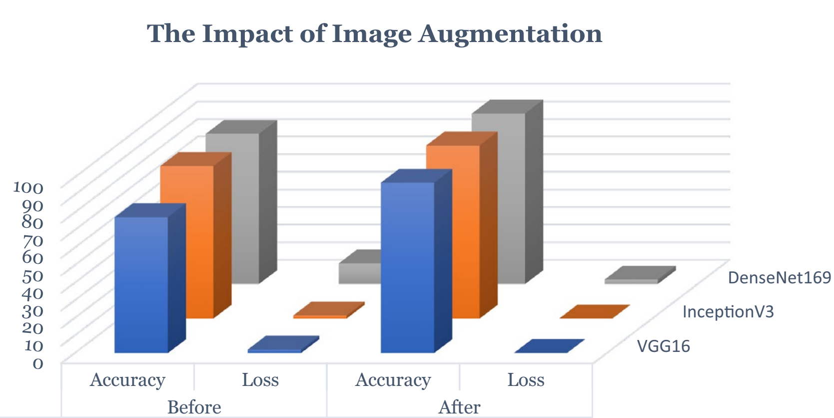


Fig. 12 The outcomes of InceptinV3 with and without applying the proposed method

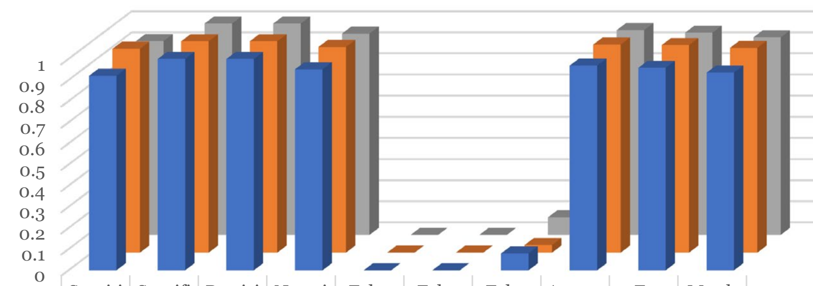
		No Brain Tumor	Brain Tumor
True Classes	No Brain Tumor	**22**	2
	Brain Tumor	0	**40**
	Predicted Classes		

Fig. 13 DenseNet169 confusion matrix after applying the proposed method



	Before Accuracy	Before Loss	After Accuracy	After Loss
VGG16	77.3333	1.977859	96.88	0.064472
InceptionV3	86.6667	1.738189	98.44	0.038528
DenseNet169	85.3333	11.747922	96.88	2.54127

Fig. 14 The impact of image enhancement methods



	Sensitivity	Specificity	Precision	Negative Predictive Value	False Positive Rate	False Discovery Rate	False Negative Rate	Accuracy	F1 Score	Matthews Correlation Coefficient
VGG16	0.92	1	1	0.9512	0	0	0.08	0.9688	0.9583	0.9355
InceptionV3	0.9643	1	1	0.973	0	0	0.0357	0.9844	0.9818	0.9686
DenseNet169	0.9167	1	1	0.9524	0	0	0.0833	0.9688	0.9565	0.9344

Fig. 15 Classification report per each class for the VGG16, InceptionV3, and DenseneNet169 models

accuracy and reliability of diagnostic processes. As the medical field continues to embrace technological advancements, the integration of image augmentation stands as a testament to its ability to contribute positively to the precision of MRI-based diagnoses and subsequent patient care. Through several transfer learning models, including VGG16, InceptionV3, and DenseNet169, this paper aimed to build a more reliable model for head tumor detection by applying an effective image augmentation method to enhance the performance of CNN architectures in identifying brain tumors. The following conclusions are drawn as a result of the study:

- Deep learning techniques were utilized in this investigation to detect brain cancers via MRI scans including VGG16, InceptionV3, and DenseNet169 architectures.
- InceptionV3 outperforms VGG16 and DenseNet169 for the given dataset due to its superior symmetric scale. However, the accuracy of VGG16 and DenseNet169 were the same.
- The three models' prediction accuracy significantly decreased without augmentation.
- The InceptionV3 architecture achieved the highest accuracy rate during the studies by 98.44 percent after employing image augmentation techniques. The accuracy rate for the VGG16 and DenseNet169 architectures was 96.88 percent.

The scientific community is still working to identify and treat brain tumors. Finally, the results demonstrated that the proposed data augmentation method results in improved performance of the models.

Acknowledgements
Our appreciation goes to the University of Halabja.

Table 1 Comparing the findings to previous related works

Paper	Technique	Accuracy percentage
[37]	GLCM	82.27
[38]	CNN	84.19
[39]	SVM	85.00
[40]	VGG19	90.28
[41]	CapsNet	90.89
[40]	BoW-SVM	91.28
[42]	DWT-Gabor-NN	91.90
[43]	CNN-ELM	93.68
[44]	VGG-16	94.42
[45]	DWT-DNN	96.27
[18]	MobileNetV2	96.88
[19]	AlexNet	98.24
[46]	Dense-Net classifier	98.26
	Dark-Net classifier	96.52
[47]	2D CNN	96.47
	Auto-encoder network	95.63
[48]	CNN	93.3
[49]	Momentum	97.71
	SMP-SGD	96.12
	SMP-Momentum	96.04
	SMP-Adagrad	97.35
	SMP-Adam	96.49
[50]	VGG16	95.11
	InceptionV3	93.88
	VGG19	94.19
	ResNet50	93.88
	InceptionResNetV2	93.58
	Xception	94.5
	IVX16	96.9
Models with applied data augmentation	InceptionV3	98.44
	VGG16	96.88
	DenseNet169	96.88

Author contributions
All parts of the paper were prepared and organized by PAA, authors BAM, and AMS contributed to the preparation of the revised version. All authors read and approved the final manuscript.

Funding
Not received.

Availability of data and materials
Available on request.

Declarations

Competing interests
The authors declare that they have no known competing financial interests or personal relationships which have, or could be perceived to have, influenced the work reported in this article.

Received: 17 February 2023 Accepted: 25 October 2023
Published online: 08 November 2023

References

1. Saeed MH, Hama JI (2023) Cardiac disease prediction using AI algorithms with SelectKBest. Med Biol Eng Comput 6:66
2. Sharifi G, Pajavand AM, Nateghinia S, Meybodi TE, Hasooni H (2020) Glioma migration through the corpus callosum and the brainstem detected by diffusion and magnetic resonance imaging: initial findings. Front Hum Neurosci 13:472
3. Chatterjee S, Nizamani FA, Nürnberger A, Speck O (2022) Classification of brain tumours in MR images using deep spatiospatial models. Sci Rep 12(1):1–11
4. Raza A et al (2022) A hybrid deep learning-based approach for brain tumor classification. Electronics 11(7):1146
5. Maqsood S, Damaševičius R, Maskeliūnas R (2022) Multi-modal brain tumor detection using deep neural network and multiclass SVM. Medicina 58(8):1090
6. (2022) Brain MRI images for brain tumor detection. https://www.kaggle.com/datasets/navoneel/brain-mri-images-for-brain-tumor-detection
7. Rawf KMH, Mohammed AA, Abdulrahman AO, Abdalla PA (2023) A comparative technique using 2D CNN and transfer learning to detect and classify Arabic-script-based sign language. Acta Inform Malays 7(1):66
8. Dong H, Yang G, Liu F, Mo Y, Guo Y (2017) Automatic brain tumor detection and segmentation using U-Net based fully convolutional networks. In: Annual conference on medical image understanding and analysis, 2017. Springer, pp 506–517
9. Amin J, Sharif M, Yasmin M, Fernandes SL (2020) A distinctive approach in brain tumor detection and classification using MRI. Pattern Recogn Lett 139:118–127
10. Wu M-N, Lin C-C, Chang C-C (2007) Brain tumor detection using color-based k-means clustering segmentation. In: Third international conference on intelligent information hiding and multimedia signal processing (IIH-MSP 2007), 2007, vol 2. IEEE, pp 245–250
11. Chandra GR, Rao KRH (2016) Tumor detection in brain using genetic algorithm. Procedia Comput Sci 79:449–457
12. Xu M, Yoon S, Fuentes A, Park DS (2023) A comprehensive survey of image augmentation techniques for deep learning. Pattern Recogn 137:109347
13. Chen Z, Pawar K, Ekanayake M, Pain C, Zhong S, Egan GF (2023) Deep learning for image enhancement and correction in magnetic resonance imaging—state-of-the-art and challenges. J Digit Imaging 36(1):204–230
14. Zhou J, Sun J, Zhang W, Lin Z (2023) Multi-view underwater image enhancement method via embedded fusion mechanism. Eng Appl Artif Intell 121:105946
15. Trabucco B, Doherty K, Gurinas M, Salakhutdinov R (2023) Effective data augmentation with diffusion models, arXiv preprint arXiv.07944
16. Alomar K, Aysel HI, Cai X (2023) Data augmentation in classification and segmentation: a survey and new strategies. J Imaging 9(2):46
17. Anaya-Isaza A, Mera-Jiménez L (2022) Data augmentation and transfer learning for brain tumor detection in magnetic resonance imaging. IEEE Access 10:23217–23233
18. Abdalla PA, Qadir AM, Rashid OJ, Rawf KMH, Abdulrahman AO, Mohammed BA (2022) Deep transfer learning networks for brain tumor detection: the effect of MRI patient image augmentation methods. Int J Electron Commun Syst 2(2):39–48
19. Kumar KK et al (2023) Brain tumor identification using data augmentation and transfer learning approach. Comput Syst Sci Eng 46(2):1845–1861
20. Shoaib MR, Elshamy MR, Taha TE, El-Fishawy AS, Abd El-Samie FE (2022) Efficient deep learning models for brain tumor detection with segmentation and data augmentation techniques. Concurr Comput Pract Exp 34(21):e7031
21. Bayoumi E, Khalaf AA, Gharieb RR (2021) Brain tumor automatic detection from MRI images using transfer learning model with deep convolutional neural network. J Adv Eng Trends 41(2):19–30
22. Olin AB et al (2021) Robustness and generalizability of deep learning synthetic computed tomography for positron emission tomography/magnetic resonance imaging-based radiation therapy planning of patients with head and neck cancer. Adv Radiat Oncol 6(6):100762
23. Preetha CJ et al (2021) Deep-learning-based synthesis of post-contrast T1-weighted MRI for tumour response assessment in neuro-oncology: a multicentre, retrospective cohort study. Lancet Digit Health 3(12):e784–e794
24. Amemiya S, Takao H, Kato S, Yamashita H, Sakamoto N, Abe O (2021) Automatic detection of brain metastases on contrast-enhanced CT with deep-learning feature-fused single-shot detectors. Eur J Radiol 136:109577
25. Tandel GS, Tiwari A, Kakde O (2021) Performance optimisation of deep learning models using majority voting algorithm for brain tumour classification. Comput Biol Med 135:104564
26. Jiang M, Zhai F, Kong J (2021) A novel deep learning model DDU-net using edge features to enhance brain tumor segmentation on MR images. Artif Intell Med 121:102180
27. Wang S-H, Zhang Y-D (2020) DenseNet-201-based deep neural network with composite learning factor and precomputation for multiple sclerosis classification. ACM Trans Multimed Comput Commun Appl 16(2s):1–19
28. Khairandish M, Sharma M, Jain V, Chatterjee J, Jhanjhi N (2021) A hybrid CNN-SVM threshold segmentation approach for tumor detection and classification of MRI brain images. IRBM
29. Al-Saffar ZA, Yildirim T (2021) A hybrid approach based on multiple eigenvalues selection (MES) for the automated grading of a brain tumor using MRI. Comput Methods Programs Biomed 201:105945
30. Sharma S, Dudeja RK, Aujla GS, Bali RS, Kumar N (2020) DeTrAs: deep learning-based healthcare framework for IoT-based assistance of Alzheimer patients. Neural Comput Appl 66:1–13
31. Qadir AM, Abdalla PA, Ghareb MI (2022) Malaria parasite identification from red blood cell images using transfer learning models. Passer J Basic Appl Sci 4(Special issue):63–79
32. Shazia A, Xuan TZ, Chuah JH, Usman J, Qian P, Lai KW (2021) A comparative study of multiple neural network for detection of COVID-19 on chest X-ray. EURASIP J Adv Signal Process 2021:1–16
33. Pandiyan V, Murugan P, Tjahjowidodo T, Caesarendra W, Manyar OM, Then DJH (2019) In-process virtual verification of weld seam removal in robotic abrasive belt grinding process using deep learning. Robot Comput Integr Manuf 57:477–487

34. Abdalla PA, Qadir AM, Rashid OJ, Karim SHT, Mohammed BA, Ghafoor KJ (2022) Transfer learning models comparison for detecting and diagnosing skin cancer. Acta Inform Malays 7(1):01–07
35. Althubiti SA, Alenezi F, Shitharth S, Reddy CVS (2022) Circuit manufacturing defect detection using VGG16 convolutional neural networks. Wirel Commun Mob Comput 2022:66
36. Luque A, Carrasco A, Martín A, de Las Heras A (2019) The impact of class imbalance in classification performance metrics based on the binary confusion matrix. Pattern Recognit 91:216–231
37. Widhiarso W, Yohannes Y, Prakarsah C (2018) Brain tumor classification using gray level co-occurrence matrix and convolutional neural network. IJEIS 8(2):179–190
38. Abiwinanda N, Hanif M, Hesaputra ST, Handayani A, Mengko TR (2019) Brain tumor classification using convolutional neural network. In: World congress on medical physics and biomedical engineering 2018: June 3–8, 2018, Prague, Czech Republic (vol 1). Springer, pp 183–189
39. Zacharaki EI et al (2009) Classification of brain tumor type and grade using MRI texture and shape in a machine learning scheme. Magn Reson Med 62(6):1609–1618
40. Cheng J et al (2015) Enhanced performance of brain tumor classification via tumor region augmentation and partition. PLoS ONE 10(10):e0140381
41. Afshar P, Plataniotis KN, Mohammadi A (2019) Capsule networks for brain tumor classification based on MRI images and coarse tumor boundaries. In: ICASSP 2019–2019 IEEE international conference on acoustics, speech and signal processing (ICASSP), 2019. IEEE, pp 1368–1372
42. Ismael MR, Abdel-Qader I (2018) Brain tumor classification via statistical features and back-propagation neural network. In: 2018 IEEE international conference on electro/information technology (EIT), 2018. IEEE, pp 252–257
43. Pashaei A, Sajedi H, Jazayeri N (2018) Brain tumor classification via convolutional neural network and extreme learning machines. In: 2018 8th International conference on computer and knowledge engineering (ICCKE), 2018. IEEE, pp 314–319
44. Sevli O (2021) Performance comparison of different pre-trained deep learning models in classifying brain MRI images. Acta Infologica 5(1):141–154
45. Mohsen H, El-Dahshan E-SA, El-Horbaty E-SM, Salem A-BM (2018) Classification using deep learning neural networks for brain tumors. Future Comput Inform J 3(1):68–71
46. Solanki S, Singh UP, Chouhan SS, Jain S (2023) Brain tumor detection and classification using intelligence techniques: an overview. IEEE Access 6:66
47. Saeedi S, Rezayi S, Keshavarz H, NiakanKalhori SR (2023) MRI-based brain tumor detection using convolutional deep learning methods and chosen machine learning techniques. BMC Med Inform Decis Mak 23(1):1–17
48. Mahmud MI, Mamun M, Abdelgawad A (2023) A deep analysis of brain tumor detection from MR images using deep learning networks. Algorithms 16(4):176
49. Qin C, Li B, Han B (2023) Fast brain tumor detection using adaptive stochastic gradient descent on shared-memory parallel environment. Eng Appl Artif Intell 120:105816
50. Hossain S, Chakrabarty A, Gadekallu TR, Alazab M, Piran MJ (2023) Vision transformers, ensemble model, and transfer learning leveraging explainable AI for brain tumor detection and classification. IEEE J Biomed Health Inform 6:66

Publisher's Note