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Classification of Brain Tumor Diseases Using Data Augmentation and Transfer Learning

Hadeel Moataz Al-Dabbas*[1] and Mohammed Salih Mahdi[2]

[1]*Department of Islamic Banking and Finance, College of Islamic Sciences, Aliraqia University, Baghdad, Iraq*
[2] *Business Information College, University of Information Technology and Communications, Baghdad, Iraq*

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Abstract

An accumulation of aberrant cells called a brain tumor is the outcome of unregulated cell division. Brain cancers can be found using magnetic resonance imaging (MRI). The exponential growth of deep learning networks has allowed us to tackle complex tasks, even in fields as complicated as medicine. However, using these models requires a large corpus of data for the networks to be highly generalizable and have high performance. This dearth of training data makes it critical to explore methods such as data augmentation. In this sense, data augmentation methods are widely used in strategies to train networks, and with small data sets being vital in medicine due to the limited access to data, this work aims to identify the best classification system by considering the prediction accuracy in this vein. Data augmentation is performed on the database and fed into the three convolutional neural network (CNN) models. A comparison line is drawn between the three models based on accuracy and performance on the Inception v3 models, Mobile Net V2, and Squeeze Net network for brain tumor detection and classifying 350 brain MR images. The statistical methods were modified in order to evaluate these algorithms. With 0.992% accuracy, 0.993% recall, 0.989% precision, and 0.994% F1 score, the Squeeze Net model performed the best. The Mobile Net V2 model, which had an accuracy of 0.964%, came next. When the research's findings were compared to those of related studies in the literature, they revealed better success rates than those of the majority of investigations.

Keywords: Convolutional Neural Networks (CNN), Transfer Learning, Brain MRI Classification.

تصنيف اورام الدماغ باستعمال زيادة البيانات ونقل التعلم

هديل معتز الدباس *1 محمد صالح مهدي2

1قسم العلوم المالية والمصرفية الاسلامي، كلية العلوم الاسلامية، الجامعة العراقية، بغداد، العراق
2كلية معلوماتية الاعمال، جامعة تكنولوجيا المعلومات والاتصالات، بغداد، العراق

الخلاصة

ينتج تراكم الخلايا الشاذة المسمى بورم الدماغ عن انقسام الخلايا غير المنظم. يمكن اكتشاف سرطانات الدماغ باستعمال التصوير بالرنين المغناطيسي .سمح لنا النمو الهائل لشبكات التعلم العميق بمعالجة المهام المعقدة مثل الطب. ومع ذلك ، يتطلب استعمال هذه النماذج مجموعة كبيرة من البيانات للشبكات لتكون قابلة للتعميم بشكل كبير وذات أداء عالٍ. هذا النقص في بيانات التدريب يجعل من الضروري استكشاف طرق مثل

*Email: hadeelmtz@gmail.com

زيادة البيانات ، وبهذا المعنى ، فإن طرق زيادة البيانات هي استراتيجيات مستعملة على نطاق واسع لتدريب الشبكات بمجموعات بيانات صغيرة ، كونها حيوية في الطب بسبب الوصول المحدود إلى البيانات ، ويهدف هذا العمل لتحديد أفضل نظام تصنيف من خلال النظر في دقة التنبؤ في هذا السياق ، يتم إجراء زيادة البيانات في قاعدة البيانات وتغذيتها في نماذج الشبكات العصبية الثلاثة (CNN). تم رسم خط مقارنة بين النماذج الثلاثة بناءً على الدقة والأداء على طرازات Inception v3 و Mobile Net V2 وشبكة Squeeze Net للكشف عن ورم الدماغ ، لتصنيف 350 صورة MR للدماغ. تم تعديل الأساليب الإحصائية من أجل تقييم هذه الخوارزميات. مع دقة 0.992٪ واسترجاع 0.993٪ ودقة 0.989٪ ودرجة 0.994٪ F1 ، كان أداء نموذج Squeeze Net هو الأفضل. جاء بعد ذلك نموذج Mobile Net V2 ، الذي كانت تبلغ دقته 0.964٪.
عندما قورنت نتائج البحث بنتائج الدراسات ذات الصلة في الأدبيات ، كشفت عن معدلات نجاح أفضل من تلك الخاصة بمعظم التحقيقات.

1. Introduction

Brain tumors pose a serious threat to human life and, if not detected and treated promptly, may become life-threatening [1]. Magnetic resonance imaging (MRI) and deep learning techniques, which are a subset of machine learning, are used for brain tumor detection [2]. Deep learning techniques are frequently used in the medical industry in a number of applications for resolving complicated issues that call for incredibly high sensitivity and accuracy [3]. However, in order for the networks to be highly generalizable and function at a high level, these applications need a big corpus of data. Because of the limited access to data, data augmentation techniques are frequently utilized with tiny data sets, which are essential in medicine. Accordingly, magnetic resonance imaging in pathology scans associated with cancer is a clear example [4]. Analysis of MR images necessitates extensive data processing [5]. The transfer-learning method is the answer to improving deep learning performance for this data processing problem. which is a collection of techniques that let computers predict outcomes using massive data [6]. Transfer learning is the process of transferring knowledge from one neural network that has already been trained to another that is comparable but untrained. The use of computers to diagnose medical conditions holds great promise for transfer learning. Transfer learning involves training the base network, which has many layers depending on the architecture, on the base dataset and then applying the learned parameters to another network. Different features are learned at each layer of the layered architecture of convolutional neural network models [7]. As a result, transfer learning may be readily achieved with a convolutional neural network, where the last layers are used to extract more precise features while the bottom layer serves as a feature extractor [5]. The literature has used a variety of MRI image categorization methods to classify brain abnormalities. Techniques for feature extraction and classification during pre-processing are commonly employed to differentiate between normal and abnormal images [8]. This research uses a variety of supervised machine-learning techniques, including the wavelet transform [9]. Additionally, sophisticated machine learning techniques, including feature reduction and feature extraction using the PCA and discrete wavelet transform (DWT), are applied [10]. In this study, MRI scan images consisting of 350 scans of the brain were used with a combination of data augmentation techniques such as flipping, rotation, and zooming to increase the size of the dataset and improve the model's ability to generalize and transfer learning techniques by using three different pre-trained models: Inception V3, Mobile Net V2, and the Squeeze Net. The work is applied by using the Python programming language and various libraries for classifying the tumor. The performance of the model was evaluated using statistical metrics such as accuracy, precision, recall, and F1-score. The results showed that the Squeeze Net model was superior in terms of all metrics.

Related works

Here is a survey of some researchers who have implemented transfer learning for computer-aided medical issue detection:
Chelghoum et al., 2020 [11] proposed an automatic classification system for three distinct epoch numbers processing three different types of brain tumors, which was developed in order to investigate the effects on classification performance and consumption time. This study achieves respectable results in a constrained amount of time using a few epochs. With 98.71% classification accuracy, the suggested system performs better than cutting-edge methods. This application of machine learning (ML) for medical diagnosis may not be applicable to other domains or use cases.

Alqudah et al., 2019 [12], proposed segmented brain tumor MRI images using a multi-grade classification of brain tumors. They used the CNN classifier, a potent tool, and it performed well overall, with accuracy and sensitivity for the clipped lesions of 98.93% and 98.18%, respectively. But they do not include any validation of the model's performance on an independent test dataset, which is necessary to avoid overfitting.

Khan et al., 2020 [13] proposed the comparison of the performance of the scratched CNN model with that of the retrained VGG-16, ResNet-50, and Inception-v3 models using the transfer learning approach, demonstrating that the model's accuracy is very active and has a very low complexity rate by reaching 100% accuracy, compared to 96% for VGG-16, 89% for ResNet-50, and 75% for Inception-V3.

Sevli 2021 [5] proposed the comparison of the performance of three pre-trained deep learning models: VGG16, ResNet50, and InceptionV3. Measures of accuracy, recall, sensitivity, and F1-score were used to assess the models. The Vgg-16 model performed the best, with 94.42% accuracy. This was followed by the ResNet50 model with an accuracy of 82.49%. Inception V3 showed the lowest accuracy.

Isaza and Jiménez, 2022 [8], proposed different traditional data augmentation techniques that affect the ResNet50 network's ability to detect brain tumors. They incorporated a principal component analysis-based approach. The network was trained from zeros, and transfer learning from the ImageNet dataset was used for the training. The investigation made it possible to achieve a 92.34% F1 detection score. Larger datasets may be needed to validate the effectiveness of their approach across a wider range of brain tumor types.

Alsaif et al., 2022 [14] proposed a technique based on CNN and data augmentation for detecting brain cancers using magnetic resonance imaging (MRI) datasets. An accuracy rate of 96% has been successfully attained by the convolutional neural network technique.
Younis et al., 2022 [15] proposed system technique had 155 cancers using MRI brain pictures in a dataset for brain tumor diagnosis out of 253. The method found brain malignancies in the MR pictures. The algorithm surpassed the already accepted methods for identifying brain tumors in the testing data, and it reached an excellent accuracy of 96% for CNN and 98.14% for the Ensemble Model. The generalization of the model might be enhanced by the use of a larger and more varied dataset.

Wahlang et al., 2022 [16] proposed a deep learning architecture technique to distinguish between normal and abnormal brain MRI pictures that was superior to AlexNet and the current SVM. The overall accuracy improved from SVM (82%) and AlexNet (64%) to 88% (LeNet Inspired Model) and 80% (CNN-DNN), respectively, with the best accuracy being 100%, 92%, 92%, and 81%. This technique may require further optimization and validation before it can be applied in clinical settings.

2. Materials and Methods

Some earlier research [5] relied on the manual extraction of tumor characteristics prior to classification. They can't become totally automated because of this. If the amount of available data is quite limited, only a tiny number of studies demonstrate the production of solutions [7].

This paper proposes a fully automated categorization solution for brain MRI data using deep convolutional neural networks and the transfer learning technique. The dataset was made up of 350 brain MRI images. The fundamental steps of the procedure are collection, preprocessing, and data augmentation, followed by the use of transfer learning techniques to reach the classification of images, as shown in Figure 1.

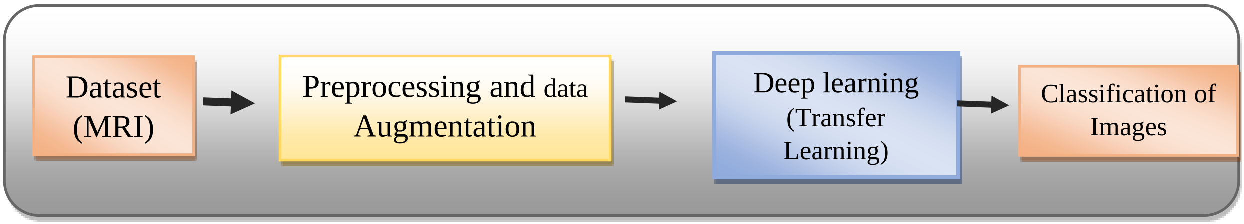

Figure 1: Flowchart for the research process.

3.1 Dataset

A free source of medical pictures gathered 300 brain MRI scans for the used dataset, which was used for instructional reasons [17]. As well as some images (50 images) taken from Al Kindy College of Medicine, University of Baghdad, most of these images were of tumors, while others were without tumors (Figure 2).

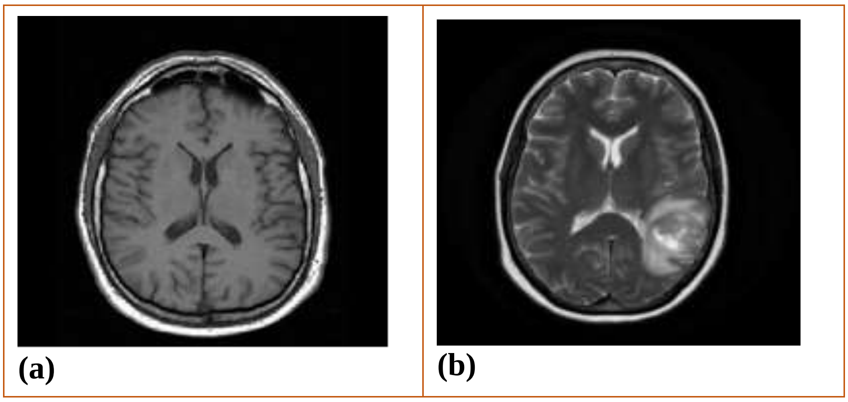

Figure 2: Samples of the original images for MRI image(a) Normal brain (b) Abnormal brain

3.2 Pre-processing of Images and Data Augmentation

During the preprocessing stage, the image was cropped using MATLAB R2021, taking into account the polar points and boundary points. The raw image was used to define the boundaries of the brain tissue, and any extra was removed. This facilitates data processing. After being cropped, images with varying width and length values were scaled to 224x224 pixels [18].

The amount of data from the dominant class restricts the generalizability of the classification success because the dataset utilized was extremely small. As a result, utilizing a constrained amount of instances, data augmentation was used to improve the class.

The most commonly used data augmentation methods are: [18][19]

• Flipping: produces a mirror image of the original;

• Rotation: tilting an image about its central pixel;
• Image translation requires shifting it in either the X or Y directions or both.

Using the current dataset as a base, an enhancement was made to four different angle rotations ranging from 45º to 120º from the horizontal and vertical axes. The scaling, rotation, and shifting ratios were discovered empirically in a manner that optimizes the improvement of the model's performance. Data augmentation was employed to restore tumor-free images using fewer samples, balancing the applied dataset. The number of photos without tumors increased by 50%, while the number of photos with cancer remained constant. Data augmentation allows for the calculation of the number of photos in each class in Table 1.

Table 1: Images after data augmentation, number

Image class	No. of Image without augmentation	No. of Image with augmentation
Images with tumor	175	1050
Images without tumor	175	1050
Total	350	2100

3.3 Deep Learning, CNN, and Transfer Learning

Machine learning is a branch of deep learning, which uses computation models with multiple layers to extract features from data at various levels of abstraction [20]. CNN is a deep learning method that is frequently used in image segmentation and classification. CNN allows for the automatic extraction and definition of features from images. Convolution, pooling, activation, and classification layers are common components of CNNs [19].

The CNN receives images that have been categorized using specified tags, and these pixels are then used to improve the network's trainable parameters in order to increase classification precision. The input pixels are subjected to a kernel application in the convolution layer, which reveals the features. The pooling layer reduces the data by taking the largest or average of the data from prior layers [16], [18]. The architecture of CNN is generally depicted in Figure 3 [5].

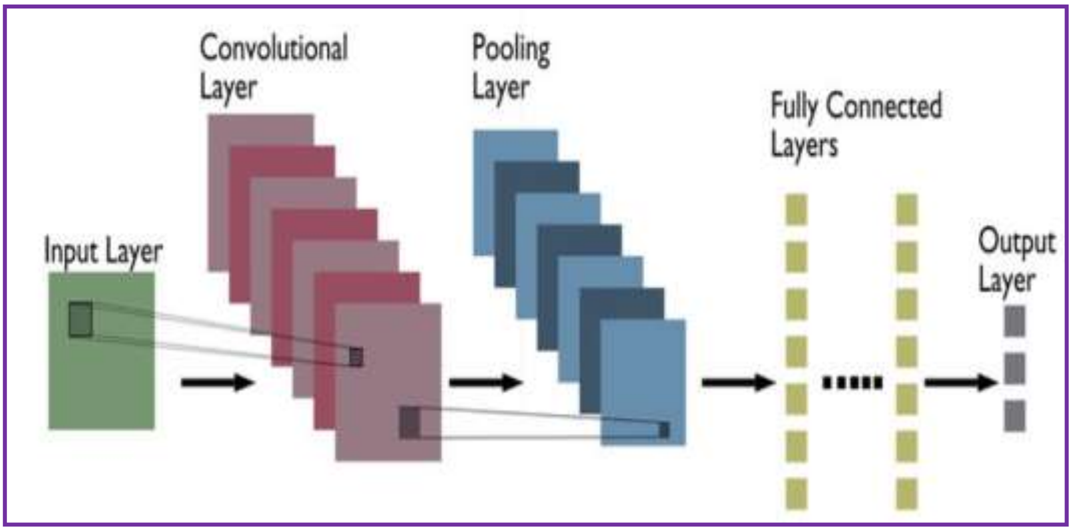

Figure 3: The architecture of CNN is generally [5].

Using the machine learning technique of transfer learning, a model created for one task is applied to another. When there is a lack of training data, it is typically employed [20]. However, the data issue can be solved by using data augmentation. Transfer learning nets are learned using huge datasets, with the model weights frozen. The final few layers are altered to fit a new dataset, and the new model's final section's classifiers are the only ones that receive training [5].

This study used a brain MRI classification task that utilized three different pre-trained models: Inception V3, Mobile Net V2, and Squeeze Net.

3.3.1 Inception V3 model

One of the crucial phases in the evolution of CNN architectures is the development of inception networks. There are four variations, each of which performs and is accurate differently [21]. The pre-trained Inception-V3 weights use Image Net and take into account the reshaped size of 150×150×3 for all pictures [5]. Figure 4 depicts the structure of the Inception v3 models [21].

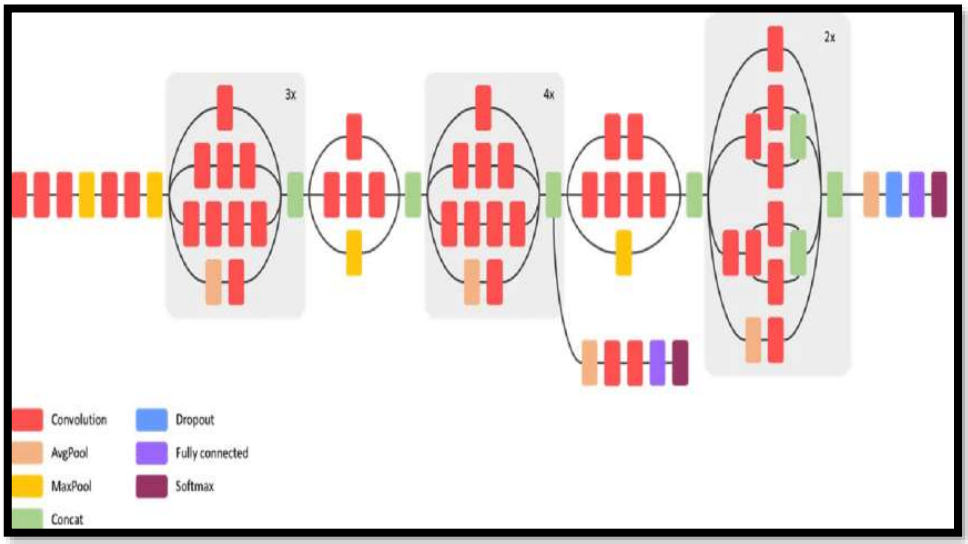

Figure 4: Structure of Inception V3 model [21]

3.3.2 Mobile Net V2

It's critical to comprehend the origins of the MobileNetV2 network. Google researchers created the MobileNetV1 network in 2017 [22]. The MobileNetV2 network, which is an advancement that expands upon the V1 variation, was introduced later. In contrast to V1, which uses a depth-wise separable convolution block, V2 adds a linear bottleneck between levels and leverages shortcut connections between those layers. Convolutional blocks in the mobile net V2 are shown in Figure 5 [22].

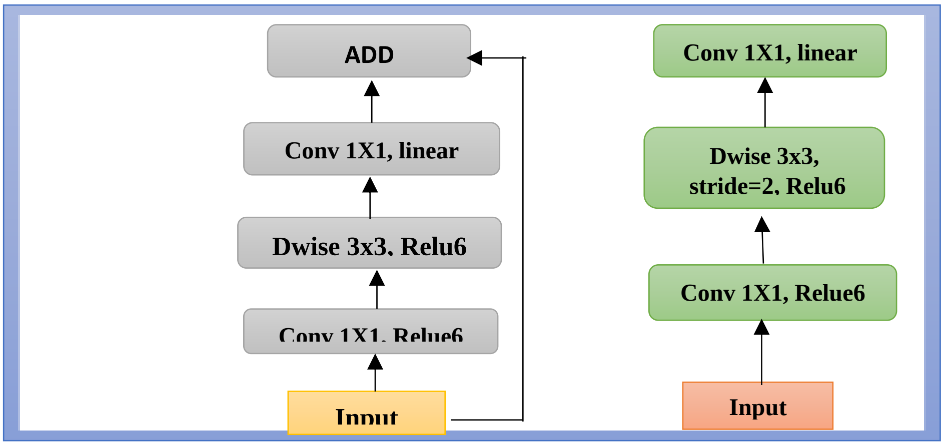

Figure 5: convolutional blocks in mobile net V2 [22].

3.3.3 The Squeeze Net Architecture

This process describes the Squeeze Net CNN architecture. 8 Fire modules (fire2-9) are next, and the final Conv layer follows (conv10) [23]. From the start of the network until its conclusion, it has been observed that the number of filters per fire module constantly increases. After layers conv1, fire4, fire8, and conv10, Squeeze Net performs max-pooling with a stride of 2. These very late placements of pooling are in accordance with Strategy 3 from Section 3.1. [22]. Figure 6 illustrates the Squeeze Net, which begins with a standalone convolution layer (conv1) and then reaches (conv10) [24].

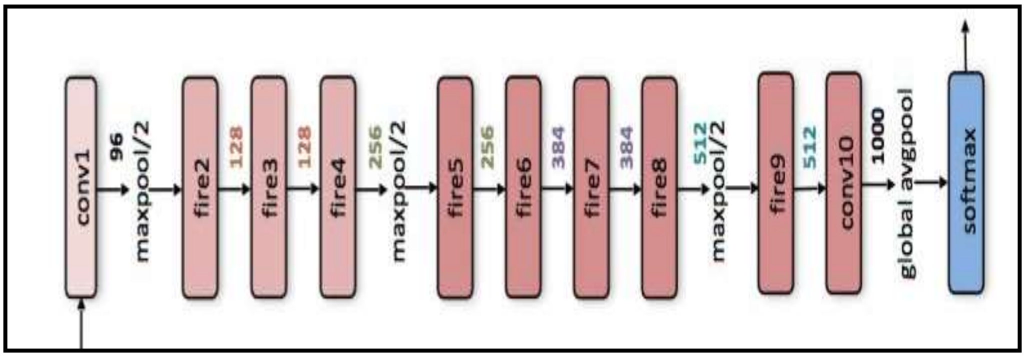

Figure 6: Squeeze Net CNN Architecture [24].

3. Experiential research

A fully automated method was provided for classifying brain tumors. The borders of the brain tissue were first automatically detected during the preprocessing of the raw MRI images, and then the images were cropped. The data augmentation method was then used to expand the dataset. By utilizing the transfer learning method, the processing burden was decreased, and successful results were produced with little data.

The effectiveness of a given strategy can be evaluated statistically using a variety of techniques. Accuracy, sensitivity, and precision are a few popular statistical techniques. The desired testing should have the maximum accuracy and the least error. The test defines its diagnostic and accuracy percents and is crucial for differentiating between healthy and patient individuals [5].

4. Performance Metrics

A classifier's performance is measured using a variety of parameters. Accuracy is the most frequently used metric. The percentage of samples that can be accurately classified from all the data is known as classification accuracy [26].

However, variations computed between real (actual) and predicted classes' measures by CM give the following phrase nominations: false positives, true positives, false negatives, and true negatives that are determined as follows:

True positive (TP) = the proportion of positive cases that were correctly identified.

False positive (FP) = the proportion of negative cases that were incorrectly identified [17].

False negative (FN) = the proportion of positive cases that were incorrectly classified as negative.

True negative (TN) = the proportion of negative cases that were classified correctly.

Will simply define and calculate the accuracy:

i. Accuracy: Accuracy is one metric for evaluating classification models. It can be calculated as follows [10] [17]:

$$\text{Accuracy} = \left(\frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}}\right) * 100 \quad (1)$$

ii. Recall (sensitivity): is represented in Eq. 2 and calculated from these results. Recall shows how well a classification system can identify real positives.

$$\text{Recall} = \left(\frac{\text{TP}}{\text{TP} + \text{FN}}\right) * 100 \quad (2)$$

iii. Precision: computed using Eq. 3's formula. Precision is a measure of how well a classification can weed out false positives.

$$\text{Precision} = \left(\frac{\text{TP}}{\text{TP} + \text{FP}}\right) * 100 \quad (3)$$

iv. The F1 score, which is the harmonic mean of these two metrics, is used to represent how recall and precision are balanced. The formula in Eq. 4 is used to calculate the F1 score.

$$\text{F1 score} = \left(2 * \frac{\text{Precision} * \text{recall}}{\text{Precision} + \text{recall}}\right) \quad (4)$$

5. Results and Discussion

In this study, three distinct pre-trained models were used to classify the dataset of 350 brain MR images. Each model used the same learning rate optimization, batch size, and number of epochs as all other external variables. Training and test sets were created from the dataset, respectively. A validation set was created using 20% of the test set.

For each model, epoch-based accuracy and loss graphs were provided. Additionally, the effectiveness of each model was evaluated in relation to the given metrics. Overfitting happens when a model learns to fit the training data too closely, including its noise and random variations, instead of learning the underlying patterns in the data, but it does not occur in this work because of the use of transfer learning using the layers of a highly trained model in the feature extraction of other models such as Squeeze Net, Inception V3, and Mobile Net. The classification accuracy results of the three algorithms will be compared in order to select the best one. Table 2 shows the experimental results of each algorithm depending on the performance measures, and Figure 7 for the Squeeze Net model displays the accuracy and loss graphs that were generated during training. The accuracy of the model is evaluated at 99.2%, which is comparatively more significant and less stable.

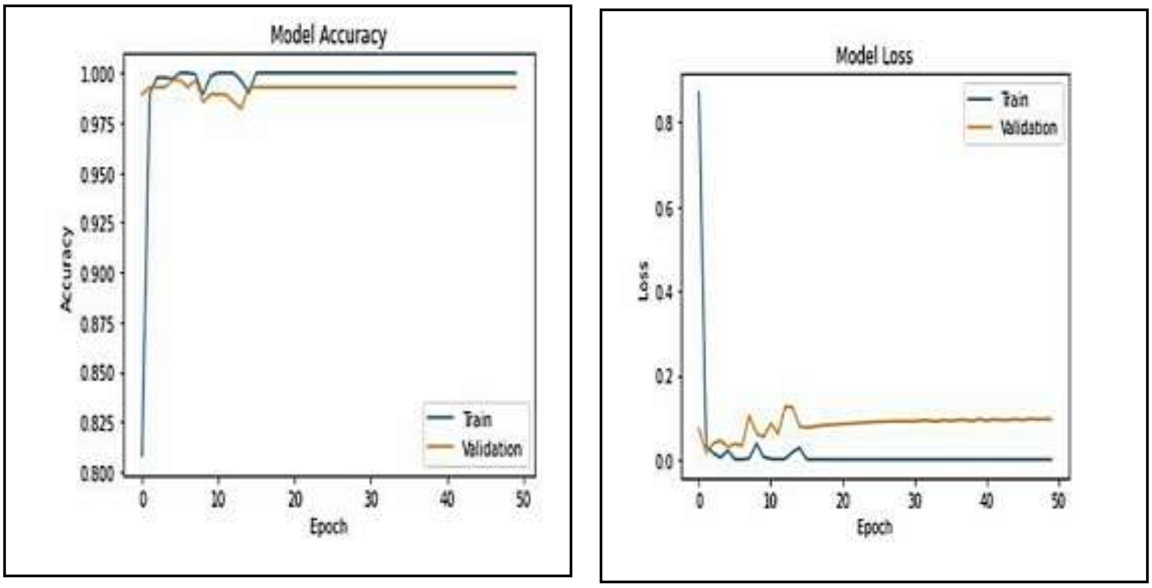

Figure 7: Accuracy and loss graphs of the Squeeze Net model

Specifically, the stability of the accuracy can be validated by the variation in the data augmentation and is found to be good compared with the Squeeze Net model. Further, Figure 8 shows the accuracy of the Inception V3 model. As the epochs increase, the accuracy is seen to increase in both training and validation by about 98.3%.

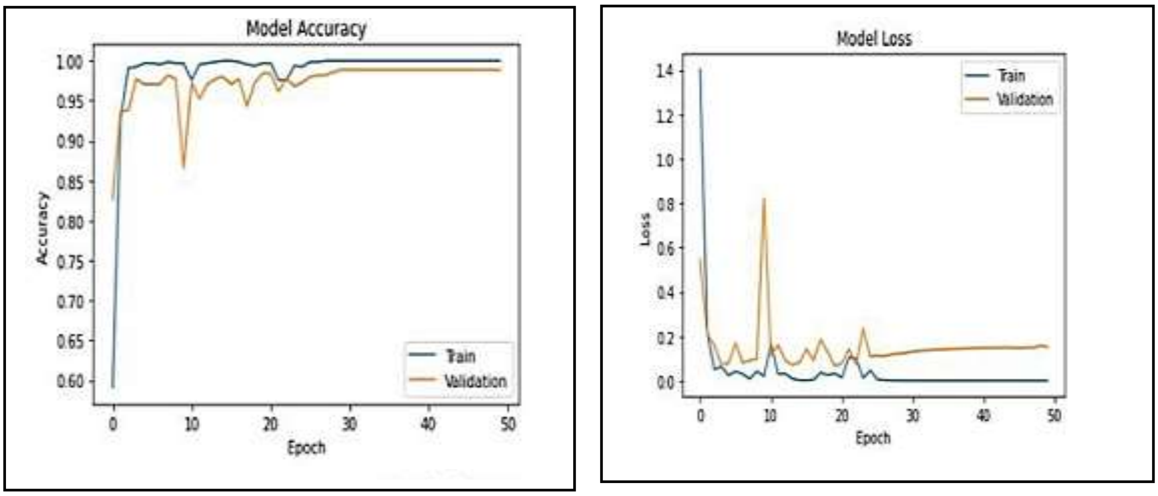

Figure 8: Accuracy and loss graphs of the Inception V3 model.

Lastly, the accuracy of the Mobile Net V2 model is illustrated in Figure 9. Increasing epochs augment the model's accuracy in both training and validation and are observed to be 96.4%.

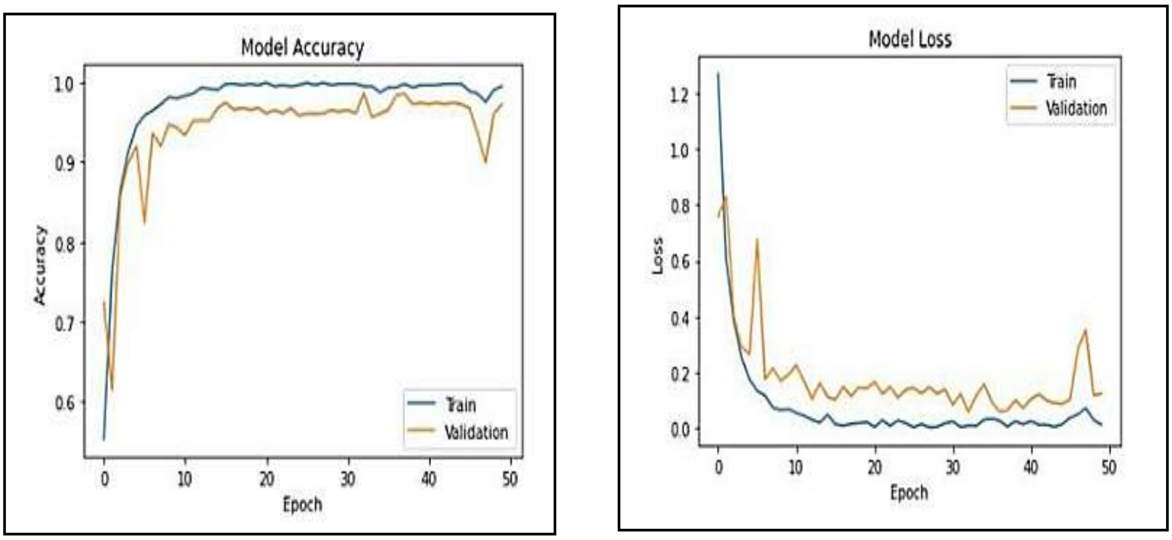

Figure 9: Accuracy and loss graphs of the Mobile Net V2 model.

The performance results for the three pre-trained models across the same number of epochs are shown in Table 2.

Table 2: Performance measurements

Model	Accuracy	Recall	Precision	F1 Score
Squeeze Net	0.992	0.993	0.989	0.994
Inception V3	0.983	0.991	0.958	0.975
Mobile Net V2	0.964	0.948	0.952	0.951

When the models are compared in terms of metric values, it is shown that the most successful model on the dataset used is the Squeeze Net, with an accuracy of 99.2%. The second successful model is Inception V3, with 98.3% accuracy. The Mobile Net V2 model showed significantly lower success compared to these two models. However, the Squeeze Net model was superior in terms of all metrics.

In the majority of the studies on the classification of brain MR images in the literature, manually derived characteristics were combined with machine learning techniques. Manual feature extraction requires a lot of work and has higher error rates. Deep learning's capacity for self-learning makes it possible for the features of MR pictures to be automatically discovered. Furthermore, when the outcomes of the proposed models are compared with the other literature, it is clear that the proposed models with augmentation offered the best brain tumor prediction accuracy. Squeeze Net overtakes other models among the proposed models due to its significant and relative accuracy scale. Table 3 illustrates the comparison of the obtained results of this study with those in other literature.

Table 3: Comparison of the obtained results of this study with the other literatures

No. of reference	Reference	dataset	method	The highest accuracy (%)
14	Alsaif et al., 2022	155 brain MR images	Custom CNN	96 %
25	Shan et al., 2022	306 brain MR images	Custom CNN	92 %
5	Onur SEVLİ, 2021	253 brain MR images	Custom CNN	94 %
This study		**350 brain MRI images**	**Custom CNN**	**99 %**

Conclusions

Because of differences in imaging technologies and changes in the morphological structure of the brain, the automatic identification of brain tumors is still a problem, even with the processing of brain MRI data using deep learning. In deep learning-based brain tumor segmentation issues, CNNs are frequently used. Transfer learning is one strategy for enhancing data processing efficiency. By transferring the learned parameters into the new model, high success is achieved while the workload of the new model is decreased. Additionally, transfer learning ensures success even when there is training data.

In this study, 350 brain MRI scans with and without tumors were used as a dataset, and classifications were made using pre-trained Inception V3, Mobile Net V2, and Squeeze Net models. To ease the effort during training, raw MR images were preprocessed. Three different models were utilized to evaluate the classification process using accuracy, recall, precision, and the F1-score measure. The best performance was demonstrated by the Squeeze Net model, which had 99.2% accuracy, 99.3% recall, 98.9% precision, and a 99.4% F1 score. This was accurately followed with 96.4% accuracy by the Mobile Net V2 model. In this investigation, as in related studies in the literature, the Inception V3 model had the lowest success rate. The results of this study were compared to more current, related investigations that have been published in the literature. The model that proved most effective was the squeeze net.

This study demonstrated that the transfer learning method produces good outcomes with little data and few epochs. Experts were given a different system of assistance that will make it easier to spot tumors on brain MR pictures.

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