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Deep Feature Extraction with SVM Classifier for Brain Tumor Classification

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Abstract

Recently, methods for classifying brain tumors have used Deep Learning (DL), in particular, Convolutional Neural Networks (CNNs), to obtain promising results. Unlike conventional Machine Learning (ML) algorithms, CNNs can automatically extract features from images; they do not, however, need the extraction regarding hand-crafted features. Many obstacles reduce the accuracy of brain tumor classification systems; to address such obstacles, we propose a DL-based feature extraction method for brain tumor classification. A total of two pretrained CNNs, VggNet-16 and ResNet-18, are applied as deep feature extractors in the scheme to accomplish deep feature extraction. Contrast Limited Adaptive Histogram Equalization (CLAHE) technique has been first used for enhancing the images. Second, each separately pretrained CNN, VggNet-16 and ResNet-18, is used for extracting the deep features from Magnetic Resonance Imaging (MRI). Lastly, a Multiclass Support Vector Machines (Multiclass -SVM) classifier is used to complete a classification task. Tests conducted on the aforementioned datasets: the effectiveness of the suggested approach is demonstrated by the CE-MRI Figshare, the REMBRANDT, and the Brain Tumor Classification, where the pre-trained CNN models and SVM classifier enhance performance. Specifically, the pretrained CNN with SVM approach produces accuracy ranging from 95.28% to 98.62% across all data-sets.

Keywords: Deep Learning, Deep Feature Extraction, Transfer Learning, Brain Tumor Classification, Convolutional Neural Network, MRI.

1. Introduction

The utilization of laboratory testing as well as clinical observations has led to the accumulation of an enormous amount of information in the medical field today. With regard to clinical practice, doctors have started to move away from haphazard analysis and the veracity regarding their observations to a variety of data analysis and organized algorithms which depend on continuously updated datasets. As a result, medical professionals who study Artificial Intelligence (AI) will be better equipped to diagnose diseases [1].

CNNs are ML algorithms that have produced notable results in the classification of medical images [2]. This research classified brain tumors using MRI of human brain. First, the collected images have been processed appropriately. Next, the best features have been extracted from the processed images using deep CNNs. Finally, a classifier was utilized for classifying the features into three categories based on two types of CNN models which are different in structure. Training the two models and evaluating their performance were the next steps.

2. Related Work

Many deep CNN-based brain tumor classifications systems were proposed in literature [3]. Zhuge et al. introduced a DL-based automated multi-modal classification technique for classifying the type of brain tumor. There are five fundamental steps in the suggested procedure. The first phase involves using Discrete Cosine Transform (DCT) and edge-based histogram equalization to extend linear covariance. Two pre-trained CNN models, VGG19 and VGG16, are utilized for extracting features in the second step of DL feature extraction. The third step involved the use of an Extreme Learning Machine (ELM) in conjunction with a co-currence-based joint learning technique. The fourth phase involved creating a single matrix by combining robust variable features depending on least squares. ELM received the combined matrix for the final classification. The BraTs2017, BraTs2015, and BraTs2018 datasets yielded accuracy values of 96.9%, 97.8%, and 92.5%, respectively [4].

Francisco et al., the authors presented a deep CNN model with a multi-scale approach that is entirely automatic for classifying and segmenting brain tumors. One distinction is that three separate processing paths and three spatial scales are used for processing the input images. The way the human visual system functions naturally served as the model for this mechanism. Meningiomas, gliomas, and pituitary adenomas are the three forms of tumors that could be detected in MRI images using the suggested neural model. The technique was tested using a dataset of 3,064 slices from 233 patients that was made publicly available for MRI images. The accuracy of the suggested system's tumor classification was 97.3 [5].

Pashaei et el., the authors proposed a CNN-based approach for extracting hidden features from images. Depending on such retrieved features, a Kernel Extreme Learning Machine (KELM) then uses them to classify the images. In their study, they assess the efficacy of the suggested approach using a dataset that includes T1-weighted contrast-enhanced MRI images regarding three different forms of brain cancers: meningiomas, gliomas, and pituitary tumors. Utilizing different classifiers, results of such ensemble of the CNN and KELM (KE-

CNN) have been compared. The accuracy of the classification that had been attained by this proposed KE-CNN approach has been 93.68% [6].

S. Deepak et al., the authors used SVMs and CNN features for classifying medical images. They used the Figshare open dataset, which included MRI images of the three different kinds of brain tumors, to assess the suggested automated system. CNN is made for extracting features from MRI images of the brain. A multi-class SVM with CNN features is utilized to increase performance. To make sure that the suggested approach performs better, a lot of testing is being done on different brain MRI datasets. The overall classification accuracy of the suggested model was 95.82% [7].

B. Srinivas et al., the authors develop a hybrid model (CNN-KNN) which combines K-Nearest Neighbor (KNN) and CNNs for classification of brain tumors from MRI. For the extraction of the features and applying those features to KNN classifier for the prediction of classes, the CNN model has been considered. An open data-set of images that have been chosen for the task of classification from BraTS2017 and BraTS2015 data-bases has been used for experimentations. The performance that has been observed after using this method on testing datasets was 96.25% accuracy [8].

H. Kibriya et al., have proposed method for the multi-class brain tumor classification where they have utilized DL and ML approaches. Initially, the authors have used an end-to-end CNN model (GoogLeNet) for the purpose of classifying brain MRIs. The SVMs are utilized in order to classify deep features taken out CNN models. Utilizing CNN-SVM-based approach, the proposed approach has been tested and trained on 15,320 MRI images, and it had achieved a 97% rate of accuracy [9].

Neelum et al., gliomas, meningiomas, and pituitary tumors were the three main categories of brain cancers on which the authors concentrated their investigation. To assess brain tumors, they employed ML and DL. In their investigation, various models, including fine-tuned Xception and Inception-v3, were applied in conjunction with DL techniques for extracting features. DL and ML methods, such as RFs, K-NNs, SVMs, and Softmax, were used to investigate the classification of brain tumors. The test accuracy for the Inception-v3 model has been 94.34% [10].

The following is the order in which this document is structured: The CNNs are explained in section 2. Section 3 presents the suggested system. Section 4 presents experimental results and methodology. Section 5 concludes with a few remarks.

3. Convolution Neural Networks (CNNs)

In order to classify an image as identity, CNN convolves it through a series of filters. After that, it passes the convolutional output through nonlinear dropping, and learns filter weights to reduce classification loss. To identify top level features, each layer makes use of the output from the layer before it. The parameters regarding a CNN dictate how many neurons are present in each layer [11]. Fig (1) provides an illustration of CNN's architecture.

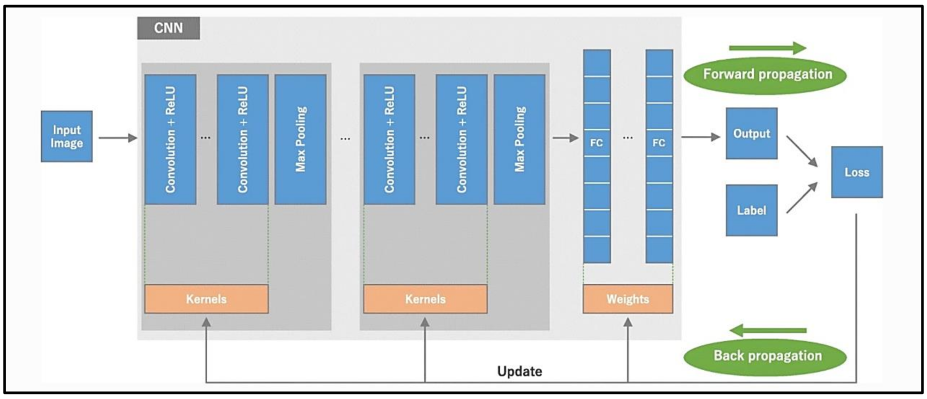


Fig (1): The architecture of typical convolutional neural networks [11].

A multidimensional array of numbers is fed into each layer of the CNN model, which consists of several layers. The convolutional layer, input layer, Batch Normalization(BN) layer, Rectified Linear Unit (RELU) layer, pooling layer, and Fully Connected Layer (FCL) are the main layers that make up the CNN architecture [12].

3.1 Pretrained CNNs models

For the aim of image recognition, many CNN models were trained on large data-sets like ImageNet data-set. After that, without having to start over during training, such models could be used to identify a different task [13]. Two pretrained CNNs were employed as deep feature extractors in this work. ResNet-18 and VggNet-16 were such networks. For extracting relevant image features for use in the classification stage, such pretrained CNNs networks were employed.

3.1.1 Pretrained ResNet-18 Model

With a top-5 error rate of 3.57%, the ResNet series model which was first suggested in 2015 [14] won the ILSVRC 2015 competition. Through stacking numerous residual structures, the network creatively suggested the residual structure and created the ResNet network. It makes advantage of a connection technique known as shortcut connection. ResNet-18 is made up of three layers: a FCL, a max-pooling layer with a 3*3 filter size, and 17 convolutional layers. A 33.16 million parameter classical ResNet-18 model applies batch normalization and the ReLU activation function to the back of each convolutional layer in a "basic block" of the model. The input of this architecture is a 224 by 224 by 3 images. Fig (2) depicts the ResNet-18 structure.

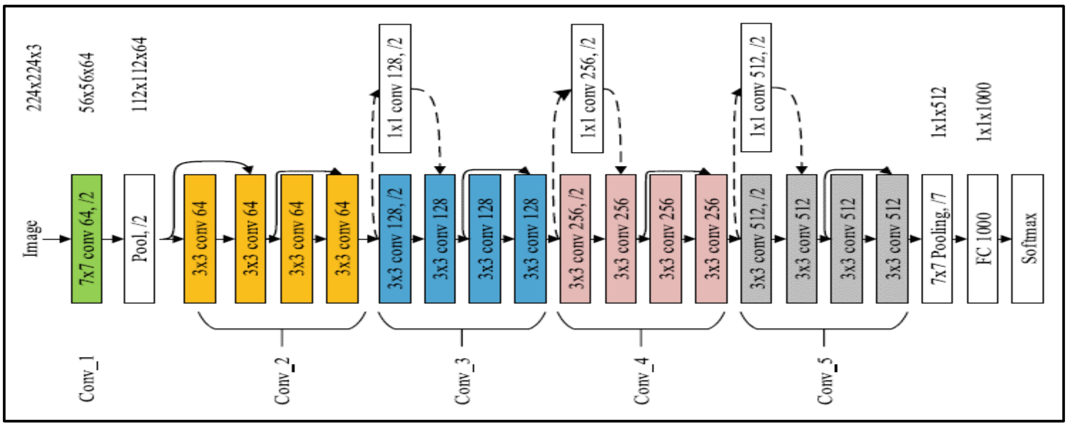


Fig (2): An illustration of the architecture of ResNet-18 model.

3.1.2 Pretrained VggNet-16 Model

Present by Simonyan et al. [15], VggNet has been the second CNN to win 2014 Image-Net competition, as shown in Fig (3) with a top 5 error of 7.3%. The simplicity of the network lies in its use of only three 3x3 convolutional layers piled deeper and deeper on top of one another. We utilize 3x3 filters in such convolution and max-pooling layers, as opposed to 11x11 in AlexNet and 7x7 in ZF-Net. Through using max pooling, volume size reduction is managed. After that comes two FCLs, each with 4,096 nodes, and a SoftMax classifier. The input of this architecture is a 224 by 224 by 3 images.

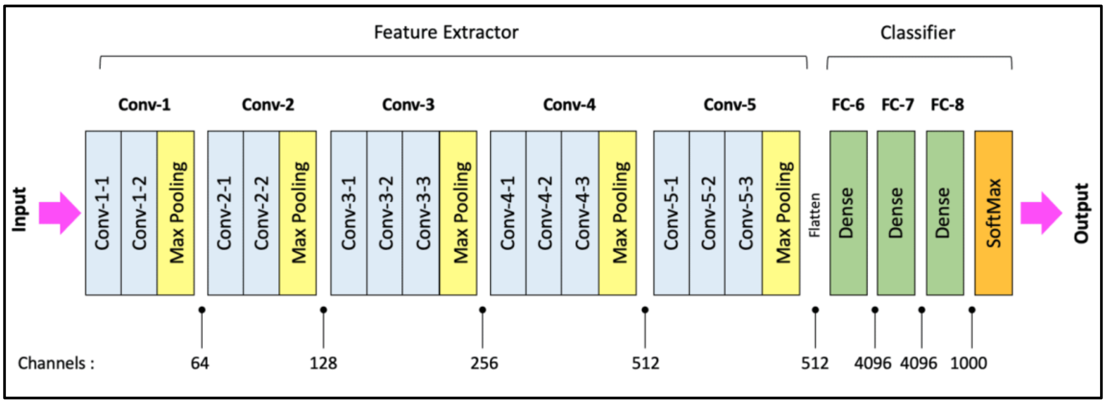


Fig (3): An illustration of the architecture of VggNet-16 model.

4. The Methodology

In this work, we propose a brain tumor classification method depending on DL features extraction as well as classification. VggNet-16 and ResNet-18, two pretrained CNNs, are applied in the approach to extract features. First, each separately pretrained CNN is used for extracting features from MIR images. Second, the task of classifying features derived from ResNet-18 and VggNet-16 is carried out by the SVM classifier in the classification process. The next phases make up the suggested plan for resolving the DL-based brain tumor classification problem shown in fig (4):

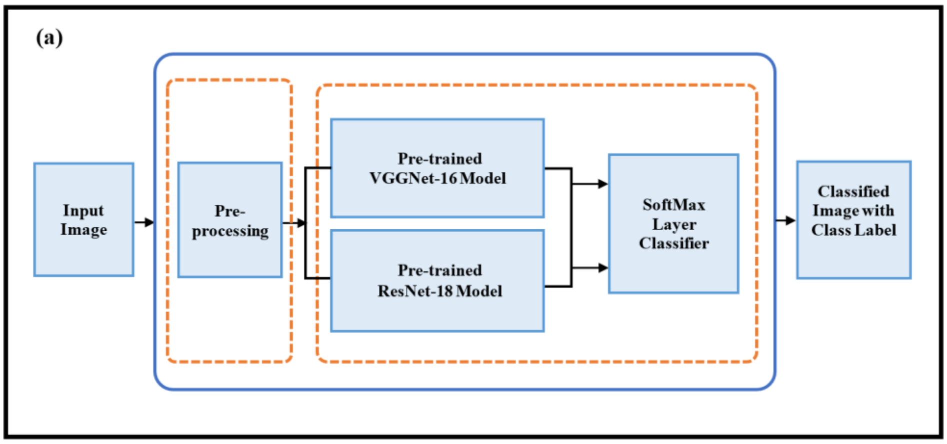
4.1 Preprocessing Step:

Prior to integrating the MIR images into deep CNN network, the preprocessing phase is crucial. The preprocessing phase of this work typically entails the next actions: the CLAHE algorithm was first used for enhancing the image. This algorithm places restrictions on the contrast value, allowing for the production of an image with improved lighting and contrast. Second, all test and training images should be downsized to 224 by 224 because the ResNet-18 and VggNet-16 networks receive RBG images at this size. We also convert all grayscale images in the collection into RGB images if they exist.

4.2 Deep Feature Extraction Stage

The improved brain images are fed to the deep feature extractor model following a little pre-processing. Strong resistance to variations is required for the retrieved features. VggNet-16 and ResNet-18, two pretrained CNNs, were used in this work to accomplish this goal. The FCL, or "fc1000," and the global average pooling layer, or "pool5," are the final two layers of ResNet-18 model. The output of the "Pool5" and "fc1000" layers respectively is a vector with 512 and 1000 dimensions.

The three FCLs (fc7, fc8, and fc6) make up the VggNet-16 model. The output of the "fc6" and "fc7" layers is a 4096-dimensional vector. The output of the "fc8" layer is a vector of 1000 dimensions. Various levels of characteristics are extracted by the various layers of the ResNet-18 and VggNet-16 networks. Edges and colors make up the majority of the features that were taken from the first layers. Various filters are utilized in the next levels, which allows the network to construct increasingly complex features in those layers. A high-level collection of characteristics that have been extracted by the earlier layers, which are found at the beginning of network, is also taught to the final layers, like "fc1000" in ResNet-18 network and "fc7" in VggNet-16 network.



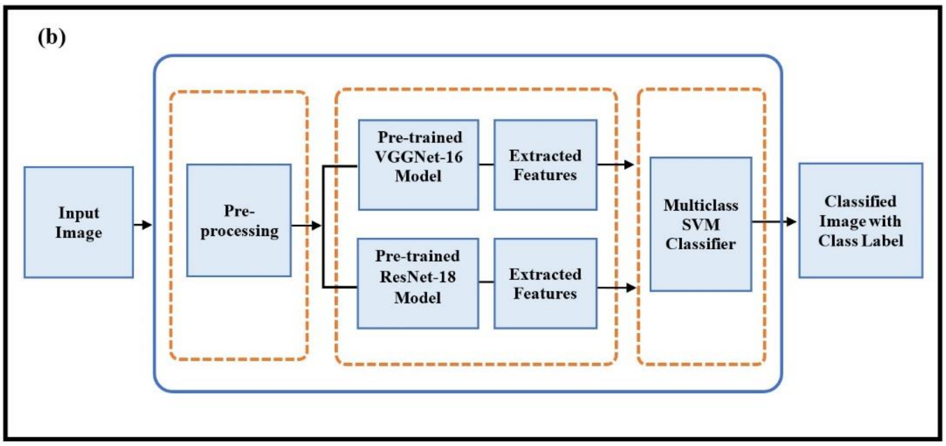


Fig (4): The main diagram for the proposed system approaches. **(a)** Applying transfer learning from pre-trained CNN models for extracting features and classification. **(b)** Pre-trained CNN model as feature extractor and an SVM for classification.

The FCLs "fc1000" and "fc7" of VggNet-16 network and the ResNet-18 network's "fc1000" layer are the ones we used for this research's features because they yield the best classification accuracy. High level layer features, which are more discriminatory for the tasks of classification, are an abstraction of low level layer features.

4.3 Classification stage

During the classification phase, a classifier is trained using the extracted characteristics. Since SVM classifiers are very effective at classifying images, they have been utilized in this study for classifying the image characteristics [16]. Despite being designed primarily for binary classification, SVM could be effectively expanded to handle multiclass classification problems. One framework that is frequently utilized to describe multi-class classification problems is Error-Correcting Output Code (ECOC) [17]. Multiclass classification can be done primarily in two ways: "one-against-all" and "one-against-one".

In this study, the SVM classifier as well as ECOC framework are used to accomplish MRI image classification. Using the extracted features, a multiclass SVM model was trained using the "fitcecoc" function. A trained ECOC model is returned by the function. K denotes a different class, and the current study employs the K binary SVM Algorithm with a "one-verses-all" coding technique. Since we are using a linear kernel function, we set the "Learners" option of the fitcecoc function to "Linear" for training a fast Stochastic Gradient Descent (SGD) solver. This facilitates training with high-dimensional CNN feature vectors more quickly. The "predict" function, which depends on ECOC model, is utilized for predicting the class label for predictor data in the matrix or table.

5. The Experimental Results

This research's suggested brain tumor classification system makes use of a number of methods that fall into two categories:

A- **Strategy-1:** As an SVMs classifier as well as a deep features extractor, two pre-trained CNNs were applied independently.
- **Approach-1:** Pretrained ResNet-18 as a deep features extractor and a SVMs classifier.
- **Approach-2:** Pretrained VggNet-16 as a deep features extractor and a SVMs classifier.

B- **Strategy-2:** Utilizing Transfer Learning (TL) for extract features and classify data from two pre-trained CNN models.
- **Approach-1:** TL from pretrained ResNet-18 for feature extraction and the task of classification.
- **Approach-2:** TL from pretrained VggNet-16 for feature extraction and the task of classification.

5.1 Experimental Setups

This section presents the hardware and software tools that were used to implement this work.

5.1.1 Hardware Tools

A laptop equipped with an Intel (R) Core (TM) i5- 11400H QH CPU @ 2.70 GHz, 8GB of RAM, and an Nvidia GeForce GTX 1650 with Max-Q design GPU was used to conduct the tests.

5.1.2 Software Tools

In order to evaluate the suggested methodologies and execute feature extraction and the classification task, MATLAB 2022b must be installed on Windows 11 Pro 64-bit. The next MATLAB toolbox and support packages will be utilized:

- Machine learning toolbox^{TM}
- Computer vision toolbox^{TM}
- Deep learning toolbox^{TM}
- Image processing toolbox^{TM}
- Neural network toolbox^{TM}
- Deep learning toolbox^{TM} for VggNet-16 Model
- Deep learning toolbox^{TM} for ResNet-18 Model

5.2 Description of Datasets

This section contains thorough descriptions of every dataset that was used in every experiment. For this, three datasets have been utilized: the brain tumor classification dataset, the REMBRANDT dataset, and the CE-MRI Figshare dataset. Those three datasets present some challenges, including significant variation in size and form and similarity in the presentation of various disease kinds. An overview of the data from each dataset used in this work can be found in Table (1).

Table (1): Details about the datasets used in the experiments.

Dataset	Dataset Description				
	Total Images	Classes	Images/ Class	Size of Images	Type of Images
The REMBRANDT	7023	AST OLI GBM	2328 2341 2354	256 x 256	JPEG
The CE-MRI Figshare	3064	pituitary glioma meningioma	930 1426 708	512x512	JPEG
The Brain tumor classification	2475	Pituitary glioma meningioma	822 826 827	different	JPEG

5.2.1 The REMBRANDT Dataset

There are just two such large collections, and Georgetown University hosts and supports the other one, called REMBRANDT (REpository for Molecular BRAin Neoplasia DaTa) [18]. The national cancer institute initially developed the REMBRANDT dataset with funding from the glioma molecular diagnostic initiative. A total of 130 brain tumor patients' pre-operative MRI multisequence images totaling 7023 are included in the REMBRANDT dataset. Oligodendroglioma (OLI), astrocytoma (AST), glioblastoma multiforme (GBM), and other tumor forms that are not yet discovered are included in the dataset. Every image is digitally converted to 256 by 256 pixels of resolution. In the REMBRANDT datasets, a single type of brain tumor is identified on each image. Fig (5) displays some datasets from the REMBRANDT datasets.

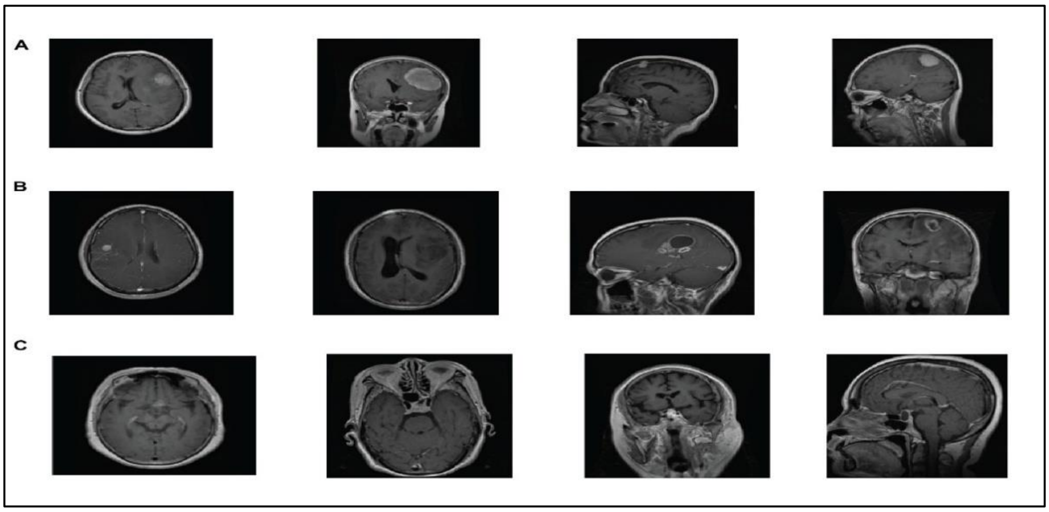


Fig (5): Sample IMR images from REMBRANDT dataset: **(a)** AST, **(b)** GBM, and **(c)** OLI.

5.2.2 The CE-MRI Figshare Dataset

A total of 3,064 2-D MRI images with T1-weighted contrast-enhanced modalities obtained from 233 affected individuals make up publicly available CE-MRI Figshare data-set [19], which is the 2nd data-set that has been utilized for brain cancer classification to meningioma, glioma, and pituitary. Brain tumors are classified to 3 classes: glioma, pituitary, and meningioma. T1 modality highlights particular features of each class. This dataset's most recent version contains 708 images of meningiomas, 1426 images of gliomas, and 930 images of pituitary tumors. There are 512 × 512 pixel MR images in the collection. In fig (6), a few dataset samples are displayed.

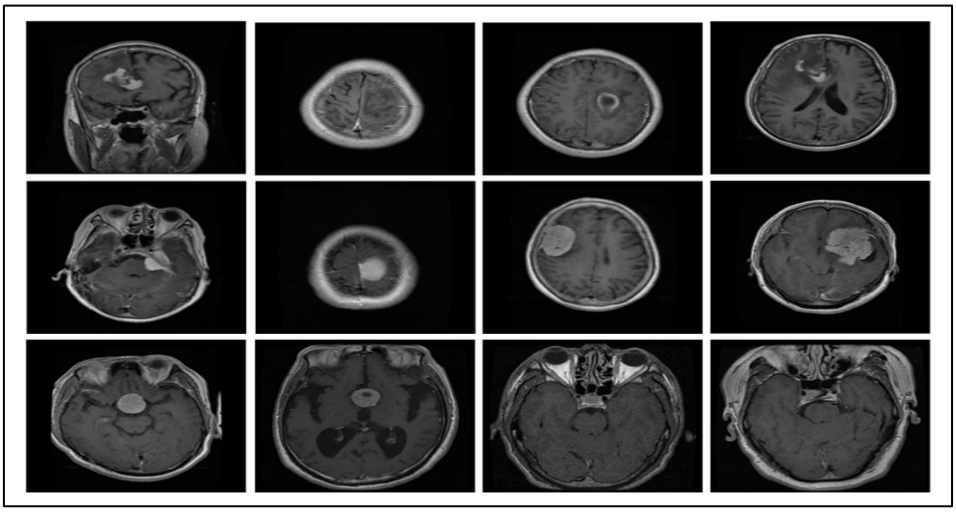


Fig (6): Sample IMR images from the CE-MRI dataset: (a) Glioma, (b) Meningioma, (c) Pituitary.

5.2.3 The Brain Tumor Classification Dataset

This research employed the Brain Tumor Classification (BTC) dataset, which can be found on Kaggle [20], to classify brain tumors into three categories: pituitary, meningioma, and glioma. The testing and training sets of MRI images of brain tumors make up the dataset. Each folder contains four distinct types of MRI images for brain cancers: no tumors, pituitary, gliomas, and meningiomas. But MRI scans of glioma, meningioma, and pituitary tumors were the only ones we used. The most recent version of the dataset contains 827 MRI scans of pituitaries, 822 MRI scans of meningiomas, and 826 MRI scans of glioma tumors in its training collection. On the other hand, 74 pituitary images, 115 images of meningioma tumors, and 100 images of gliomas are included in the testing collection. After combining the images from the two collections, we used them for both training and testing. The dataset's images are displayed in fig (7).

5.3 Performance Evaluation

Accuracy is a metric used to assess brain tumor classification ability. The percentage of the correct labels divided by total number of the test images is how accuracy is calculated. The confusion matrix has been used in order to calculate the accuracy. The true positive and negative values are added, and the result is divided by the total number of samples to determine accuracy. To compute its percentages, multiply the values by 100%.

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

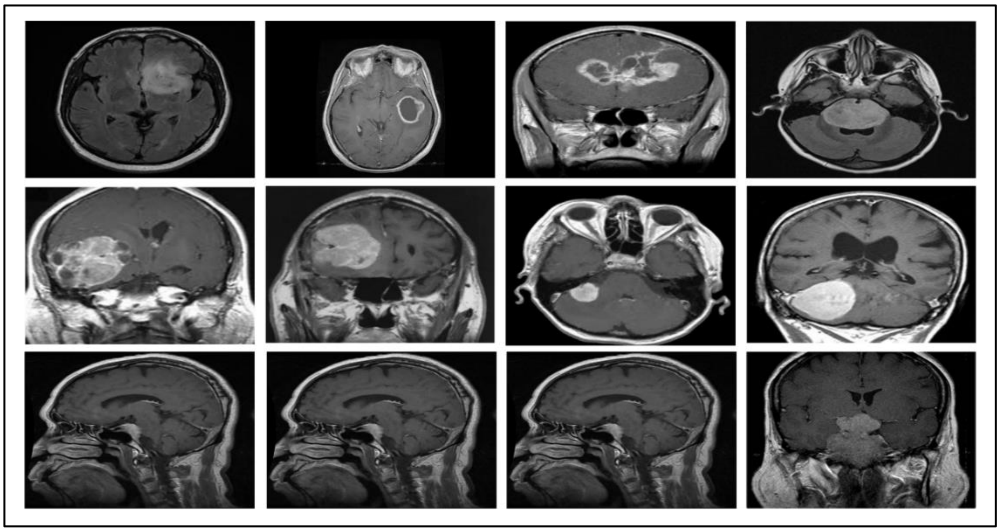


Fig (7): Sample IMR images from BTC dataset: (a) Glioma tumor, (b) Meningioma tumor, (c) Pituitary tumor.

5.5 The Experimental Results

This section provides all the findings and experiments which were used to assess the brain tumor classification system's efficacy utilizing two alternative methodologies depending on several standard databases. In the first approach, we examined the outcomes of extracting MIR image features with the use of separately pretrained ResNet-18 and pretrained VggNet-16, then classifying the image features utilizing an SVM classifier. We examine the efficacy of using TL from two pre-trained CNN models, VggNet-16 and ResNet-18, for feature extraction and classification in the second method.

5.5.1 The Analysis Results for Pretrained ResNet-18 with SVM

To get its results, this approach uses SVM in conjunction with the ResNet-18 CNN model. During the preprocessing phase, the CLAHE technique was used to improve the images. Each MRI image was after that resized to 224 × 224, which is the ResNet-18 model's input size. To avoid biasing the results, we utilized random sampling and utilized 80% of data for training and 20% for testing.

In the experiment, this study extracted features from "fc1000" FCL to obtain a 512-dimensional feature vector. After that, a classifier called a SVM is utilized to carry out the classification operation. This method's results are estimated utilizing every dataset that was previously discussed in section (4-2). The classification accuracy for each dataset with the use of ResNet-18 and an SVM classifier is displayed in Fig (8). ResNet-18 model with SVM outperformed the other models in terms of classification accuracy, achieving 98.62% on the CE-MRI Figshare dataset. Furthermore, on the brain tumor classification dataset and the REMBRANDT dataset, our method achieved classification accuracy of 97.83% and 96.89%, respectively.

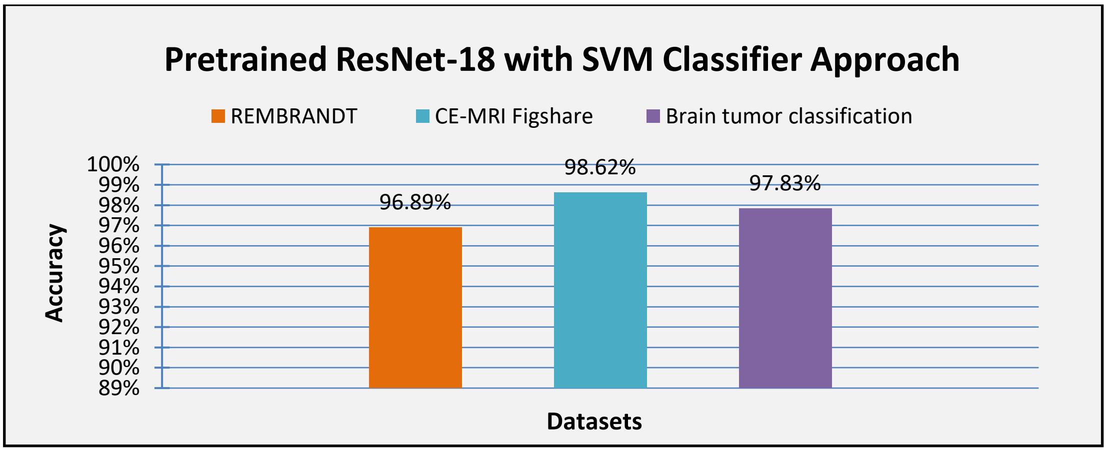


Fig (8): The classification accuracy for Strategy-1, approach-1.

5.5.2 Analysis of Results for Pretrained VggNet-16 with SVM

To get the desired results, this approach combines SVM with the VggNet-16 CNN model. The preprocessing step involved applying CLAHE method to improve the images, and after that rescaling each processed MRI image to 224 × 224 input size required by the VggNet-16 model.

We used random sampling for dividing the data into train and test groups by 80% and 20%, respectively, to prevent biasing the results. In the experiment, this study extracted features from the FCL "fc7" to obtain a 4096-dimensional feature vector. After that, a classifier called SVM is employed to carry out the classification operation. Every database that was previously specified in section (4-2) is used to estimate the results of this method. The classification accuracy for each dataset with the use of VggNet-16 and an SVM classifier is displayed in Fig (9).

This method was used to conduct the numerous experiments, and the results are displayed in table (2). The tests conducted on all datasets demonstrate that, on the CE-MRI Figshare dataset, VggNet-16 network with SVM classifier achieved a higher classification accuracy of 97.33% compared to the other datasets. Furthermore, the results showed that this method achieved 95.52% classification accuracy on the REMBRANDT dataset and 95.28% classification accuracy on the brain tumor classification dataset.

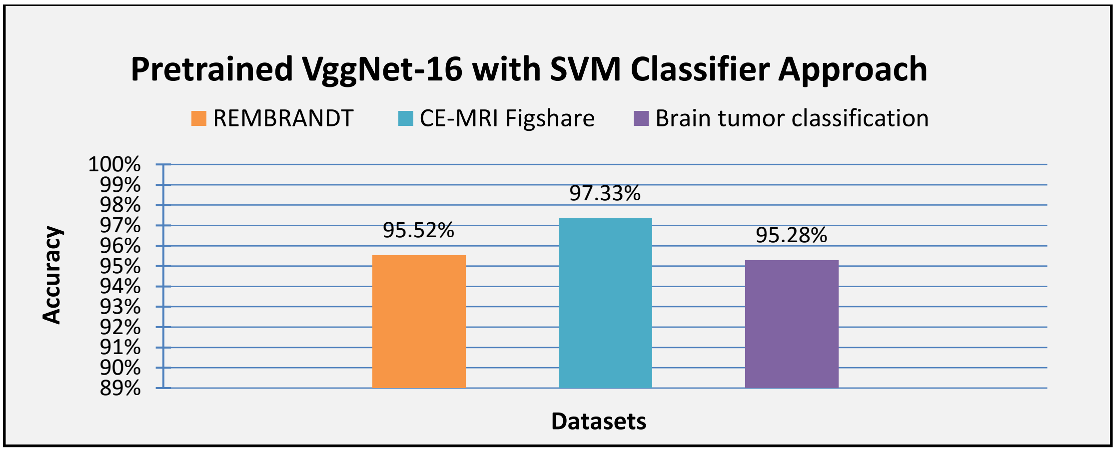


Fig (9): The classification accuracy for strategy-1, approach-2.

5.5.3 Analysis of Results for Transfer Learning from ResNet-18

This method's experiments used TL from pre-trained ResNet-18 CNN to analyze performance. The ResNet-18 has 71 layers total; the first 68 layers are used for extracting features, while the final three layers are used for classifying the features into 1,000 classes. Therefore, the previous three layers, "fc1000," "prob," and "classificationlayer_pridection," were removed in this stage in order to transfer the layers to the new classification task. A new FCL, "braintumer_classification," with three classes, was added in its place.

In this experiment, we discovered that the most accuracy was achieved when we set the mini-batch size to 30 and used an epoch of 25. Throughout training, the software used a validation frequency of three for validating the network. Next, with the use of random sampling, the data have been divided into two groups: test data (20%) and training data (80%). Fig (10) illustrates the results of this method for feature extraction and classification with the use of pre-trained ResNet-18 network.

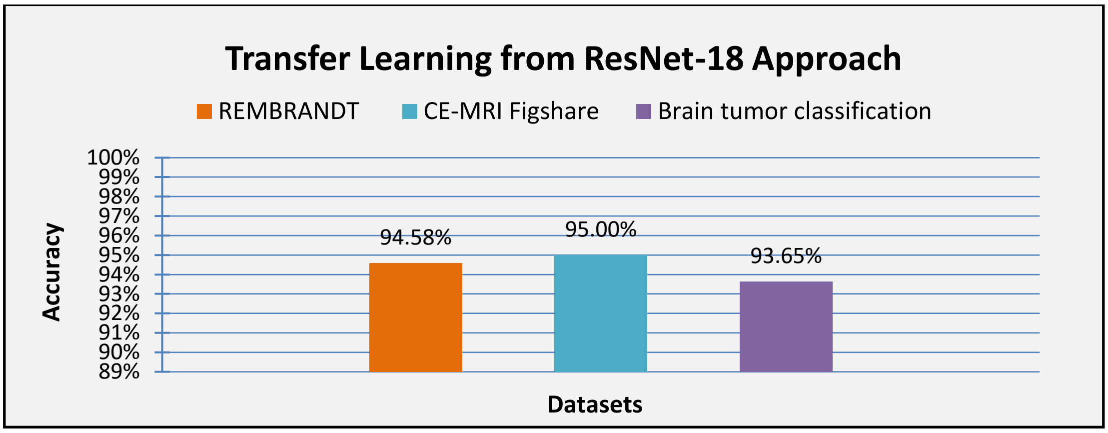


Fig (10): The classification accuracy for strategy-2, approach-2.

Classification accuracy using this method was 94.58% on the REMBRANDT dataset and 95% on CE-MRI Figshare dataset. Additionally, using the brain tumor classification dataset, the TL based on the ResNet-18 technique achieved a classification accuracy of 93.65%.

5.5.4 Analysis of Results for Transfer Learning from VggNet-16

In this experiment, as seen in fig (11) we assessed the performance in the case when feature extraction as well as classification tasks are performed using TL from VggNet-16 network. A pre-trained network called VggNet-16 has been trained on a 1000-class task using millions of images. It has 41 layers total; the first 38 are used for feature extraction, and the final 3 are used to classify the extracted features into 1000 classes. In order to transfer the layers to the new classification task, the final three layers were removed in this stage, and a new FCL was added in their place. This allowed the new layer to be around the same size as the number of classes in the new data based on dataset classes.

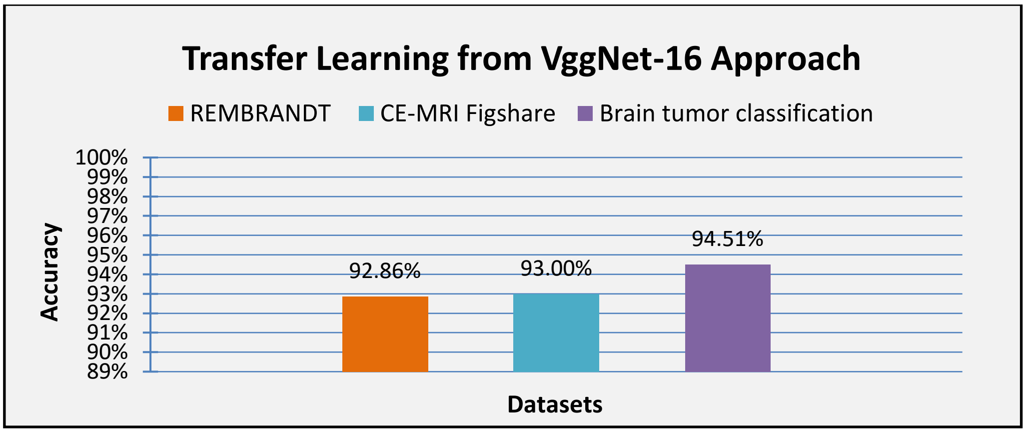


Fig (11): The classification accuracy for strategy-2, approach-2.

In the experiment, this study varied the number of epochs used to evaluate the model until it achieved a high level of accuracy. We discovered that an epoch of 20 produced the best accuracy. Mini-batch size is fixed at ten. Throughout training, the software used a validation frequency of three for validating the network. Additionally, 20% of the data was used for validation and 80% for training. The results of this experiment demonstrated that, following training the network on the brain tumor classification dataset, the maximum classification accuracy was 94.51%, as shown in fig (11). Additionally, with CE-MRI Figshare dataset, the TL from the VggNet-16 technique obtained 93%, and with REMBRANDT dataset, 92.86%.

5.6 Comparison of Strategy-1 with Strategy-2

The outcomes of using TL from pretrained CNN models for feature extraction as well as classification, also utilizing pretrained CNN models as a deep feature extractor and SVM as a classifier, are compared in this section. Table (2) presents the findings of two models VggNet-16 and ResNet-18's stratgy2 and stratgy1, with all datasets. Figures (12) and (13) show the results of all techniques, with all datasets, according to each dataset and approach, respectively.

Table (2): Comparing the transfer learning approaches and the deep feature extraction with SVM approaches.

CNN Model	Experiment performed on		
	REMBRANDT	CE-MRI Figshare	Brain tumor classification
Pretrained ResNet-18 with SVM	96.89%	98.62%	97.83%
Pretrained VggNet-16 with SVM	95.52%	97.33%	95.28%
Transfer Learning from ResNet-18	94.58%	95%	93.65%
Transfer Learning from VggNet-16	92. 86%	93%	94.51%

We can see that, across all datasets and methods, pretrained ResNet-18 with the use of SVM achieved the maximum classification accuracy of 98.62% and 97.83% on the brain tumor classification dataset and the CE-MRI Figshare dataset, respectively. Furthermore, we might observe that on CE-MRI Figshare dataset, the pretrained VggNet-16 with SVM model has the maximum accuracy of 97.33%. On CE-MRI Figshare dataset, the greatest accuracy attained by the TL from the pretrained ResNet-18 model is 95%. The greatest accuracy achieved for VggNet-16 model's TL on the brain tumor classification dataset was 94.51%.

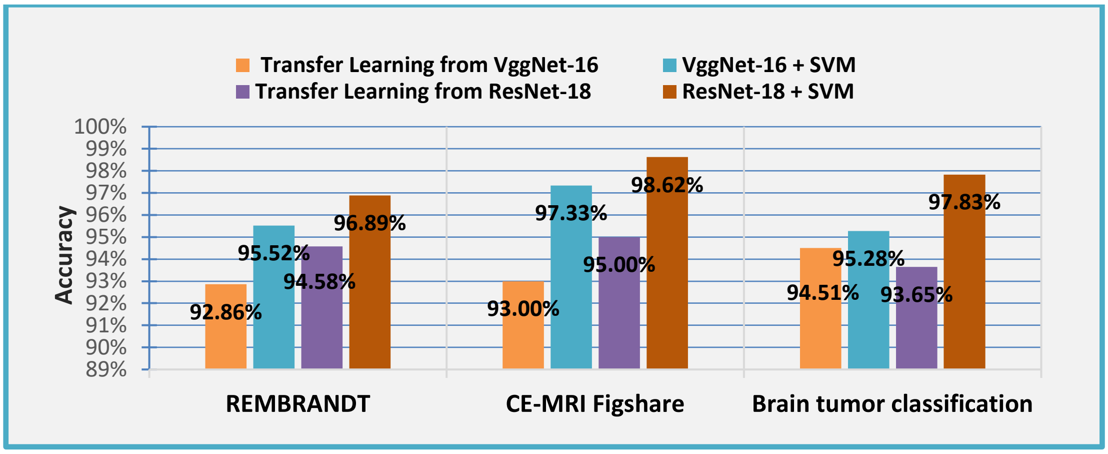


Fig (12): The mean classification accuracy according to each dataset.

In the case when utilized for extracting features and classification for all utilized datasets, the pre-trained network approaches as a deep feature extractor solely with SVM classifier produced better results compared to TL with pre-trained network approaches, according to the comparison of the findings. Better classification accuracy was attained by the pretrained ResNet-18 with SVM approach and the pretrained VggNet-16 with SVM than by the TL from VggNet-16 and the pretrained ResNet-18 approaches.

We find that the pretrained ResNet-18 with SVM approach outperforms the pretrained VggNet-16 method in terms of classification accuracy when we compare the two pretrained with SVM approaches. TL from the ResNet-18 model outperformed the TL from the VggNet-16 model in the case when we compared the TL from the pretrained models with one another.

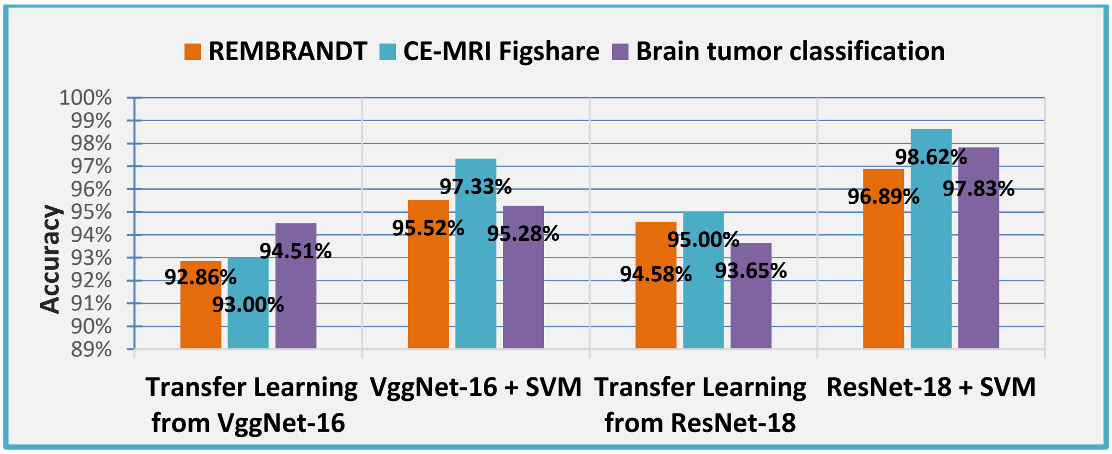


Fig (13): The mean classification accuracy according to each approach.

5.7 Comparison with other Models

A comparison of the results of several brain tumor classification methods is shown in this section. This study aims to evaluate the brain tumor classification system by employing pretrained CNNs with various datasets. While some of them are simple data-sets, others are difficult datasets with challenges. In this research, the deep feature extraction from ResNet18 using the SVM yielded a greater classification accuracy than previous approaches. The suggested methods' performance in comparison to the other models is shown in Table (3).

Table (3): Comparing between the proposed system and other models.

References	Model	Classification accuracy
Pashaei at el. [6] (2019)	CNN + KELM Classifier	93.68%
B. Srinivas et al. [8] (2020)	CNN + KNN Classifier	96.25%
Hareem K. et al. [9] (2021)	GoogLeNet + SVM Classifier	97%
Francisco et al. [5] (2021)	CNN + softmax Classifier	97.3
S. Deepak et al. [7] (2021)	CNN + SVM Classifier	95.82%
The Proposed System (2024)	**Deep Feature Extraction from ResNet-18 + SVM Classifier**	**98.62 %**

6. Conclusion

In this study, pretrained convolutional neural networks architectures was utilized for brain tumor classification system with several methods. Firstly, we utilized the pretrained ResNet-18 and VggNet-16 models for extract deep feature and SVMs as classifier. Second, we utilized the transfer learning from pretrained models from the ResNet-18 and VggNet-16 models for feature extraction and classification. We conducted four experiments to evaluate the proposed approaches by using several datasets (REMBRANDT, CE-MRI Figshare, and brain tumor classification). The findings indicated from 92.86% to 98.62% accuracy range for models achieved using all datasets. The outcomes for ResNet-18 with SVM classifier certain that the best deep features were extracted from “fc1000” and for VggNet-16 with SVMs certain that the best deep features were extracted from “fc7”. We compare the proposed system to current models using three datasets.

The outcomes demonstrated that TL from pre-trained CNNs to feature extraction as well as classification combined is inferior to utilizing pre-trained CNNs as a deep feature extractor and after that utilizing an SVM classifier for classifying such features. The results showed that the suggested system performed more accurately than the majority of the existing models. In the future, we want to improve the classification accuracy. In order to achieve this, brain tumor classification systems could be improved by using the cross validation method, extracting features from different layers, and testing alternative CNN models, like ResNeXt, InceptionNet-v4, and DenseNet, for improved performance.

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