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Classification of brain MRI using hyper column technique with convolutional neural network and feature selection method

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超柱技术，在深的结构中获取局部特征

ABSTRACT

A proper and certain brain tumor MRI classification has a significant role in current clinical diagnosis, decision making as well as managing the treatment programs. In clinical practice, the examination is performed visually by the specialists, this is a labor-intensive and error-prone process. Therefore, the computer-based systems are in demand so as to carry out objectively this process. In the traditional machine learning approaches, the low-level and high-level handcrafted features used to describe the brain tumor MRI are extracted and classified to overcome the mentioned drawbacks. Considering the recent advances in deep learning, we propose a novel convolutional neural network (CNN) model that is combined with the hypercolumn technique, pretrained AlexNet and VGG-16 networks, recursive feature elimination (RFE), and support vector machine (SVM) in this study. One of the great advantages of the proposed model is that with the help of the hypercolumn technique, it can keep the local discriminative features, which are extracted from the layers located at the different levels of the deep architectures. In addition, the proposed model exploits the generalization abilities of both AlexNet and VGG-16 networks by fusing the deep features achieved from the last fully-connected layers of the networks. Furthermore, the discriminative capacity of the proposed model is enhanced using RFE and thus the most effective deep features are revealed. As a result, the proposed model yielded an accuracy of 96.77% without using any handcrafted feature engine. A fully automated consistent and effective diagnostic model is ensured for the brain tumor MRI classification. Consequently, the proposed model can contribute to realizing a more objective evaluation in the clinics, supporting the decision-making process of the experts, and reducing misdiagnosis rates.

1. Introduction

The brain is an enormous organ in the skull of the human body that controls the nervous system and contains approximately 100 billion nerve cells (Uzbay, 2015). This vital organ located in the center of the nervous system. Therefore, tumors that occur in the brain are one of the life-threatening diseases. The malignant tumor of the brain causes the risk of life. In such cases, early diagnosis is vital (Lundervold & Lundervold, 2019; Varuna Shree & Kumar, 2018). The most common diagnostic method used in clinical examination of such cases is to take magnetic resonance imaging (MRI) of the patient and examine them by specialist doctors and radiologists. Brain tumors are generally divided into two classes as benign and malignant. Tumor detection can be performed by MRI and it can be determined that these tumors are benign/malignant (Mabray, Barajas & Cha, 2015). Therefore, the procedure to be followed in the treatment of a brain tumor depends on the experience and knowledge of the doctor. The aim of deep learning is to present the results obtained from MRI to doctors in a perfect and automatic way and to support the diagnosis process (Swati et al., 2019). 深度学习自动完美的向医生展示MRI结果，辅助诊断

Many techniques and methods have been proposed for the classification of brain tumor MRI. (Varuna Shree & Kumar, 2018) managed to divide brain MRI into two classes as normal and abnormal by using the gray level co-occurrence matrix (GLCM). They used the GLCM method with a probabilistic neural network (PNN) architecture. PNN is a deep learning architecture developed on a Bayesian algorithm with feedforward (MN & Basheer, 2002). The success rate of the study was reported as 95%. (Ari & Hanbay, 2018) performed the classification and segmentation of brain 相关研究

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相关研究

tumors. The proposed method used the deep learning architecture, extreme learning machine (ELM), and local receptive fields (LRF) techniques. Image smoothing techniques were also used on the dataset and 97.18% of the classification success rate was obtained. (Sajjad et al., 2019) augmented the dataset and fine-tuned the dataset was processed with the proposed convolutional neural network (CNN) method. Softmax was used as a classifier. The proposed method was applied separately on both original and augmented datasets within the scope of experimental studies. The success in the augmented dataset was 94.58%. (Sachdeva, Kumar, Gupta, Khandelwal & Ahuja, 2016) used the region of interest (ROI) method for the dataset consisting of MRI. They then segmented ROI images to remove tissue and color characteristics. Then, they selected the most efficient features by the genetic algorithm (GA) method and performed the classification process. In this study, they achieved a 94.9% classification success. (Afshar, Mohammadi & Plataniotis, 2018) classified the dataset into four different categories using the capsule net (CapsNet) network. The achieved success in this study was 84.56%. (Nazir, Wahid & Ali Khan, 2015) presented a new method for automatic detection and classification using brain tumor MRI. The dataset was divided into two classes as benign and malignant. The proposed model follows three basic steps. In the first stage, image noise was cleaned by filter methods. In the second stage, the mean color moment of each image in the dataset was obtained by extracting the features. In the last stage, the feature set consisting of color moments was classified by an artificial neural network (ANN) and 91.8% classification accuracy was obtained.

In summary, as can be inferred from the related studies, some traditional studies focused on the handcrafted feature engine, such as GLCM and LRF, and machine learning techniques such as ELM, PNN, and ANN to describe and classify the brain tumor MRI. On the other hand, some studies employed additional segmentation and ROI techniques to improve the performances of the models. Similarly, the data augmentation techniques were considered to ensure more proper training for the models. A set of preprocessing procedures was applied to brain tumor MRI in order to reach more precise diagnosis systems in some studies. The traditional approaches require additional procedures for feature extraction and classification. Also, applying ROI and segmentation techniques lead to extra calculations and costs. These processes require serious labor. With the help of the proposed model, an end-to-end learning scheme has been presented and the requirement for additional processing has been eliminated. 端到端不需要额外处理

深度学习算法是主流之一

Recently published studies are examined, it is clearly seen that deep learning algorithms have become one of the mainstream of the medical image analysis, expert and intelligent systems as well. In addition, MRIs are a prime preference in brain analysis, since it has no known risk Ghassemi, Shoeibi & Rouhani, 2020). For this reason, the basic motivation of this study relies upon ensuring a novel precise diagnosis model that allows brain tumor MRI as the input and automatically produces classification results without using any handcrafted feature engine. In this study, a novel model consists of pretrained AlexNet and VGG-16 models equipped with hypercolumn technique, recursive feature elimination (RFE) and support vector machine (SVM) models is proposed for brain tumor MRI classification. In this scope, the main contributions of this study in expert and intelligent systems can be aligned as follows: ((1) The hypercolumn technique grants the inherent characteristics of the previous layers to be transferred to the last layer in a vector. With the help of this technique, the proposed model keeps the local discriminative features, which are extracted from the layers located at the different levels of the deep architectures, so as to increase the classification performance. (2) The proposed model exploits the generalization abilities of the AlexNet and VGG-16 models by fusing the deep features provided from the last fully-

MRI扫描脑优势

新模型包括预训练两个网络，RFE，SVM

文中的第一点贡献：超列技术赋予了前几层的固有特性以向量形式转移到最后一层。利用该技术，该模型保留了从不同层次的深层结构中提取的局部判别特征，提高了分类性能。
第二点贡献：利用了两种网络，并将最后一层获取的特征进行融合。

一种RFE和SVM集成的方式获取有效的特征

connected layers of the models. (3) An integrated approach covering the RFE and SVM reveals the most effective deep features by reducing the dimension of the deep feature set. (4) As a result, thanks to the proposed model, a promising and high sensitivity diagnosis model has been introduced for brain tumor MRI classification. To be more specific, the model relies on an end-to-end learning scheme. It means that when a brain tumor MRI is applied as the input to the proposed model, the model can fully automatically process the input sample and classify it as normal or tumor. Lastly, we hope that the proposed model can be a strong candidate in daily clinical applications of brain tumor MRI analysis. The proposed model can contribute to realizing a more objective evaluation in the clinics, supporting the decision-making process of the experts, and reducing misdiagnosis rates. 高效的脑肿瘤分类，直接输入，全自动分正常和肿瘤，实现客观评价，辅助决策，降低误诊

The rest of the paper is organized as follows: the dataset and methods are presented in Section 2. The proposed method explained in Section 3. The experimental results are reported in Section 4. In Sections 5 and 6, discussion and concluding remarks are given, respectively.

2. Materials and methods

2.1. Dataset

The dataset consists of open-access brain tumor MRI containing two classes of the tumor and normal (Chakrabarty, 2019). The samples belonging to the normal and tumor classes are illustrated in Fig. 1. The dataset consists of 155 and 98 tumor and normal brain MRI, respectively. The dataset is heterogeneous MR images collected from 253 patients. The images in the dataset has not high resolution and each image has a different resolution. The image format is JPEG.

In this study, the number of samples over the classes was balanced by increasing the number of normal brain tumor MRI so as to use the dataset more efficiently. In other words, the number of samples in the normal class was increased from 98 to 155 by using image augmentation methods. The augmented images were randomly selected from the original normal brain tumor MRI. In total, 310 (155 + 155) images were used for this study. 数据增强正常图像增强到155个

2.2. CNN models

In this section, AlexNet and VGG-16 models are summarized in technical terms. Since the last fully connected layer of these two architectures is FC-8, the RFE algorithm was used on the features obtained from these layers. The schematic representations of the CNN architectures are illustrated in Fig. 2.

The AlexNet is one of the popular CNN architectures that famed its name in the ImageNet competition in 2012 (Krizhevsky, Sutskever & Hinton, 2012). This architecture consists of convolutional, pooling and fully connected layers. The input size is 227 × 227 pixels. It is based on the process of moving 3 × 3 or 5 × 5 pixel filters on the image in the convolution layer. Thus, activation maps containing more efficient features are created for transfer to the next layer. The most important feature of activation maps is that they have unique features (Koushik, 2016). The pooling layer is used to reduce the size and cost of the image without disturbing its features (O'Shea & Nash, 2015).

VGG-16 architecture consists of convolutional, pooling and FC layers like AlexNet architecture. It contains a total of 21 layers (Simonyan & Zisserman, 2014). This architecture has an increasing network structure. The input size is 224 × 224 pixels. The filter size in the convolutional layer is 3 × 3 pixels. In this architecture, the final layers have a fully connected layer used for feature extraction.

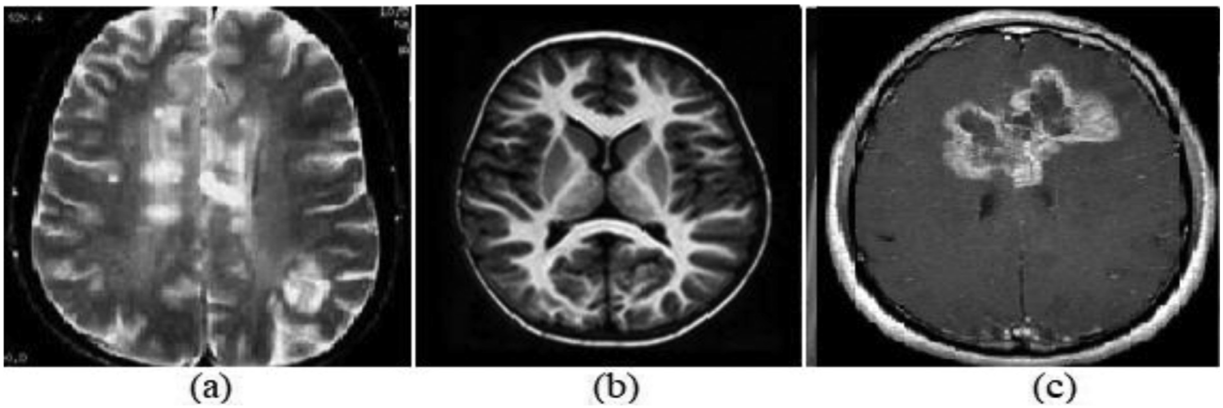

Fig. 1. (a) and (b) Normal class sample (c) tumor class sample.

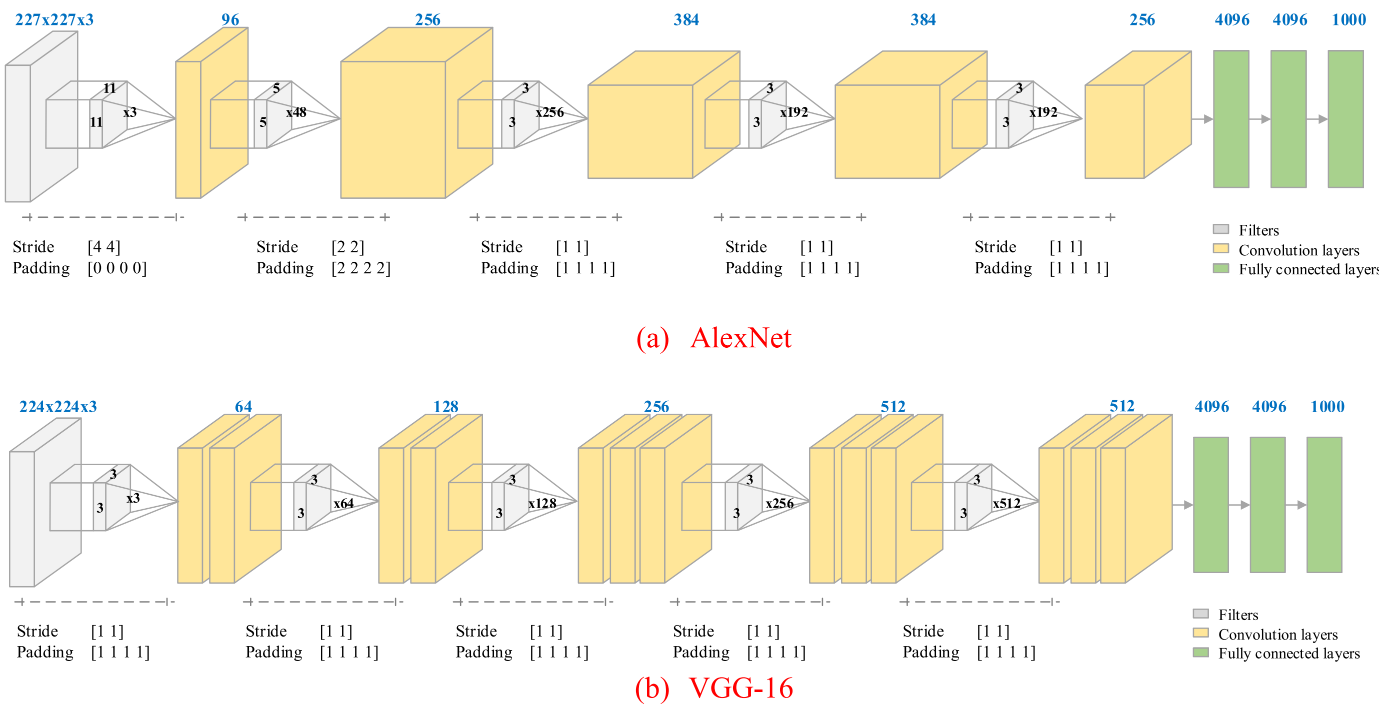

Fig. 2. Schematic representation of CNN models: (a) AlexNet (b) VGG-16.

In this study, CNN architectures are used for feature extraction. 1000 deep features were extracted from each FC-8 layer of the models (Zhong, Yan, Huang, Cai & Dong, 2018). For both models, the filter size is set to 3 × 3 pixels, the number of strides is two, and the docking type is maximum.

In addition, the dataset was divided into two classes as training and test sets with 70% and 30% rates.

2.3. Support vector machine (SVM) classifier

The SVM method is a widely used machine learning method for regression and classification tasks. This method places the features obtained from the data in a new coordinate plane. In the next step, it creates a hyperplane to perform the classification (Huang et al., 2017). Fig. 3 illustrates the classification process of the SVM classifier. The aim of Eq. (1) is to minimize the problems that occur during the classification. In Eq. (3), X_i represents the weight vector of the input sample whereas the Y_i corresponds to the actual class of the samples. This equation performs an estimation to determine the class of the input sample (Huang et al., 2017).

$$u = \vec{w} \cdot \vec{x} - b \tag{1}$$

$$\frac{1}{2}\|\vec{w}\|^2 \tag{2}$$

$$y_i(\vec{w} \cdot \vec{x}_i - b) \geq 1, \forall i \tag{3}$$

2.4. Image augmentation technique

数据增强有助于平衡样本分布

Data augmentation techniques are useful to balance the distribution of the samples over the classes when imbalanced datasets are available (Kulkarni & Panditrao, 2015; Shashi B. Rana, 2011). In this study, the image augmentation technique was used to equalize the number of samples in the normal class brain tumor MRI to the number of brain tumor MRI class. For this purpose, the image augmentation methods provided by the Keras library in Python were used (Francois Chollet, 2016). For normal-class MRI, rotation, width, and height changing, cutting, zooming, horizontal rotating,

用Keras中的包增强数据

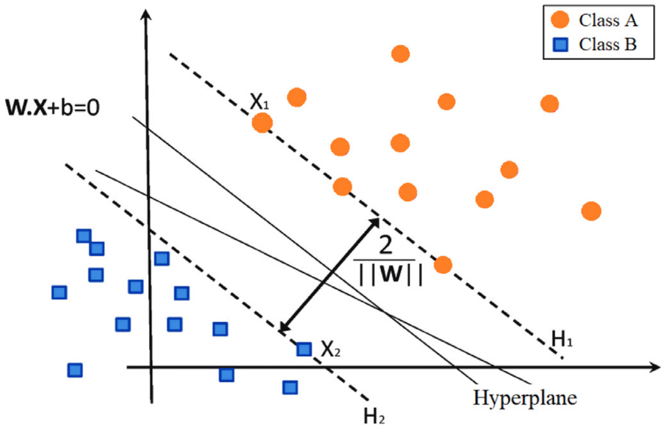

Fig. 3. SVM Classification diagram.

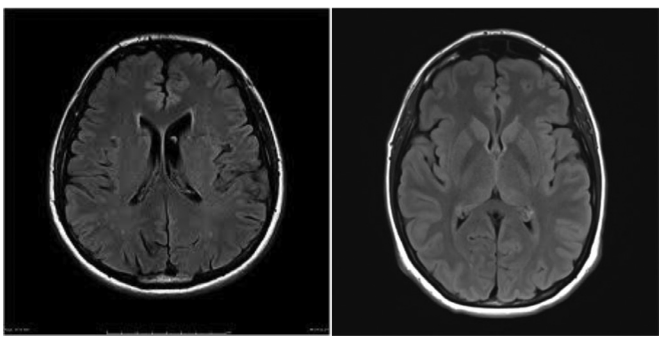

Fig. 4. Two original samples from the normal brain tumor MRI class.

brightening and filling operations were performed. The degree of image rotation was set to randomly generate from 0 to 20. The values of the width-height changing, zooming, and the horizontal rotating ratio parameters were adjusted to 0.15. Two samples belonging to the normal-class brain tumor MRI are shown in Fig. 4. A subset of the images obtained by using the data augmentation technique is presented in Fig. 5.

2.5. Hypercolumn technique

CNN前一层中的特征不会移动到最后一层。
超柱技术允许将先前层的固有特性转移到向量中的最后一层，像素中的超列是该像素上所有CNN单元的激活向量。

CNN architectures use the features of the latest layer in their architecture to perform classification or segmentation. The features in the previous layers are not moved to the last layer. The hypercolumn technique allows the inherent characteristics of the previous layers to be transferred to the last layer in a vector (Pilly, Stepp, Liapis, Payton & Srinivasa, 2019; Ramachandram & W Taylor, 2018). In other words, the hypercolumn in a pixel is a vector of activations of all CNN units above that pixel. Thus, the spatial position information can be retrieved from the previous layers and a more accurate prediction result can be obtained. This enables the network to achieve better results (Hariharan, Arbeláez, Girshick & Malik, 2015). Fig. 6 shows an example of applying the hypercolumn technique on the original image. When Fig. 6 is examined, the bottom image is the input image and the processing steps above it represent the feature map in the layers of the CNN model. A red icon indicates a pixel. Each pixel in the last layer of the CNN model carries the features of the previous layers vectorically.

可以从前一层提取位置信息，得到更好的结果

超柱技术实际上是一种掩蔽技术。这项技术将从CNN模型的前几层获得的有效特征叠加在原始图像上。这将使原始图像更可见，并增加特征数。

The hypercolumn technique is actually a masking technique. This technique stacks the efficient features obtained from the previous layers of the CNN model on the original image. This makes the original image more visible and increases the number of features. A subset of the mask images obtained from the images by the hypercolumn technique is shown in Fig. 7. Hypercolumn masks carry the characteristics of layers in the CNN architecture of each pixel of the original image as a series of vectors. In this study, colored masks were obtained because three main color channels were used in the masking step. The goal is to produce more efficient features. Because color channels affect the depth and resolution of the input image (Ye, Lin, Dehmeshki, Slabaugh & Beddoe, 2009).

2.6. Feature selection method

The RFE is known as a recursive feature reduction method. This method handles all the features obtained in the dataset and evaluates them in order of their priority. If the variable R is considered to be an array representing the features, multiple features sequences are sorted by priority $R_1 > R_2 > R_3$. In this method, each time an iteration is performed, the top-ranked features of the Ri sequence (the most efficient sequence of features) are maintained, improved, and accuracy is reassessed. In the next step, the best accuracy values are compared with the Ri sequence, and if the accuracy values are better than the most efficient Ri features, the accuracy values are updated in due to importance in the model (Sean Escanilla et al., 2018). In this study, the RFE feature selection method is implemented by using the open-source code in Python.

3. Proposed method

The proposed method consists of three basic steps. In the first step, image augmentation techniques are used to ensure that the data is distributed equally between the classes. Thus, more efficient features can be extracted by CNN models. In the second step, it is aimed to make the images more prominent (creating new efficient features) by using the hypercolumn masking technique on the balanced dataset. This is done on the image pixels in the FC-8 layer of both models. In the used CNN models, the features obtained from the previous layers are kept in the FC-8 layer in a vector format. In the last stage, a total of 2000 deep features obtained from the FC-8 layers are evaluated by the RFE feature selection method, and the dimension of the feature set is reduced. In the last step, the SVM classifier is employed. In the feature selection method, the SVM classifier is chosen for its generalization performance on real-world problems (Onel, Kieslich & Pistikopoulos, 2019). The overall design of the proposed method is shown in Fig. 8.

Other parameter selections of the CNN models used in this study are used as shown in Table 1. Mini-batch value is the case where more than one input is processed on the model at the same time (Yang, Wang, Zhang & Li, 2019). This may interfere with the operation of the model if the computer's hardware resources are not sufficient. Therefore, the mini-batch value was chosen as 16 in this study.

Table 1
Parameter values of CNN models.

Software used	CNN Architecture	Image Size	Optimization	Momentum	Decay	Beta	Mini Batch	Learning Rate
Matlab	AlexNet VGG-16	227 × 227 224 × 224	Sigmoid Gradient Descent	0.95	1e-6	–	16	0.0001

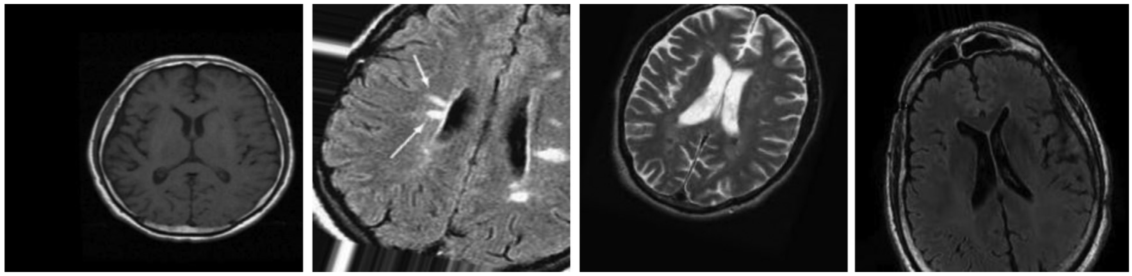

Fig. 5. A sub-images obtaining from normal brain tumor MRI using the image augmentation technique.

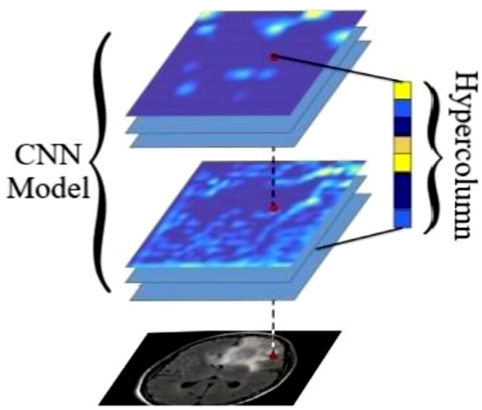

Fig. 6. Hypercolumn illustration.

4. Experimental results

The validity of this study is associated with the performance metrics such as sensitivity, specificity, F-score and accuracy derived from the confusion matrix. The parameters used in the calculation of these metrics are true positive (TP), true negative (TN), false positive (FP), false negative (FN) (Cömert & Kocamaz, 2019; Toğaçar, Ergen, & Cömert, 2020). 混淆矩阵参考文献

$$Sensitivity = \frac{(TP)}{(TP+FN)} \tag{4}$$

$$Specificity = \frac{(TN)}{(TN+FP)} \tag{5}$$

$$F\text{-}score = \frac{(2xTP)}{(2xTP+FP+FN)} \tag{6}$$

$$Accuracy = \frac{(TP+TN)}{(TP+FN)+(FP+TN)} \tag{7}$$

The experimental study was compiled using MATLAB (R2018b) software installed on a 64-bit Windows 10 operating system. The computer has an NVIDIA GeForce 2 GB graphics card, Intel© i5 - Core @2.5 GHz processor and 8 GB RAM. matlab做深度学习

三种不同的实验方法

In this study, the experiments were divided into three steps. In the first step, the balanced dataset was directly trained by using only CNN models without using the hypercolumn and feature selection method. SVM was used as a classifier in this experiment. The success rate was 90.32% with AlexNet and 87.10% with VGG-16.

In the second step, two CNN architectures were processed with the hypercolumn technique and classified with the SVM model. In this experiment, it was aimed to observe the contribution of the hypercolumn technique. The achieved success rate was 92.47% with AlexNet and 90.32% with VGG-16. The contribution of the hypercolumn masking technique to the classification process was 2.38% in AlexNet and 3.68% in VGG-16.

In the third step, the features of CNN models under hypercolumn masking were combined (1000 + 1000 = 2000). Then, the RFE feature selection algorithm was applied on 2000 deep features and sub-feature sets of 100, 200, 300 and 400 features were obtained respectively. In this step, it was aimed to increase the classification success with the selected features by using the RFE. As a result, the best performance was achieved with an accuracy of 96.77% by using 200 selected deep features. In this study, all results of the experiments are shown in Table 2. In addition, when

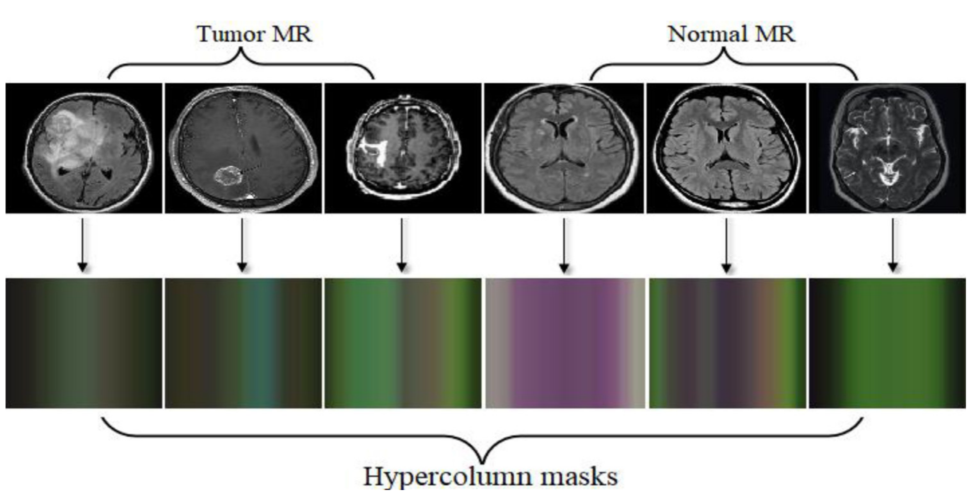

Fig. 7. A subset of the hypercolumn masks created with the hypercolumn technique of tumor and normal data.

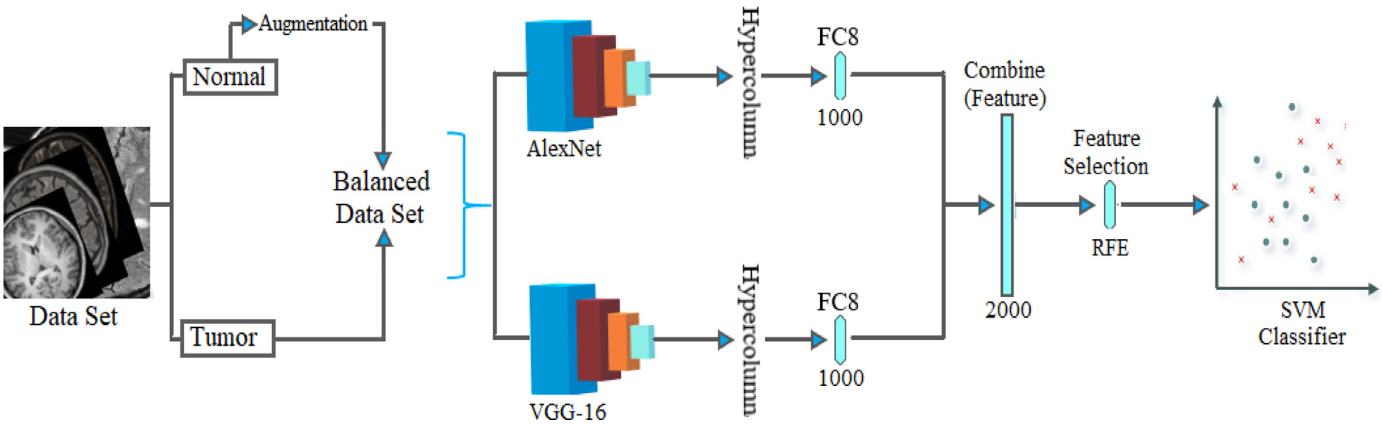

Fig. 8. The overall block diagram of the proposed model.

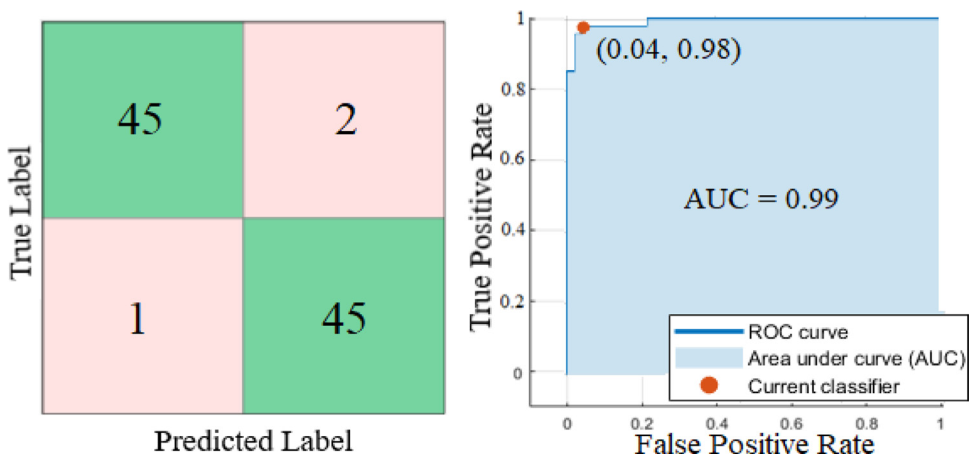

Fig. 9. The confusion matrix and ROC curve of the best analysis result of the proposed approach.

Table 2 is examined, it can be seen that selecting 400 features was not used because of decreasing classification accuracy.

As a result, the combined dataset achieved the best performance with 200 features with the hypercolumn masking technique and the RFE feature selection method. The confusion matrix and ROC curve of this analysis are shown in Fig. 9. The contribution of the proposed model on the classification performance is shown in Fig. 10.

The results of this study show that although pretrained CNNs can produce high generalization performances, it is still possible to enhance the model achievement using advanced techniques such as hypercolumn masking technique, fused deep features, RFE, and SVM. The experiments carried out in three steps indicate that deep features extracted from the last fully connected layers of the pretrained models ensure the discriminative features for brain tumor MRI classification. To exploit the generalization abilities of both AlexNet and VGG-16 models in a single diagnosis model, fusing the deep features extracted separately from these models was useful. The hypercolumn masking technique contributed to improving model performance. Lastly, the most efficient results were achieved by using the RFE and SVM on the fused deep feature set. In this manner, the gradual performance increase in the performance of the proposed model was observed as shown in Fig 10.

5. Discussion

The brain tumor is a vital disease among hundreds of cancer diseases. The incidence of this disease in the world is increasing day by day. If this disease is not diagnosed timely, the probability of death becomes considerably stronger. Early detection of this

Table 2
Classification results of the experiments performed in this study.

CNN Architecture	Hypercolumn Technique	Features (FC8)	RFE / Features	Sensitivity (%)	Specificity (%)	F-Score (%)	Accuracy (%)
AlexNet	No	1000	No / -	95.24	86.27	89.89	90.32
VGG-16	No	1000	No / -	87.23	86.96	87.23	87.10
AlexNet	Yes	1000	No / -	95.45	89.80	92.31	92.47
VGG-16	Yes	1000	No / -	89.58	91.11	90.53	90.32
AlexNet & VGG-16	Yes	2000	Yes / 100	95.65	95.74	95.65	95.70
AlexNet & VGG-16	**Yes**	2000	**Yes / 200**	97.83	95.74	96.77	**96.77**
AlexNet & VGG-16	**Yes**	2000	**Yes / 300**	95.83	97.78	96.84	**96.77**
AlexNet & VGG-16	Yes	2000	Yes / 400	95.74	95.65	95.74	95.70

Table 3
Analysis results of the brain tumor MRI dataset.

Study	Year	# of Classes	# of Samples	Model/Method	Classifier	Acc. (%)
(Varuna Shree & Kumar, 2018)	2018	2	650	GLCM & Discrete Wavelet Transform (DWT)	PNN	95.0
(Ari & Hanbay, 2018)	2018	2	–	LRF	ELM	97.18
(Fayaz et al., 2016)	2016	2	100	Color Features	kNN	92.5
(Nouman Tajik et al., 2016)	2016	2	60	Genetic Algorithm (GA) & GLCM	kNN	96.67
Proposed method	2019	2	310	CNN & Hypercolumn & RFE	SVM	**96.77**

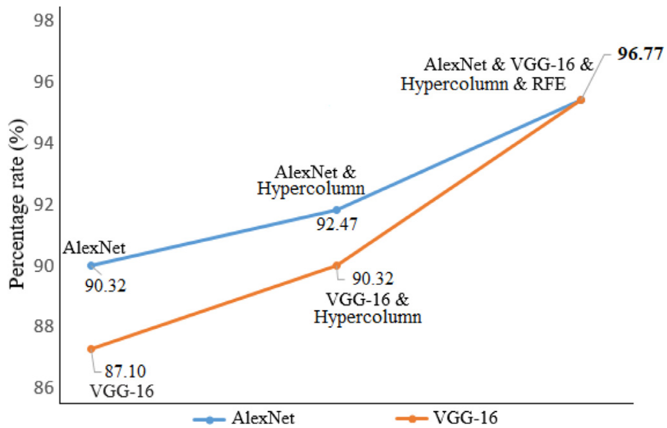

Fig. 10. Performance graph of the proposed approach on CNN architectures.

disease is associated with the rapid and accurate results of image processing techniques in relation to computational approaches. Conventional methods and techniques can be used to improve the efficiency of CNN models. As a result, numerous studies have been conducted based on machine learning and deep learning models for early detection of brain tumors with brain tumor MRI. Some of these studies are shown in Table 3.

Table 3 shows the superiority of the proposed method. (Varuna Shree & Kumar, 2018) used the statistical feature extraction method and the DWT method in their studies. They classified the features, which were obtained from color, texture, and shape, using the PNN model. The dataset consisted of an image set obtained from five patients.

(Ari & Hanbay, 2018) investigated regionally the open-access dataset. For this purpose, a combination of LRF and ELM methods was used as a diagnosis model. As a result, the success rate was reported as 97.18%. Integrating the LRF method into the proposed model may contribute to improving classification accuracy.

(Fayaz et al., 2016) described brain tumor MRI using feature extraction methods and classified them with *k*NN classifier. In here, a median filter was applied to each image in the dataset in the preprocessing step. Grayscale images were then converted to RGB images. Separating features from three color channels was thought to be easier and more efficient than grayscale. 92.5% classification success was obtained with the extracted features and *k*NN classifier. The use of RGB channels contributed to performance in terms of the efficient extraction of features. Similarly, in the proposed method, the masks obtained by the hypercolumn technique include RGB channels.

(Nouman Tajik, Rehman, Khan & Jadoon, 2016) applied GLCM and DWT to brain tumor MRI and performed classification using *k*NN method using a genetic algorithm for feature selection. The success rate of classification was 96.67%. However, the limited number of samples in the dataset used in this study created doubt on the generalization performance of the model. In addition, the GA feature selection method used in the study contributed to the model performance. Similarly, the hypercolumn and RFE feature selection method in the proposed method gradually increased the accuracy of classification.

6. Conclusion

We proposed a novel model for binary classification of brain tumor MRI using deep learning algorithms. The proposed model consists of four key stages: (1) The pretrained AlexNet and VGG-16 models were used as a feature extractor. (2) The hypercolumn technique was employed to enhance the classification success. (3) To exploit the generalization abilities of both AlexNet and VGG-16 models, the deep features extracted from the last fully-connected layers of the models were fused. (4) The most efficient deep features were determined using the RFE feature selection method and the SVM classifier. The results of the study proved that the hypercolumn technique enhanced classification performance. Also, a combination of the RFE and SVM model reduced the dimension of the feature set and ensured the most satisfactory results. As a result, the accuracy of 96.77%, the sensitivity of 97.83%, and the specificity of 95.74% were achieved. Consequently, a precise and consistent diagnosis model was achieved for brain tumor MRI classification. The proposed model can contribute to realizing a more objective evaluation in the clinics, supporting the decision-making process of the experts, and reducing misdiagnosis rates.

Thanks to the end-to-end learning scheme of deep learning, an input brain tumor MRI sample could be located automatically into a normal or tumor class using the selected effective deep features. In other words, the proposed model no needs any handcrafted feature engine to fulfill the classification process. Although there is a wide variety of tumor types, the proposed model was addressed this issue with binary classification. To diagnose all types of tumors with the help of such a system, a quite large scale dataset is required for providing a properly trained deep model. Providing such a dataset can be a really difficult task and taken too long times. Also, the training of the deep learning models requires high computing capacity and lasts rather long compared to the traditional machine learning algorithms.

The results of this study validate that the classification success of deep learning models can be improved using advanced techniques such as hypercolumn, fused deep features, RFE, and SVM. In future studies, we will examine the different datasets using adding the attention modules to the proposed model (Vaswani et al., 2017). Also, only series deep learning models were addressed in this study. Actually, the directed acyclic graph (DAG) networks may also produce efficient results. The performance of the DAG networks, the impacts of the residual blocks and the inception modules in the proposed model should also be examined. Moreover, an investigation on the optimization methods and setting of the hyperparameters of the deep learning models may be useful regarding future research directions. The proposed method can be also used to design high-performance computer-aided systems for other future medical imaging tasks.

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Ethical approval

This article does not contain any data, or other information from studies or experimentation, with the involvement of human or animal subjects.

Declaration of Competing Interest

The authors declare that there is no conflict to interest related to this paper.

Credit authorship contribution statement

Mesut Toğaçar: Conceptualization, Data curation, Formal analysis, Methodology, Validation, Visualization, Writing - original draft, Writing - review & editing. **Zafer Cömert:** Formal analysis, Methodology, Validation, Visualization, Writing - original draft, Writing - review & editing. **Burhan Ergen:** Conceptualization, Resources, Supervision, Validation, Visualization, Writing - review & editing.

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