Brain Tumor Detection using a Combination of Bayesian Optimization Based SVM Classifier and Fine-Tuned Based Deep Features

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(First received 7 July 2021 and in final form 9 September 2021)

DOI: 10.31590/ejosat.963609

ATIF/REFERENCE: Turkoglu, M. (2021). Brain Tumor Detection using a Combination of Bayesian Optimization Based SVM Classifier and Fine-Tuned Based Deep Features. European Journal of Science and Technology, (27), 251-258.

Abstract

Brain tumor, one of the most common types of cancer, is a fatal disease. Therefore, accurate diagnosis of this disease and determining the type of tumor are of great importance in terms of early treatment. In this context, research, and interest in the development of automatic systems for the problems experienced in brain tumor classification, based on deep learning, have increased recently. In this study, a unique framework is proposed, which is based on Bayesian optimization-based Support Vector Machine (SVM) classifier and Convolutional Neural Network (CNN) based deep features ensemble, for the classification of brain tumors. In this model, brain MRI images are first improved. Second, the deep features are extracted using pre-trained CNN-based deep architectures and then combined. Later, effective, and distinctive features are selected from these deep features with the MrMr algorithm. Finally, these features are used in the training of the SVM classifier based on the Bayesian optimization algorithm. A dataset named Figshare, containing brain tumor images such as meningioma, glioma, and pituitary, is used to test the proposed system. In the experimental studies, the accuracy score of the model proposed was observed to be more successful than that of the other studies.

Keywords: Brain Tumor Classification, Feature selection, Convolutional Neural Network, Support Vector Machine, Bayesian optimization

Bayes Optimizasyon Tabanlı SVM Sınıflandırıcısı ve İnce-Ayar Tabanlı Derin Özelliklerinin Kombinasyonu Kullanılarak Beyin Tümörü Tespiti

Öz

En sık görülen kanser türlerinden biri olan beyin tümörü ölümcül bir hastalıkır. Bu nedenle bu hastalığın doğru teşhisi ve tümörün tipinin belirlenmesi erken tedavi açısından büyük önem taşmaktadır. Bu bağlamda, son zamanlarda beyin tümörü sınıflandırılmasında yaşanmış problemler için derin öğrenme otomatik sistemlerin geliştirilmesine yönelik araştırmalar ve ilgi artmıştır. Bu çalışmada, beyin tümörlerinin sınıflandırılması için Bayesian optimizasyon tabanlı Destek Vektör Makinesi (DVM) sınıflandırıcısı ve Evrişimsel Sinir Ağları (ESA) tabanlı derin öznitelikler topluluğu dayalı benzersiz bir tasarım önerilmiştir. Bu modelde öncelikle beyin MRI görüntüleri iyileştirildi. İkinci olarak, derin öznitelikler, önceden eğitilmiş ESA tabanlı derin mimariler kullanılarak çıkartıldı ve ardından birleştirildi. Daha sonra, MrMr algoritmasının etkili ve uygun edici özellikler seçildi. Son olarak, bu özellikler, Bayes optimizasyon algoritmasına dayalı DVM sınıflandırıcısının eğitiminde kullanıldı. Önerilen sistem test etmek için, meningioma, glioma ve hipoфиз gibi beyin tümörü görüntüleri içeren Figshare adlı bir veri seti kullanıldı. Deneylerin sonuçlarında, önerilen modelin doğru lu skoru diğer çalışmalarдан daha başarılı olduğu gözlemlemiştir.

Anahtar Kelimeler: Beyin Tümör Sınıflandırılması, Özellik Seçimi, Evrişimsel Sinir Ağları, Destek Vektör Makinesi, Bayes Optimizasyon.

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1. Introduction

Worldwide, the number of deaths from brain tumors is increasing day by day (Ari, 2019). A brain tumor can be categorized into one of two types, benign or malignant. Early diagnosis of brain tumors and determination of the tumor type are critical for increasing survival rates and effective treatment options (Afshar et al., 2019).

Magnetic Resonance Imaging (MRI) is an important medical imaging tool for the detection of brain tumor (Amin et al., 2019; Amin et al., 2020). Determination of the type and detection of tumors using MRI devices is performed by experts. This identification process is a time-consuming process and entails a high margin of error. The reason for this is that tumors have different shapes and sizes, and they can also be found in different parts of the brain. In addition, manual detection of brain tumor is not a practical method in cases where the number of patients is high. For all these reasons, there is a need for automatic detection of brain tumors. Recently, systems developed to meet this need based on computer vision and machine learning are on demand. Thanks to computer-aided systems that help experts, accurate and rapid diagnosis of brain tumors has been achieved (Ari, 2019).

In recent years, many studies have been performed for classification of the brain tumor based on MRI images. In these studies, CNN-based deep learning models, and machine learning methods were widely used. In this regard, Ali et al. (2020) proposed a model based on pre-trained deep architectures and ELM classifier for brain tumor classification. In this study, deep features are extracted using the fc6 and fc7 layers of AlexNet and VGG16 models. Later, these feature vectors were used for classification of MR images with the help of Extreme Learning Machines (ELM) classifier. They reported a highest accuracy score of 97.64%. Similarly, Rehman et al. (2020) developed a deep learning-based framework using transfer learning method for classification of brain tumors. In line with this purpose, they used three architectures of convolutional neural networks (AlexNet, GoogLeNet, and VGGNet). In addition, the dataset was expanded using data augmentation methods. They achieved a highest accuracy score of 98.69% using the fine-tune VGG16 architecture. Cheng et al. (2016) proposed a unconventional feature extraction framework to enhance the classification performance. They extracted features using Adaptive Spatial division and Fisher Vector Representation. Later, SVM classifier was used for training the model proposed and the performance of the system was calculated. In this study, mean precision value was obtained as 94.68%. Abir et al. (2018) developed a system based on pre-processing methods and GLCM (Gray Level Co-occurrence Matrix) to extract the feature values. The features obtained were used as the input of a PNN classifier and the performance of the system proposed was calculated. In this study, the highest accuracy acore was obtained as 83.33%. Finally, Afshar et al. (2018) used Capsule networks (CapsNets) for the problem encountered in classification of brain tumor type. They made investigations to increase the accuracy by changing the number of feature maps in the convolutional layer of the Capsule network. The results of this study show that the method proposed achieved an accuracy score of 86.56%. Additionally, other previous studies used the Figshare dataset are summarized in the Discussion section.

In this paper, a unique Bayesian optimization based deep classifier approach is proposed for classification of brain tumors. Firstly, image enhancement techniques were used in the system proposed. Later, deep features were extracted from brain tumor images using pre-trained deep architectures based on the transfer learning approach. Effective and distinctive features were selected using MrMr method for these representative features. Finally, parameters that had the best performance of the SVM classifier based on the Bayesian optimization method were determined and the training and testing phases of the system proposed were carried out. A brain tumor dataset named Figshare (Cheng, 2018) was used to evaluate the performance of the system proposed.

The main contributions of this study are as follows:

- The proposed model used classification capabilities of features obtained from the last fully connected layers of pre-trained deep architectures: AlexNet, and DenseNet201.
- The current study adapted the MrMr feature selection algorithm in order to both reduce the dimension of the features obtained from pre-trained deep networks and reveal the best effective deep features. In experimental studies, a high success diagnosis model has been achieved by using these selected and effective features for brain tumor MRI classification.
- The deep features obtained from pre-trained CNN networks were fed into an SVM, and the best SVM classifier parameters have been optimized using the Bayesian optimization method. Thanks to this approach, the highest performance has been achieved as 98.04% for the SVM classifier based on selected features in classifying brain tumors.

The remaining part of this paper is structured as follows: the proposed approach is presented in Section 2, while the dataset and the experimental results are detailed in Section 3. The discussion of the results is given in Section 4, and the conclusion of the current research is outlined in Section 5.

2. Proposed Methodology

In this paper, a unique system that is based on selected deep features and Bayesian optimization based SVM classifier is proposed for classification of brain tumors. Extensive experimental studies were carried out for the determination of feature selection and classifier parameters. In addition, the well-known CNN architectures were examined to identify the effects on the classification performance. Finally, a brain tumor dataset named Figshare, which is widely used in the literature, was used in experimental studies, and the accuracy scores were used for evaluation of the performance of the system proposed. The flowchart of the system proposed is presented in Fig. 1.

The proposed system incorporates four phases: pre-processing, feature extraction, feature selection and classification. These stages are detailed below under subheadings.
In the pre-processing phase, brain MRI images are enhanced using max-min algorithm (Algorithm 1). Thus, an MRI image with a black background and a more prominent edge was obtained. Procedure of the proposed pre-processing phase is shown in Algorithm 1.

Algorithm 1. The pseudo-code of the proposed pre-processing.

Input: Input image (img) with size of K x L
Output: Output images (new_img)
1: minX= min(min(img));
2: maxX= max(max(img));
3: for i=1 to length(K) do
4:   for j=1 to length(L) do
5:     img1(i,j)=(img(i,j) - minX) / (maxX-minX);
6:   end
7: end
8: new_img = cat(3, img1, img1, img1);

2.2. Feature Extraction Phase

In feature extraction phase, pre-trained architectures based on transfer learning were used for recognition of Brain MR images. The transfer learning approach is the adaptation of pre-trained CNN-based deep architectures that use the learned weights to solve another problem. In this study, AlexNet, and DenseNet201 architectures, which are pre-trained CNN models with different characteristics, were used. The characteristics of these architectures are presented in Table 1.

Table 1. The characteristics of the deep architectures

| Name               | Depth | Size (MB) | Parameters (Millions) |
|--------------------|-------|-----------|-----------------------|
| AlexNet (Krizhevsky et al., 2012) | 8     | 227       | 61                    |
| DenseNet201 (Huang et al., 2018) | 201   | 77        | 20                    |

These architectures shown in Table 1 were trained using the ImageNet dataset that had a very large collection of annotated images designed for developing machine learning methods. AlexNet architecture developed by Krizhevsky et al. consists of 25 layers: convolution, pooling layer, ReLU layer, and fully connected layer. The general structure of this architecture is shown in Fig. 2.

The DenseNet network architecture is that the features obtained from the previous layers are directly combined with much more advanced layers (Fig. 3). Thus, the features obtained in the first layers are protected. The DenseNet201 network which one of the versions of this new approach has become a high-performance and multi-layer network model (Huang et al., 2018).

These architectures were combined. Then, deep features obtained from deep architectures with different structures were combined. Procedure of the proposed feature extraction phase is shown in Algorithm 2.

2.3. Feature Selection Phase

In feature selection phase, it is an important process to select the best feature subset from feature vectors for overcoming classification problems. The feature selection process has an important advantage of reducing the processing...
time by decreasing the number of features (Yaslan & Cataltepe, 2009; Demir et al., 2020). In this study, it is aimed to determine better and distinctive features from combined deep features obtained during the feature extraction stage by using MrMr algorithm. This MrMr method is a filtering algorithm that tries to select the most relevant attributes with the class tags, while minimizing the redundancy between the selected attributes, simultaneously (Yaslan & Cataltepe, 2009; Gulgezen et al. 2009; Toğar et al., 2020a).

**Algorithm 2. The pseudo-code of the proposed feature extraction.**

| Input: | Input image (img) with size of K x L x 3 |
| Output: | Deep features (feat) |
| 1: | img1=imresize (img, [224 224]); |
| 2: | img2=imresize (img, [227 227]); |
| 3: | Net_Parameters1= load_model (AlexNet, pretrained=true); |
| 4: | Net_Parameters2= load_model (DenseNet201, pretrained=true); |
| 5: | Features1 = activations (Net_Parameters1, img2, ‘fc6’); |
| 6: | Features2 = activations (Net_Parameters2, img1, ‘fc1000’); |
| 7: | feat= [ Features1; Features2]; |

The MrMr based feature selection method used in this study are includes 2 basic steps. There: (1) The weights of the deep features are calculated, (2) sort weight scores, and select features as much as specific t value. The selection procedure including these steps is demonstrated in Algorithm 3.

**Algorithm 3. The pseudo-code of the proposed feature extraction.**

| Input: | Deep features (dfeat), label (lab), and t value (selected features) |
| Output: | Selected features (feat) |
| 1: | w= fscmrmr (dfeat,lab); |
| 2: | for i=1 to t do |
| 3: | feat(:,i)=dfeat(:,w(i)); |
| 4: | end for i |

### 2.3. Classification Phase

In classification phase, SVM classifier was used for training of selected deep features. SVM method is a statistical algorithm used in classification problems (Cortes & Vapnik, 1995). This method places the features on the coordinate plane and then performs the classification process by selecting the best hyperplane that can distinguish the two classes. Hyperplane parameters with two variables such as weight vector (w) and trend value (b) are adjusted to maximize symmetrical spacing between classes (Turkoglu & Hanbay, 2019). The working principle of the SVM classifier is shown in Fig. 4.

Equation (1) aims to minimize the problems arising during the classification process. In Equation (2), \( x_i \) ve \( y_i \) represent features. This equation makes an estimate to determine the class of data (Cortes & Vapnik, 1995; Turkoglu, 2020; Toğar et al., 2020b).

\[
\min \frac{1}{2} ||w||^2 \\
y_i(x_i^T w + b) \geq 1, \quad i = 1, ..., n
\]

In this study, the SVM classifier was preferred due to the fact that it is easy to apply, has high generalization performance, and is effective in high dimensional feature vectors. Additionally, the SVM method includes parameters such as Box constraint level, Kernel scale, and Kernel Function. The change in these parameter values significantly affects the classification performance. For this reason, it is aimed to select the best performance parameters of the SVM classifier by using Bayes optimization method (Pelikan et al., 1999), which is widely used and is faster than other optimization methods. A sample demonstration of these operations shown in Fig. 5.

![Bayes optimization based SVM classifier model](image)

As can be understood from Fig. 5, the best parameters of the Bayes optimization based SVM classifier were selected for the training set and the performance of the system proposed for the test set was calculated using these parameters. In current study, the optimized hyperparameters and hyperparameters search ranges of SVM classifier based on Bayesian optimization are listed in Table 2. Additionally, the MATLAB Classification Learner toolbox is used for the application of Bayesian and SVM methods.

**Table 2. The optimized hyperparameters and search ranges**

| Kernel function | Box constraint level | Multiclass method | Standardize data |
|-----------------|----------------------|-------------------|-----------------|
| Gaussian        | [0.001-1000]         | One-vs-One        | true / false    |
| Linear          |                       | One-vs-All        |                 |
| Quadratic Cubic |                       |                   |                 |
| Cubic           |                       |                   |                 |

e-ISSN: 2148-2683
3. Experimental Studies

The Bayesian optimization based deep classifier proposed in this study was created using MATLAB software. In the experimental studies, a computer with a Nvidia M4000 GPU with 8 GB of memory was utilized. Additionally, using the random separation approach, 80% of the data was used for training and the rest for testing. This procedure was repeated only once, and the same training/test sets were used in all experimental studies. The code of the proposed model was shared at https://github.com/mturkoglu23/Brain-Tumor-Detection.

The experimental results and dataset are explained in the following subsections.

3.1. Dataset

In this paper, publicly available brain tumor dataset named Figshare (Cheng, 2018) was used. This dataset, developed by Cheng in 2017, contains 3064 brain MRI images. In addition, Figshare dataset includes three types of brain tumors namely pituitary, meningioma, and glioma. These brain tumor types are illustrated in Fig. 6.

![Figure 6 Types of Brain Tumors, a) Meningioma, b) Glioma, c) Pituitary.](image)

3.2. Results

In this section, pretrained CNN models are adapted to the classification of brain tumors using a fine-tuning based on the transfer learning approach. The fine-tuning method is focused on the transfer of new layers to our classification mission, instead of the last three layers of the pre-trained networks. These layers are a fully connected, a softmax, and a classification. In this study, accuracy scores were calculated using this approach for AlexNet, and DenseNet201 architectures. The network parameters used for these deep architectures are given in Table 3. Accuracy scores achieved from this experimental works are shown in Table 4.

![Table 3. The deep network parameters used in current study.](image)

| Mini-batch size | 8 |
| Maximum epoch number | 10 |
| Weight decay factor | 0.01 |
| Initial learning rate | 0.001 |
| Optimization method | SGDM (Stochastic Gradient Descent with Momentum) |

![Table 4. Accuracy scores (%) of fine-tuned deep architectures](image)

| AlexNet | DenseNet201 |
|---------|-------------|
| 92.17   | 89.72       |

As is apparent from Table 4, the highest accuracy score between deep architectures based on fine-tuning process was 92.17% with the AlexNet architecture. In addition, the accuracy score of DenseNet201 architecture was obtained as 89.72%. As another experimental work, features were extracted from fully connected layers of these deep architectures, and then deep features were fed into an SVM classifier. The confusion matrixes (accuracy scores) achieved from this experimental works are given in Figure 7.

![Figure 7 Confusion matrix of deep models, a) AlexNet, b) DenseNet201](image)

As can be seen in Figure 7, the highest accuracy score between deep architectures based on deep feature extraction approach was 96.74% with the AlexNet architecture. In addition, the accuracy score of DenseNet201 architecture was obtained as 93.8%. According to the results given in Table 4 and Figure 7, performance results based on deep features and SVM classifier for all deep architectures is more successful than fine-tuning. For these reasons, deep feature extraction and SVM approaches used in the remainder of the study.

In the second experiment, combinations of AlexNet, and DenseNet201 deep architectures were evaluated. In accordance with this purpose, features obtained from deep architectures were combined, and their performances were calculated using an SVM classifier. The analysis results of the combined deep features are given in Figure 8. According to these results, the
highest accuracy score among combined deep networks was achieved as 97.39% using a combination of AlexNet, and DenseNet201 architectures. In addition, the accuracy score of combined deep networks was a 1% performance increase from the AlexNet architecture which has the highest performing. As a result, the combined method used in the second experiment improved the accuracy score of the individual deep architecture. The confusion matrixes for the combined deep networks are shown in Fig. 8.

In the last experimental study, a combination of selected deep features and Bayesian optimization based SVM classifier is proposed for the classification of brain tumors. In line with this purpose, features were obtained from deep architectures with different structures, and then these deep features were combined. More meaningful and effective features were selected from the combined features obtained using MrMr method and trained with Bayes optimization based SVM model. Consequently, the performance of the features selected in different numbers were calculated, and these results are presented in Fig. 9.

As can be understood from Fig. 9, the distinguishing features (except for 500 and 1000 selected features) selected using MrMr algorithm are observed to be more successful than the raw features. Moreover, the 500 features obtained from the combined deep properties have the worst accuracy at 96.25%. The best accuracy score of the model proposed based on MrMr algorithm for classifying brain tumors was achieved as 98.04% as selected 2,500 effective features. Additionally, 2000, and 3000 most relevant features selected from deep features have approximately the same accuracy. The confusion matrix of the best performance (98.04%) for the model proposed are shown in Fig. 10.

In the proposed model, the highest performance (98.04%-2500 deep features) using the Bayesian optimization method for SVM classifier was achieved with kernel function (Cubic), box constraint level (244.4749), and multiclass method (one-vs-all). The minimum classification error plot of the Bayesian optimization process based SVM classifiers is presented in Fig. 11.

As can be seen in Figure 11, 30 iterations were executed for the Bayesian optimization process based on the SVM classifier. The best-point of hyperparameters is accomplished at the end of the 14th iteration.

4. Discussion

In this paper, the Bayesian optimization based SVM classifier proposed, and selected CNN based deep features were compared to the existing systems in the literature, and the results are presented in Table 8.
5. Conclusion

Proposed in this study is a hybrid model based on the Bayesian optimization based SVM classifier, four pre-trained CNN models and MrMr feature selection method for classification of brain tumors. In line with this purpose, a publicly available brain tumor dataset consisting of 3024 MRI images in total was used. The method proposed entailed three experiments. In the first experiment, pre-trained deep architectures based on the transfer learning approach were used as feature extractors, and representative features were obtained from brain MRI images. In the second experiment, MrMr feature selection method was used to select distinctive and more effective features from combined deep features. Finally, Bayesian optimization method was used for SVM classifier parameters and hyperparameters with the best performance were selected. According to the experimental results, the best accuracy score of 98.04% was achieved using model proposed for classification of brain tumors.

In future works, a real-time web-based system is planned to be developed, which will aim to support health professionals to detect brain tumors and other diseases. In addition, other CNN-based models, machine learning classifier and attention modules will be investigated to help classification of brain tumors.

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Table 8. Comparison of the existing studies with model proposed

| References       | Feature extraction          | Classification | Accuracy  |
|------------------|-----------------------------|----------------|-----------|
| Ari et al. (2020)| AlexNet and VGG16           | ELM            | 97.64%    |
| Cheng et al. (2016)| Local features using Fisher Vector | SVM            | 94.68%    |
| Abir et al. (2018)| GLCM                        | PNN            | 83.33%    |
| Afshar et al. (2019)| Capsule networks (CapsNet)     | SVM            | 86.56%    |
| Cheng et al. (2015)| Bag of words               | SVM            | 91.28%    |
| Deepak and Ameer (2019)| GoogleNet                | SVM            | 97.1%     |
| Kaur and Gandhi (2020)| Fine-tuned AlexNet         | SVM            | 96.95%    |
| Ayadi et al. (2020)| DSURF and HoG              | SVM            | 90.27%    |
| Pashaie et al. (2018)| CNN                       | ELM            | 93.68%    |
| Swati et al. (2019)| Fine-tune VGG19            | SVM            | 94.80%    |
| Deepak and Ameer (2020)| CNN                       | SVM            | 95.82%    |
| Bodapati et al. (2020)| Xception and InceptionResNetV2 | Softmax       | 95.23%    |
| Proposed model   | AlexNet and DenseNet201     | Bayes optimization based SVM | 98.04%    |
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