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An expert system for brain tumor detection: Fuzzy C-means with super resolution and convolutional neural network with extreme learning machine

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ABSTRACT

Super-resolution, which is one of the trend issues of recent times, increases the resolution of the images to higher levels. Increasing the resolution of a vital image in terms of the information it contains such as brain magnetic resonance image (MRI), makes the important information in the MRI image more visible and clearer. Thus, it is provided that the borders of the tumors in the related image are found more successfully. In this study, brain tumor detection based on fuzzy C-means with super-resolution and convolutional neural networks with extreme learning machine algorithms (SR-FCM-CNN) approach has been proposed. The aim of this study has been segmented the tumors in high performance by using Super Resolution Fuzzy-C-Means (SR-FCM) approach for tumor detection from brain MR images. Afterward, feature extraction and pretrained SqueezeNet architecture from convolutional neural network (CNN) architectures and classification process with extreme learning machine (ELM) were performed. In the experimental studies, it has been determined that brain tumors have been better segmented and removed using SR-FCM method. Using the SqueezeNet architecture, features were extracted from a smaller neural network model with fewer parameters. In the proposed method, 98.33% accuracy rate has been detected in the diagnosis of segmented brain tumors using SR-FCM. This rate is greater 10% than the rate of recognition of brain tumors segmented with fuzzy C-means (FCM) without SR.

Introduction

The brain has a complex structure consisting of millions of cells. Brain tumors are caused by the rapid growth of cells. Uncontrolled growth of cells affects brain activity and may damage normal cells [1]. Imaging technologies have played a role in the analysis of brain anatomy and functions with the development of technology. The tumor region can be detected by using Magnetic Resonance Imaging (MRI). However, radiologists need to measure the size of the tumor site for treatment. Image processing methodologies play an important role in the monitoring of tumor sites between radiologists and computers in the diagnosis and treatment process with machine learning. Radiologists improve diagnostic accuracy from a different perspective in interpreting medical images with these hybrid techniques [2].

Using a higher resolution on medical images makes it easier for the doctor to diagnose diseases. Super-resolution (SR) is used to increase the resolution. In the literature, SR is used in medical images [3–5], MR images [6], brain MR images [6–9], cardiac MR images [10], and retinal fundus images [11]. Many methods were used in the detection and automatic classification of tumor regions using MR images in the literature. Saad et al. [12] established a hybrid system with Fuzzy C-Mean (FCM) region growing for tumor analysis. Sachdeva et al. [13,34] classified the brain tumor by using the support vector machine (SVM) and artificial neural network (ANN) machine learning model in a hybrid structure with Genetic Algorithm (GA) (GA-SVM and GA-ANN). Mallick et al. [14] used a hybrid method with image compression of wavelet transform and image compression using Deep Wavelet Autoencoder (DWA) for brain MR images. In addition, images were classified using Deep Neural Networks (DNN). Performance comparison of DWA-DNN model with other conventional classification techniques was performed. Zeng et al. [9] suggest a deep convolutional neural network model for single and multiple contrast super-resolution reconstructions for artificial and real brain MR images. Swati et al. [15] suggest a method based on learning to transfer brain MR images using a pretrained deep CNN model. The proposed method has a coverage accuracy of 94.82% under five-fold cross-validation since it does not use any handmade features and requires minimal pretreatment. Deepak and Ameer [16] classified three types of brain tumor types using a pre-

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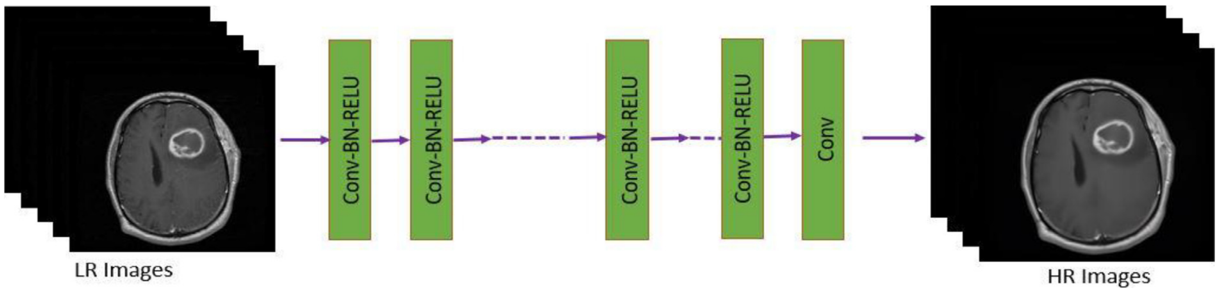


Fig. 1. Proposed SISR Model.

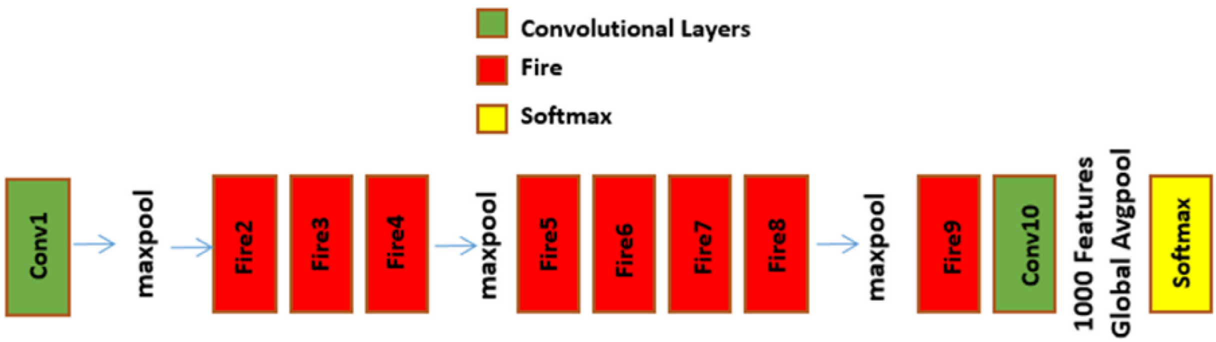


Fig. 2. Sample Illustration of SqueezeNet layers.

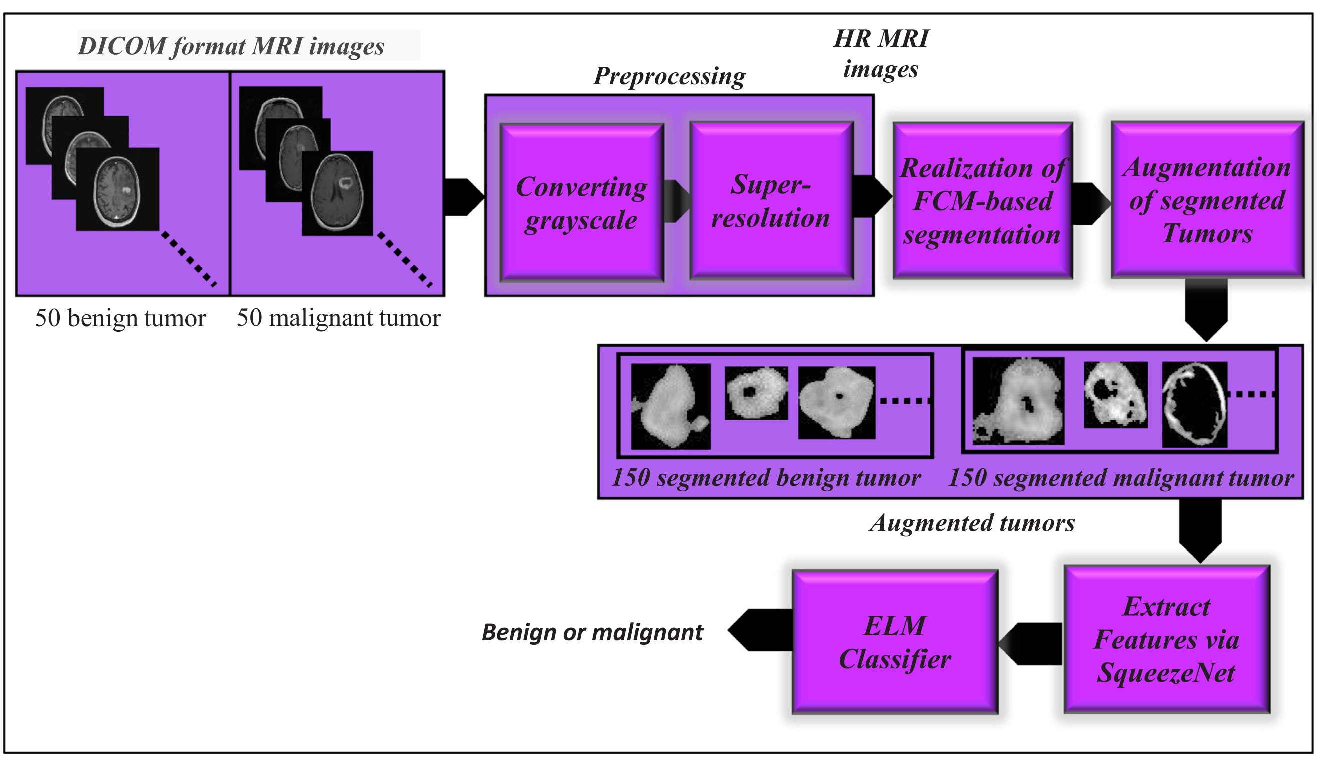


Fig. 3. Scheme of the proposed method.

trained GoogLeNet to extract features from brain MR images with deep CNN. Selvapandian and Manivannan [17] used Non-Sub sampled Contourlet Transform (NSCT) to enhance the brain image, and then the tissue features were removed from the enhanced brain image. These extracted features were trained and classified using the Adaptive Neuro Fuzzy Inference System (ANFIS) approach for classification. In their study, Pan et al. [18] used 2D brain MR images to compare performance with CNN and RPNN based algorithms. In addition, the kernels were trained in separate layers.

In this study, brain tumor detection based on fuzzy C-means with super-resolution and convolutional neural networks with extreme learning machine algorithms (SR-FCM-CNN) approach was proposed. DICOM format MRI images were used in the study and low-resolution (LR) MRI images were transformed into high-resolution (HR) MRI images by the super-resolution (SR) approach developed by Zhang [20]. Segmentation of tumors in HR MRI images is then performed using the

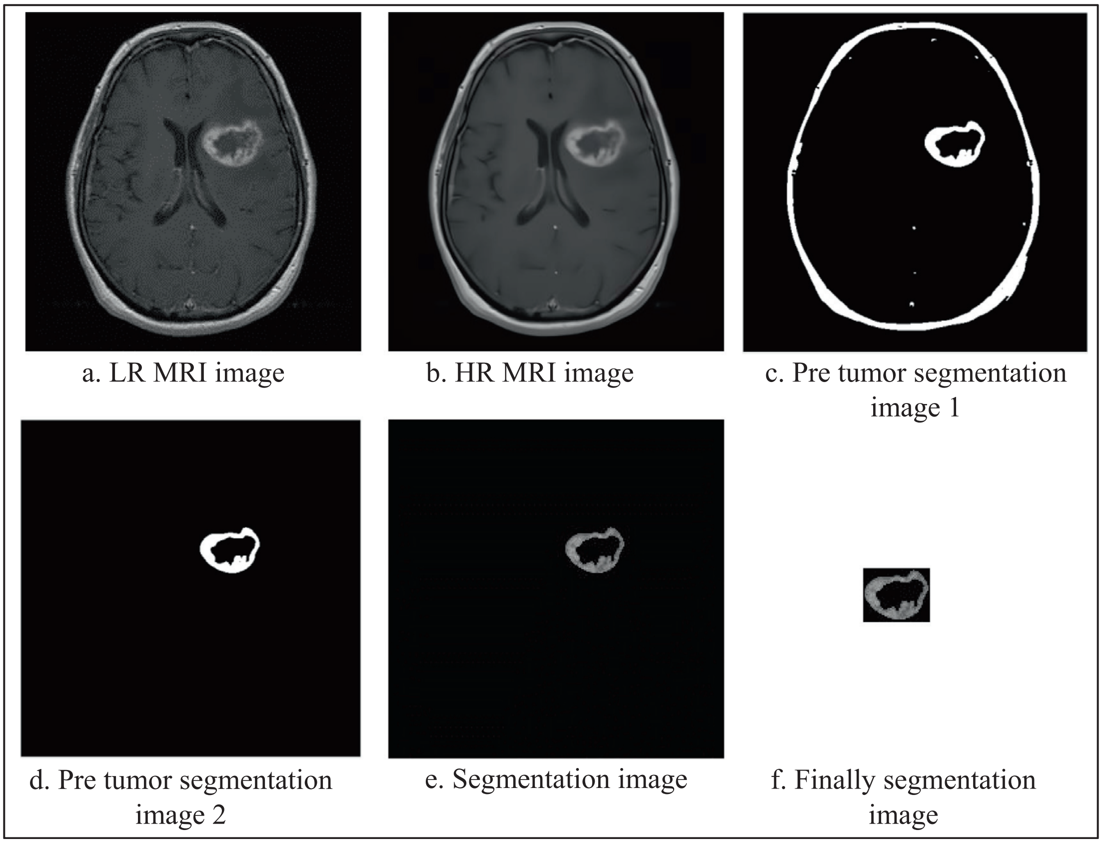


Fig. 4. Result images.

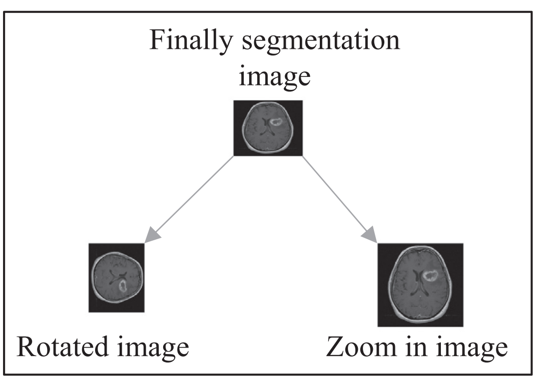


Fig. 5. Augmentation images.

FCM method [19] and image processing techniques. It has been found that segmentation based on fuzzy C-means with super-resolution (FCM-SR) approach designed specifically for this study performed more successful segmentation of MRI images by using SR approach [20]. SqueezeNet architecture, which is one of the wide spreadings pertained CNN algorithms, has been used as feature extractor to increase the applicability of the proposed method on various platforms. In connection with this, segmented images are exported to SqueezeNet architecture to extract features. The acquired features are then given to the ELM classifier for benign or malignant detection of tumors.

The main innovations presented in this study are presented below:

1) The resolutions of the images have been raised very successfully and their quality increase to the highest levels with the SR approaches, which are based on deep learning based on a new topic that has emerged recently.
2) SRI was applied to MRI images to increase the segmentation performance of FCM, resulting in better detection of the tumor site.
3) A smaller and faster pertained CNN model with fewer parameters, SqueezeNet has been used for easy integration into embedded systems and for successful results.
4) The features extracted in the SqueezeNet architecture are given to the ELM classifier, which has a generalizable performance, does not require parameters such as learning speed, momentum, etc., and can give fast results and thus the detection of tumors is provided.
5) The smaller Retrained CNN architecture, SqueezeNet, and the SR-FCM-CNN hybrid method, which can be easily integrated into embedded systems with the fast ELM classifier, have been proposed for the first time.

The rest of this study is organized as follows. Section “Theoretical background” presents the theoretical background, Section “Proposed method” presents the proposed method, Section “Experimental results” presents the experimental results, and Section “Conclusion” presents the conclusion.

Theoretical background

Database

In order to conduct experimental studies on the proposed SR-FCM-CNN approach, the Cancer Genome Atlas Glioblastoma Multiform (TCGA-GBM) (23) database in the Cancer Imaging Archive (TCIA) was preferred. In the relevant database, approximately 500 samples were selected per different types of cancer and tissues were obtained from different locations in the world. TCGA-GBM database is open access and MRI images in this database can be used with reference. Therefore, there is no need to make an ethical committee decision in order to use the images in this database. Since T1-weighted post contrast (T1-gadolinium (Gd)) gave sequence, T1-Gd sequence MRI images were used

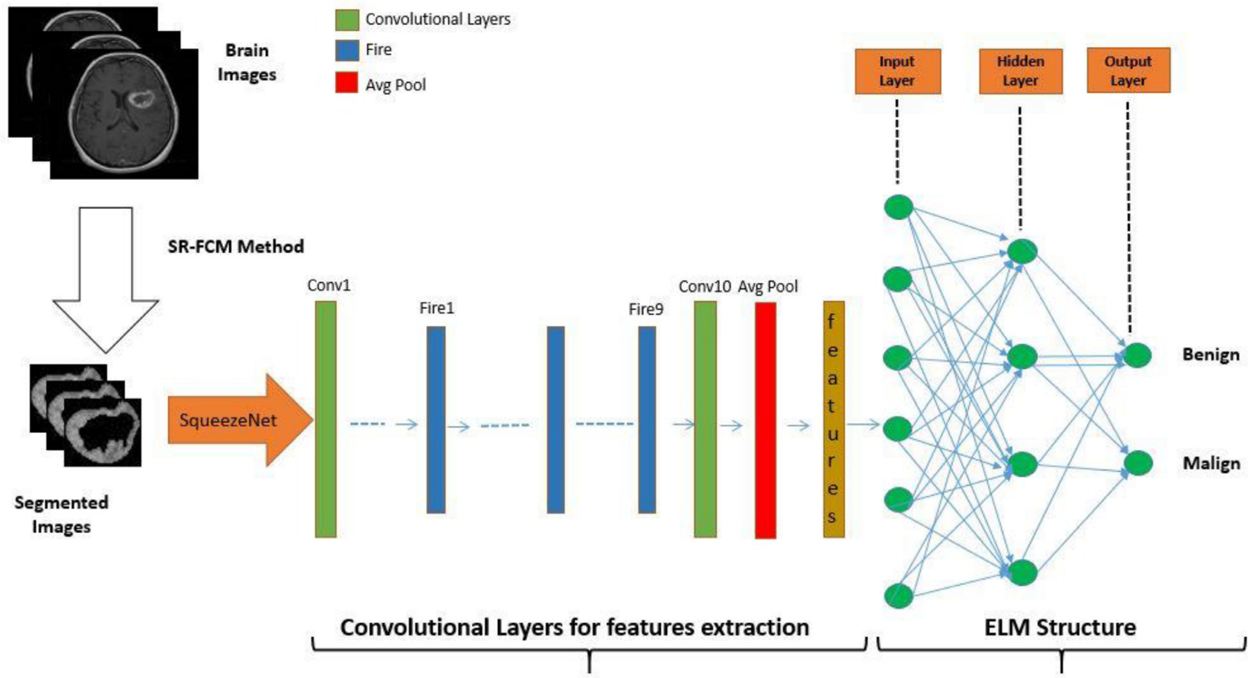


Fig. 6. General Diagram of Step 6 and 7.

in order to obtain the most accurate information about the tumor site in MRI images containing brain tumor. More information on the TCGA-GBM database is available from [21].

Learning a single convolutional Super-Resolution network for multiple degradations

Super Resolution (SR) is a widely used field in image and video processing [20,22–24]. It aims to improve image quality from the given LR image or video sequence [20]. HR rendering using one or more LR images is called SR [20]. SR imaging has proven successful with one or more LR images from the same scene in many areas such as satellite imaging, video applications and medical imaging [22–24]. In this study, LR MRI images are converted to HR MRI images by the approach developed by K. Zhang [20]. Single image super-resolution (SISR) is an active research topic with high practical values in the field of computer vision [25].

The SISR model is a CNN-based model. In this model, convolution layers consist of 3x3 convolution layers. In the SISR model, the layers consist of three types of processes, such as Convolution (Conv), Rectified Linear Units (ReLU) [26] and Batch Normalization (BN) [27]. An example of a super-resolution network proposed for multiple distortions is given in Fig. 1 [20].

Convolutional neural network

CNN architectures are frequently used in the literature as image classification, object recognition and detection methods [28–30]. These methods are remarkable with high classification accuracy. [28–30]. ESA is inspired by artificial neural networks and is an end-to-end architecture that can gather collected information. CNN can handle large-scale data with its sufficient capacity and intelligent model structure. This article uses one of the latest pertained CNN architectures, the SqueezeNet architecture.

SqueezeNet is one of the CNN architectures developed by researchers at the University of California, DeepScale, Stanford and the University of Berkeley in 2016. The purpose of the SquezeeNet architecture is to create a smaller neural network model with fewer parameters that can easily fit into computer memory [31].

SqueezeNet was first described in a study titled "SqueezeNet: AlexNet-level accuracy with 50x fewer parameters and less than 0.5 MB model size" [32]. AlexNet is a CNN architecture with 240 MB parameter, while SqueezeNet has only 5 MB parameters. The reason for comparison with the AlexNet architecture is that although it has a much less complexity level, ImageNet achieves approximately the same level of accuracy when evaluated on the image classification validation dataset. The main advantages of SqueezeNet architecture can be listed as follows:

1. More efficient distributed layers: The workload of the CNN architecture is directly proportional to the number of parameters in the architecture [32]. In short, smaller models run faster because they have fewer parameters.
2. Usability as Mobile: Applications developed in SqueezeNet architecture are easier to move to mobile platforms. Due to its small architectural structure, it requires less communication, which makes frequent updates possible.
3. Compatibility with embedded systems and FPGAs: FPGAs typically have less than 10 MB of chip memory. This is not a problem for the SqueezeNet architecture, but it can be a problem due to the large size of other architectures.

An example representation of SqueezeNet architecture is given in Fig. 2.

Fcm

The FCM algorithm is one of the most commonly used fuzzy division clustering techniques. This algorithm was developed in 1981 by Bezdek. The FCM approach works on the basis of the objective function and, in addition, allows objects to be included in two or more clusters. In the FCM approach, each data belongs to each of the clusters with a membership value ranging from 0 to 1. The sum of membership values for all classes of any data must be 1. Since the FCM approach works with the objective function, the clustering process terminates by approaching the minimum increment value of the objective function to

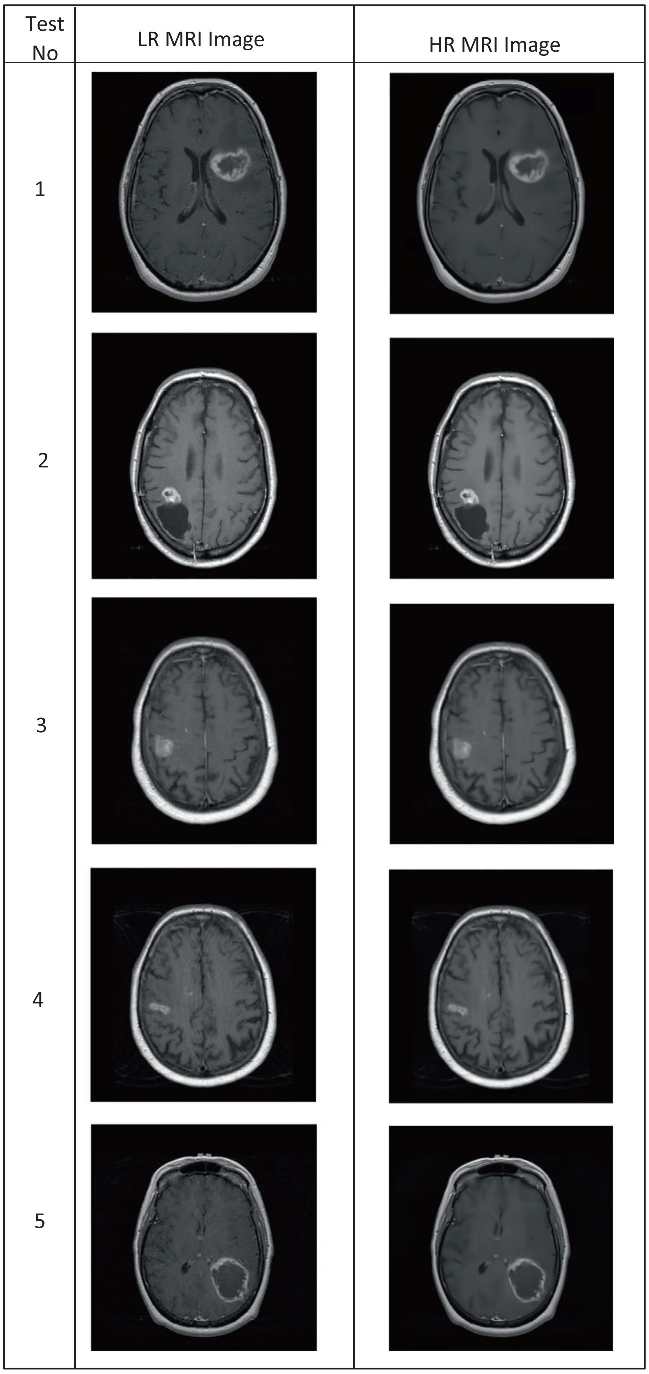


Fig. 7. LR and HR MRI images.

the predetermined minimum increment value. The objective function used in the FCM approach is given below [19]:

$$\mathrm{Jm} = \sum_{i=1}^{Cl}\sum_{k=1}^{N} u_{ik}^{m}\|im_k - v_i\|^2,\ 1 < m < \infty \tag{1}$$

where im = {im1, im2,…., ImN} refers to an N pixel image to be allocated to Cl setsm is the exponent weight on each fuzzy member. The variable vi is the ith cluster center, u_{ik} is the degree of membership. u is a membership matrix and is initialized with a random value. When calculating center vectors, centers are calculated based on the following equation:

$$v_i = \frac{\sum_{i=1}^{N} u_{ik}^{m} im_k}{\sum_{i=1}^{N} u_{ik}^{m}} \tag{2}$$

In the FCM approach, u_{ik} is calculated based on the following formula:

$$u_{ik} = \frac{1}{\sum_{j=1}^{C}\left(\frac{\|im_k - v_i\|}{\|im_k - v_j\|}\right)^{\frac{2}{m-1}}} \tag{3}$$

Elm

In this study, the features obtained by SqueezeNet architecture are classified with the ELM algorithm and benign and malignant classification of brain tumor is performed. Since ELM is a new, very fast and high performance algorithm, it has been preferred in this study. ELM is a forward-feed neural network with a single hidden layer. The input weights of the hidden layer are randomly selected and the output weights are calculated analytically. In the hidden layer, activation functions such as Sigmoid, sinus, and Gauss are used, while linear activation functions are used in the output layer. The weights in the input layer of the feed forward neural network do not affect the performance of the network with a single hidden layer [33]. The mathematical expression of an ELM network is defined as follows [34]:

$$\boldsymbol{Yp} = \sum_{j=1}^{m} \beta j,\ k g\left(\sum_{i=1}^{n} wi,\ k\boldsymbol{x}i + bj\right) \tag{4}$$

where wi is the weights between the inlet and the hidden layer, bj are the bias values acting on the inlet. βj values are the weights between the hidden layer and the output and g (.) is the activation function [33]. Further information on ELM is found in Ref. [33].

Proposed method

The flowchart of the proposed SR-FCM-CNN approach is given in Fig. 3. The proposed approach has an 8-step working structure, with these steps detailed below:

Step-1: Obtaining MRI images

LR MR images containing 50 benign and malignant tumors in DICOM format were obtained.

Step-2: Conversion to grayscale

Since the initial LR MRI images are in DICOM format, the relevant images are converted to grayscale. Thus, these images can be processed faster. An example of MRI image converted to a grayscale image is given in Fig. 4**a**.

Step-3: Applying the super-resolution approach to images

LR MRI images were applied by the SR approach developed by Zhang et al. [20] and related images were converted to HR MRI images. Thus, the resolution of the pictures has been increased and the image quality has been improved. This process aims to increase segmentation performance. At the end of this process, the image in Fig. 4**a** was converted to the image in Fig. 4**b**.

Step-4: Realization of FCM-based segmentation

In the first step, pre-segmentation of MRI images converted to HR MRI images is performed by FCM approach. As a result of the segmentation of the HR MRI image given in Fig. 4b with the FCM approach, the image in Fig. 4c was obtained.

Then, the points corresponding to the coordinates of the white dots in this obtained image are determined in the LR MRI image, which is

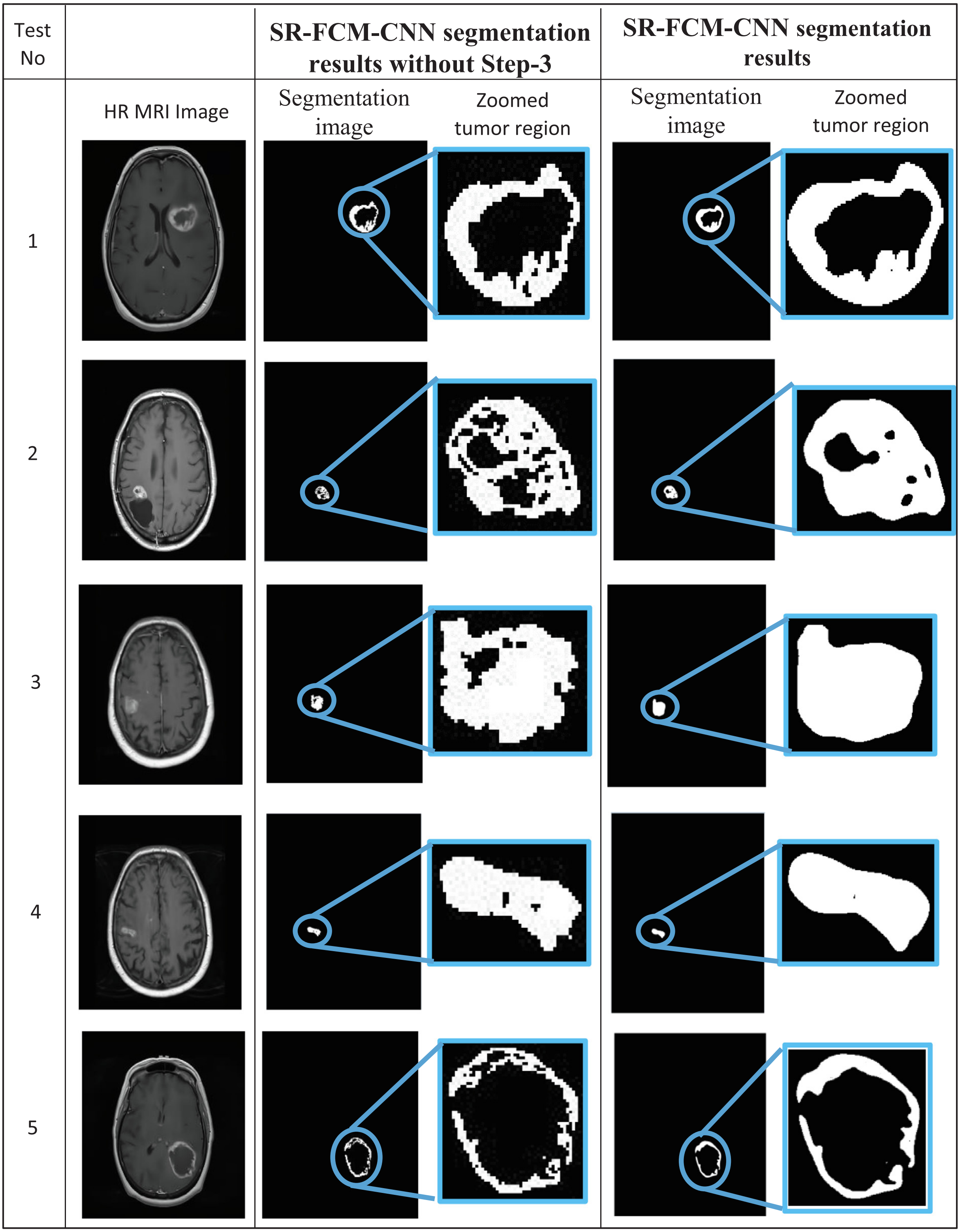


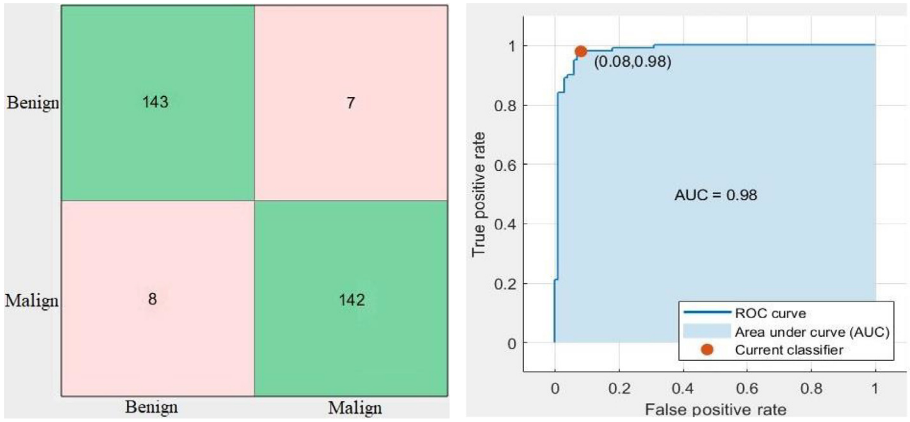
Fig. 8. Test results.

converted to grayscale, so that only these points remain in the LR MRI image. Thus, only the tumor tissue remains in the LR MRI image and the remaining parts are deleted and the segmentation image given in Fig. 4e is created. In the final step, the tumor region in the resulting image is cropped and finally the segmentation image as shown in Fig. 4f is generated.

In the proposed approach, the pre-segmentation performance was increased by using SR method, the tumor site was detected more successfully and tumor segment was successfully obtained from LR MRI image by using this segmentation image.

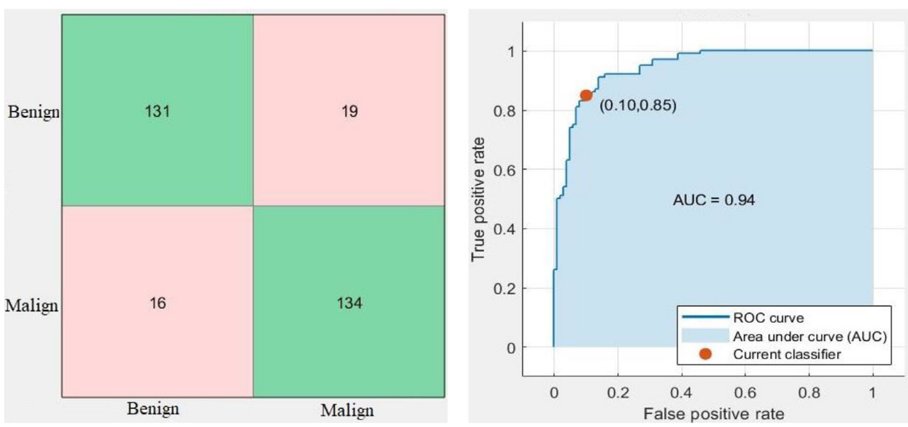
Step-5: Augmentation of segmented tumors

At the end of the realization of the FCM-based segmentation



a) Confusion matrix b) ROC of FCM-CNN method

Fig. 9. Confusion matrix and ROC of SR-FCM-CNN method.



a) Confusion matrix b) ROC of FCM-CNN method

Fig. 10. Confusion matrix and ROC of FCM-CNN method.

process, 50 benign and malignant finally segmentation images are passed through augmentation process. As can be seen in Fig. 5, in this process, finally segmentation images are rotated and enlarged by 25% to obtain 150 benign final segmentation images and 150 malignant finally segmentation images. With this process, segmented tumor images were reproduced to provide more images to SqueezeNet architecture and to increase feature extraction and tumor type detection performances.

Step-6: Extract features via SqueezeNet

In order to extract the features of 150 benign finally segmentation images and 150 malignant finally segmentation images, the related images are given to SquezeeNet architecture.

Step-7: ELM classifier

SR-FCM segmented brain images were extracted with SqueezeNet architecture and classified with ELM classifier.

The performance of the ELM classifier depends on the number of neurons in the hidden layer and the activation function to be used. Therefore, parameters suitability was determined by experiments. Activation functions such as “hardlim”, “radbas”, “lin”, “sin”, “tribas”, and “sig” were used for this purpose. The optimal activation function and the number of neurons were determined according to the training and test performance of the network. The most appropriate activation function in brain tumor detection was sigmoid and the number of neurons was 1500. Step 6 and Step 7 are summarized in Fig. 6.

Experimental results

To test the performance of the SR-FCM-CNN approach proposed in this section, two-step test procedures are performed. In the first stage testing process, all the steps in the “3. Proposed Methods” section were applied to LR MRI images containing 150 benign and 150 malignant tumors in DICOM format, in which a detailed study of the proposed SR-FCM-CNN approach was described. 1000 features were obtained from the last layer of SqueezeNet pretrained architecture. The obtained features were evaluated by 10 k-fold cross validation method in ELM classifier. Total accuracy of 98.33% has been achieved. In order to illustrate the sample results obtained during this test process, 5 randomly selected MRI images used in this process are shown in Fig. 7. HR MRI images obtained from the proposed algorithmic process of these pictures are shown in Fig. 7 and the segmentation results are shown in the SR-FCM-CNN segmentation results column in Fig. 8. The confusion matrix and ROC graphs obtained at the end of this process are given in Fig. 9.

In the second stage of the testing process, all processes except Step-3 in the “3. Proposed Method section”, where a detailed study of the proposed SR-FCM-CNN approach was described and applied to DICOM format LR MRI images containing 150 benign and malignant tumors. In this process, it was aimed to obtain tumor classification results without applying SR approach to MRI images. In order to show the sample results obtained during this test process, 5 LR MRI images, which are also used in the first test process and whose visuals are given in Fig. 7, are preferred. In addition, segmentation results are given in the Step-3 SR-FCM-CNN segmentation results column in Fig. 8. In this process, 1000 features were obtained from the last layer of SqueezeNet pertained CNN architecture. These features have been evaluated by 10 k-fold cross-validation method in ELM classifier. Total accuracy of 88.33% has been achieved. The confusion matrix and ROC graphs obtained at the end of this process are given in Fig. 10.

It is clear that the “Zoomed tumor region” results in the “SR-FCM-CNN without Step-3 segmentation results” column shown in Fig. 8 are better quality than the “Zoomed tumor region” results in the “SR-FCM-CNN segmentation results” column. This clearly demonstrates that the use of the SR approach in the preprocessing step maximizes segmentation performance. Thus, in the proposed SR-FCM-CNN approach, the tumor site was more successfully detected. Therefore, it has been proved with experimental results that tumor types are detected with superior performance with the proposed approach.

Conclusion

In this study, a powerful approach that can detect brain tumors and predict the type of tumor has been proposed. In the proposed approach, the resolution of MRI images is initially increased with the SR approach. Thus, it is aimed to increase segmentation performance. The segmentation of the MRI image is then performed with the FCM approach. In the proposed approach, SqueezeNet, one of the most recent pertained CNN architectures, is used and the features of segmented tumor images are extracted and classification of these features by ELM is provided. By the help of the proposed approach, both tumor segmentation and tumor classification have been performed. It is seen that the proposed SR-FCM-CNN approach in experimental studies performs tumor classification with a very high success rate. In the proposed approach, both segmentation and tumor classification performance are significantly reduced when brain tumor is detected without using SR.

In this study, a novel brain tumor classification system has been designed by using SqueezeNet CNN architecture, ELM and FCM approaches together, and gained into the literature. In addition, the designed system can make quick decisions without loss of performance by the help of combination of SqueezeNet and ELM. The main disadvantage of the proposed SR-FCM-CNN approach is that its performance varies depending on the training dataset.

In our future studies, the proposed SR-FCM-CNN approach will be used as a classifier in different areas. In addition, it is planned to increase both the speed and performance of the algorithm as a result of trying different approaches on the proposed algorithm.

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Ethical approval

This article does not contain any studies with human participants or animals performed by any of the authors.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.mehy.2019.109433.

References

[1] Elsoud MA, Alkhambashi M. Optimal feature level fusion based ANFIS classifier for brain MRI image classification.
[2] Mohan G, Subashini MM. MRI based medical image analysis: survey on brain tumor grade classification. Biomed Signal Process Control 2018;39:139–61.
[3] Mahapatra D, Bozorgtabar B, Garnavi R. Image super-resolution using progressive generative adversarial networks for medical image analysis. Comput Med Imaging Graph 2019;71:30–9.
[4] Wei S, Zhou X, Wu W, Pu Q, Wang Q, Yang X. Medical image super-resolution by using multi-dictionary and random forest. Sustain Cities Soc 2018;37:358–70.
[5] Ren S, Jain DK, Guo K, Xu T, Chi T. Towards efficient medical lesion image super-resolution based on deep residual networks. Signal Process Image Commun 2019;75:1–10.
[6] Lu X, Huang Z, Yuan Y. MR image super-resolution via manifold regularized sparse learning. Neurocomputing 2015;162:96–104.
[7] Zhang Y, Yap PT, Chen G, Lin W, Wang L, Shen D. Super-resolution reconstruction of neonatal brain magnetic resonance images via residual structured sparse representation. Med Image Anal 2019;55:76–87.
[8] Rueda A, Malpica N, Romero E. Single-image super-resolution of brain MR images using overcomplete dictionaries. Med Image Anal 2013;17(1):113–32.
[9] Zeng K, Zheng H, Cai C, Yang Y, Zhang K, Chen Z. Simultaneous single-and multi-contrast super-resolution for brain MRI images based on a convolutional neural network. Comput Biol Med 2018;99:133–41.
[10] Velasco NF, Rueda A, Santa Marta C, Romero E. A sparse Bayesian representation for super-resolution of cardiac MR images. Magn Reson Imaging 2017;36:77–85.
[11] Das V, Dandapat S, Bora PK. A novel diagnostic information based framework for super-resolution of retinal fundus images. Comput Med Imaging Graph 2019;72:22–33.
[12] Saad NM, Bakar SARSA, Muda AS, Mokji MM. Review of brain lesion detection and classification using neuroimaging analysis techniques. Jurnal Teknologi 2015;74(6).
[13] Sachdeva J, Kumar V, Gupta I, Khandelwal N, Ahuja CK. A package-SFERCB-Segmentation, feature extraction, reduction and classification analysis by both SVM and ANN for brain tumors. Appl Soft Comput 2016;47:151–67.
[14] Mallick PK, Ryu SH, Satapathy SK, Mishra S, Nguyen GN, Tiwari P. Brain MRI image classification for cancer detection using deep wavelet autoencoder-based deep neural network. IEEE Access 2019;7:46278–87.
[15] Swati ZNK, Zhao Q, Kabir M, Ali F, Ali Z, Ahmed S, et al. Brain tumor classification for MR images using transfer learning and fine-tuning. Comput Med Imaging Graph 2019;75:34–46.
[16] Deepak S, Ameer PM. Brain tumor classification using deep CNN features via transfer learning. Comput Biol Med 2019;111:103345.
[17] Selvapandian A, Manivannan K. Fusion based glioma brain tumor detection and segmentation using ANFIS classification. Comput Meth Programs Biomed 2018;166:33–8.
[18] Pan Y, Huang W, Lin Z, Zhu W, Zhou J, Wong J, Ding Z. Brain tumor grading based on neural networks and convolutional neural networks. 2015 37th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC). IEEE; 2015. p. 699–702.
[19] Bezdek JC. Pattern recognition with fuzzy objective function algorithms. Kluwer Academic Publishers Norwell; 1981.
[20] Zhang K, Zuo W, Zhang L. Learning a single convolutional super-resolution network for multiple degradations. Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition. 2018. p. 3262–71.
[21] Scarpace L, Mikkelsen T, Cha S, Rao S, Tekchandani S, Gutman S, et al. Radiology data from the cancer genome atlas glioblastoma multiforme [TCGA-GBM] collection. Cancer Imaging Archiv 2016;11(4).
[22] Çatalbaş MC, Gülten A. A novel super-resolution approach for computed tomography images by inverse distance weighting method. J Faculty Eng Architect Gazi Univ 2018;33(2):697–711.
[23] Zhang Y, Li K, Li K, Wang L, Zhong B, Fu Y. Image super-resolution using very deep residual channel attention networks. Proceedings of the European Conference on Computer Vision (ECCV). 2018. p. 286–301.
[24] Bulat A, Tzimiropoulos G. Super-FAN: Integrated facial landmark localization and super-resolution of real-world low resolution faces in arbitrary poses with GANs. Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition. 2018. p. 109–17.
[25] Baker S, Kanade T. Limits on super-resolution and how to break them. IEEE Trans Pattern Anal Mach Intell 2002;24(9):1167–83. 1.
[26] Krizhevsky A, Sutskever I, Hinton GE. Imagenet classification with deep convolutional neural networks. Advances in Neural Information Processing Systems. 2012. p. 1097–105.
[27] Ioffe S, Szegedy C. Batch normalization: accelerating deep network training by reducing internal covariate shift. International Conference on Machine Learning. 2015. p. 448–56.
[28] Özyurt F, Sert E, Avci E, Dogantekin E. Brain tumor detection based on Convolutional Neural Network with neutrosophic expert maximum fuzzy sure entropy. Measurement 2019;147:106830.
[29] Özyurt F, Tuncer T, Avci E, Koç M, Serhatlioğlu İ. A novel liver image classification method using perceptual hash-based convolutional neural network. Arab J Sci Eng 2019;44(4):3173–82.
[30] Doğantekin A, Özyurt F, Avcı E, Koç M. A novel approach for liver image classification: PH-C-ELM. Measurement 2019;137:332–8.
[31] Ganesh, Abhinav. Deep Learning Reading Group: SqueezeNet“. KDnuggets. Retrieved 2018-04-07.
[32] Iandola FN, Han S, Moskewicz MW, Ashraf K, Dally WJ, Keutzer K. SqueezeNet: AlexNet-level accuracy with 50x fewer parameters and < 0.5 MB model size. arXiv preprint arXiv:1602.07360; 2016.
[33] Özyurt F. A fused CNN model for WBC detection with MRMR feature selection and extreme learning machine. Soft Comput 2019. https://doi.org/10.1007/s00500-019-04383-8. (in press).
[34] Suresh S, Saraswathi S, Sundararajan N. Performance enhancement of extreme learning machine for multi-category sparse data classification problems. Eng Appl Artif Intell 2010;23(7):1149–57.