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A new approach for brain tumor diagnosis system: Single image super resolution based maximum fuzzy entropy segmentation and convolutional neural network

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ABSTRACT

Magnetic resonance imaging (MRI) images can be used to diagnose brain tumors. Thanks to these images, some methods have so far been proposed in order to distinguish between benign and malignant brain tumors. Many systems attempting to define these tumors are based on tissue analysis methods. However, various factors such as the quality of an MRI device, noisy images and low image resolution may decrease the quality of MRI images. To eliminate these problems, super resolution approaches are preferred as a complementary source for brain tumor images. The proposed method benefits from single image super resolution (SISR) and maximum fuzzy entropy segmentation (MFES) for brain tumor segmentation on an MRI image. Later, pre-trained ResNet architecture, which is a convolutional neural network (CNN) architecture, and support vector machine (SVM) are used to perform feature extraction and classification, respectively. It was observed in experimental studies that SISR displayed a higher performance in terms of brain tumor segmentation. Similarly, it displayed a higher performance in terms of classifying brain tumor regions as well as benign and malignant brain tumors. As a result, the present study indicated that SISR yielded an accuracy rate of 95% in the diagnosis of segmented brain tumors, which exceeds brain tumor segmentation using MFES without SISR by 7.5%.

Introduction

Brain tumors are comprised of tissues that are uncontrollably generated by brain cells. Although brain tumors increase the size of a brain, they may also lead to various fatal health problems in the long term. According to the National Brain Tumor Foundation (NBTF) data, brain tumor mortality rate has recently increased by nearly 300% in developed countries [1–3].

Similar to other types of cancer, early diagnosis plays a vital role in the improvement of brain tumor treatment process, increasing the chance of survival for a patient. Various techniques such as magnetic resonance imaging (MRI), magnetic resonance spectroscopy (MRS), computed tomography (CT), and positron emission tomography (PET) are widely used to diagnose brain tumors. These imaging techniques can offer useful data about the location, size and type of a brain tumor. However, MRI can be considered as the most popular imaging techniques because it provides physicians with detail information about brain tumors [1].

Various factors such as resolution, noise, tissue contrast and artifacts significantly affect the quality of an MRI image [4]. These factors also bring about a number of problems such as partial volume (PV) effect which prevents the processing of the obtained MRI image and extraction process using various algorithms in the upcoming process [5]. Using high resolution images in medical applications can effectively eliminate these problems, and help physicians diagnose diseases more easily. For instance, a physician examining a high resolution MRI image with a brain tumor is more likely to detect tumor region easily.

Image processing, segmentation and classification processes are used for brain tumor diagnosis with a specialized system. Various image improvement methods such as filtering and higher resolution are used to perform a successful segmentation in image pre-processing. Tumor tissues in an MRI image can be diagnosed in this segmentation process. Finally, the tissues segmented in the classification process is classified as a benign or malignant brain tumor.

Super resolution (SR) approaches are widely preferred in order to improve the resolution of medical images [6]. SR techniques aim at

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converting one or more low-resolution (LR) input images into high resolution (HR) images. SR techniques are divided into three groups as interpolation based methods, reconstruction based methods and learning based methods [4]. It can be understood from the literature review that SR approaches were applied to medical images [7–9], MRI images [10], brain MRI images [5,11,12], cardiac MR images [13], and retinal fundus images [14]. The studies in question usually benefited from SR approaches in order to improve the resolution and quality of input images.

In the existing literature, brain tumor segmentation or classification was performed using various approaches such as entropy based [15], fuzzy c-means (FCM) algorithm [16], deep neural networks [17], fully convolutional neural networks (FCNNs) and conditional random fields (CRFs) [18], neutrosophic set [19,20], optimal symmetric multimodal templates and concatenated random forests [21], sparse representation [22], superpixel based classification [23], support vector machines (SVM) [24], watershed [25]. In addition, ANFIS [26], deep convolutional neural network (CNN) [27], transfer learning and fine-tuning [28] and other different approaches [1] were used for brain tumor segmentation or classification.

The present study proposes a brain tumor diagnosis approach using single image super resolution [29] based maximum fuzzy entropy segmentation [30] and convolutional neural network (SISR-MFES-CNN). The proposed method used MRI images containing 100 benign or malignant images in DICOM format. In the first step, the segmentation of tumor regions was performed by applying maximum fuzzy entropy segmentation (MFES) [30] method to MRI images. ResNet architecture, which is one of the most popular pre-trained CNN algorithms, was used as a feature extractor in the present study. The obtained segmentation results were transferred to the ResNet architecture for feature extraction. Later, these features were used by an SVM classifier to classify benign and malignant brain tumors. In the second experiment, the resolution of LR MRI images was improved using single image super-resolution (SISR) approach [29] to obtain HR MRI images. Later, tumors in these obtained images were segmented using MFES method [30]. In this step, the use of SR approach increased the segmentation performance. This step was followed by feature extraction using ResNet architecture where the obtained segmentation results were transferred. Finally, these features were used by SVM classifier in order to classify benign and malignant brain tumors [31–33]. The performances of both classification approaches obtained from experimental studies were compared in order to analyze the impact of SISR on the brain tumor classification performance. It was understood that the proposed SISR-MFES-CNN method displayed a higher performance.

The contributions of the present study can be summarized as follows:

1. SISR and MFES were used together to improve segmentation performance.
2. ResNet architecture, which is a CNN architecture, was used for feature extraction of the segmented brain tumors.
3. ResNet is a deeper architecture compared to all previous architectures.
4. SVM classifier was used to diagnose brain tumors.
5. The proposed SISR-MFES-CNN was used for the first time in the literature.

Section “Theoretical Background” describes the data set, single image super-resolution (SISR) method, MFES method and pre-trained ResNet architecture used in the theoretical background of the present study. Section “The Proposed Method” presents the details of the proposed method. Section “Experimental Results” gives the results of the experimental studies related to the proposed method. Section “Conclusion” concludes the present study.

Theoretical background

Database

Cancer Genome Atlas Glioblastoma Multiforme (TCGA-GBM) [34] database in the Cancer Imaging Archive (TCIA) was used to test the proposed SISR-EMFSE-CNN approach. Numerous tissues were collected for TCGA around the world in order to offer nearly 500 samples for each type of cancer. Being a heterogeneous database in terms of scanning methods and acquisition protocols, it brings MRI images from different places in the world together, and thus makes it possible to draw accurate conclusions on brain tumors. MRI images in TCGA-GBM database are open access for all researchers around the world as long as they refer to the database for any image(s) that they use in a scientific article. Therefore, no ethical approval is needed for using images in the database. Because the most accurate information about tumor regions in brain MRIs is provided by T1-weighted postcontrast (T1-gadolinium (Gd)) sequence, T1-Gd sequence MRI images in TCGA-GBM were used in the present study. Further information about TCGA-GBM can be found in [34].

Learning a single convolutional Super-Resolution network for multiple degradations

In the present study, “Learning a Single Convolutional Super-Resolution Network for Multiple Degradations” approach by Zhang et al. was used to convert LR MRI images to HR [29]. It can be observed that recent studies have often concentrated on single image super-resolution (SISR) [29]. This is because information loss in pixels reaches a considerable degree when a LR image is converted to a HR image, and SISR offers an effective solution to this problem. Tasks such as image recognition and classification display a lower performance in LR images. On the other hand, SR may overcome multiple and even local degradations, and thus increase image quality. SISR method aims to convert a LR image to a HR image. A conventional problem, SISR is a popular and challenging research topic due to its high practical value in the field of computer imaging [35]. y, which is a LR image according to SISR, is modelled as an output of the following degradation:

$$y = (x \otimes k)\downarrow_s + n \quad (1)$$

Here $x \otimes k$ represents the convolution between k, which is the fuzzification kernel, and x, which is a hidden HR image. $\downarrow s$ is the downscaling process followed by s, which is the scale factor. n usually represents standard deviation (noise level) σ and Additive White Gauss Noise (AWGN).

LR images are usually noisy, and SR process increases image resolution following denoising process. However, it also saves detailed information in the images during the pre-processing step [36]. SISR proposed by Zhang et al. [29] offers a highly successful CNN based model for multiple degradations. This method consists of 3 × 3 convolutional layers in order to perform non-linear matching. Each layer involves three types of tasks as Convolution (Conv), Rectified Linear Units (ReLU) [37] and Batch Normalization (BN) [38]. While the first layers of SISR model consists of a compound Conv + Bn + ReLU structure, the last layer only consists of Conv layer. The number of convolutional layers was set to 12, and the number of feature maps in each layer was set to 128. The proposed super resolution network for multiple degradations is shown in Fig. 1 [29].

Maximum fuzzy entropy segmentation (MFES) approach

It is of vital importance in segmentation and image recognition processes to find the optimal threshold value that converts an image to an ideal binary format. Many studies in the existing literature often

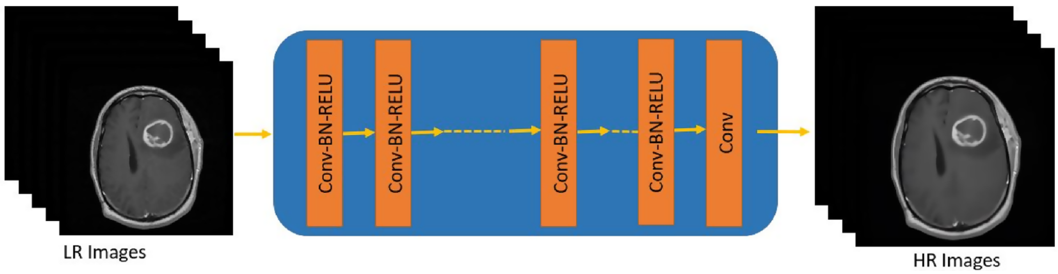

Fig. 1. The proposed super resolution network.

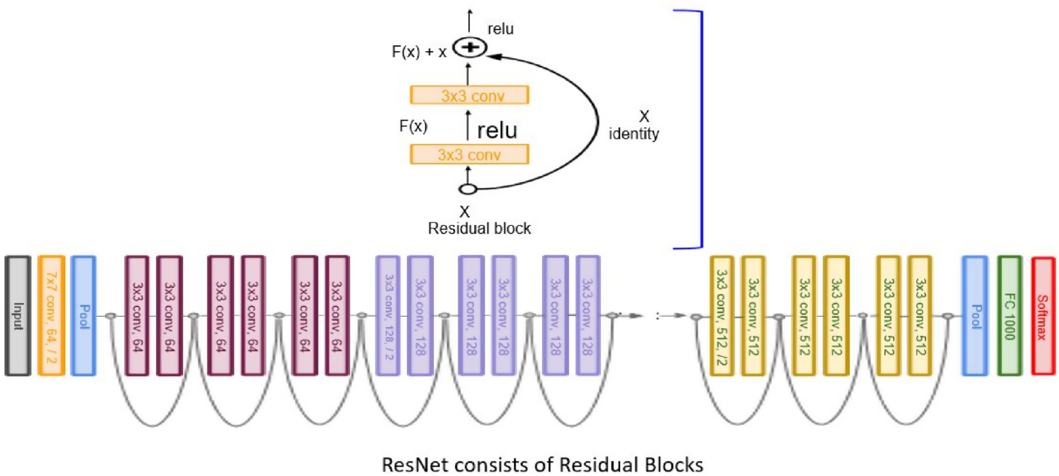

Fig. 2. Illustration of ResNet architecture.

benefit from maximum fuzzy entropy (MFE) and fuzzy c-partition (FCP) approaches to calculate an optimal threshold value that converts grayscale images to binary format. MFE and FCP approaches were used in the expert maximum fuzzy-Sure entropy (EMFSE) method to calculate the optimal threshold value of a grayscale image [30]. Further information on EMFSE can be found in [30]. In the present study, norm entropy based MFES in the EMFSE approach developed by Avci et al. [30] was used for brain tumor segmentation.

Convolutional neural network

A deep learning architecture, CNN became popular with the advent of ImageNet competitions in 2012 [39]. Until 2016, competitors designed various CNN architectures in order to win ImageNet competitions [37,40–42]. Each of these models are considered as an important milestone in the field of deep learning. ResNet, which is the last CNN architecture to have won ImageNet competition, was used for brain tumor detection in the present study.

ResNet architecture

Consisting of 152 layers and developed by Microsoft in a research laboratory in Beijing, ResNet [42] is a deeper architecture compared to all previous architectures. Given that an individual has an error rate of 5 to 10% percent depending on their area of specialization, it won ImageNet competition with an error rate of 3.6%. It offered the following advantages:

- A quicker training duration for a deep network,
- A network structure with less parameters thanks to a “deep” network structure rather than “large” network structure
- Offering a solution to the “Vanishing Gradient” problem
- Reaching a higher performance rate particularly in terms of “Image Classification”

In ResNet architecture, residual value is formed by adding the residual block to the model. An example representation of the ResNet architecture is shown in Fig. 2.

The proposed method

The present study proposes a method for brain tumor diagnosis using SISR, MFES and CNN. The general structure of the proposed SISR-MFES-CNN approach is shown in Fig. 3. As can be understood, MRI images in DICOM format containing 100 LR benign tumor images and 100 LR malignant tumor images are converted to HR MRI images using SISR [29] approach developed by Zhang et al., which is expected to increase the segmentation performance eventually. Following this process, tumor segmentation is performed using MFES approach developed by Avci et al. [30]. Thus, tumor selection process is completed after benign or malignant tumors in HR MRI images are segmented in binary format. This segmentation result is used to extract the tumor in a LR MRI image. These obtained images are given to ResNet model for feature extraction process. Finally, the features of the segmented tumor

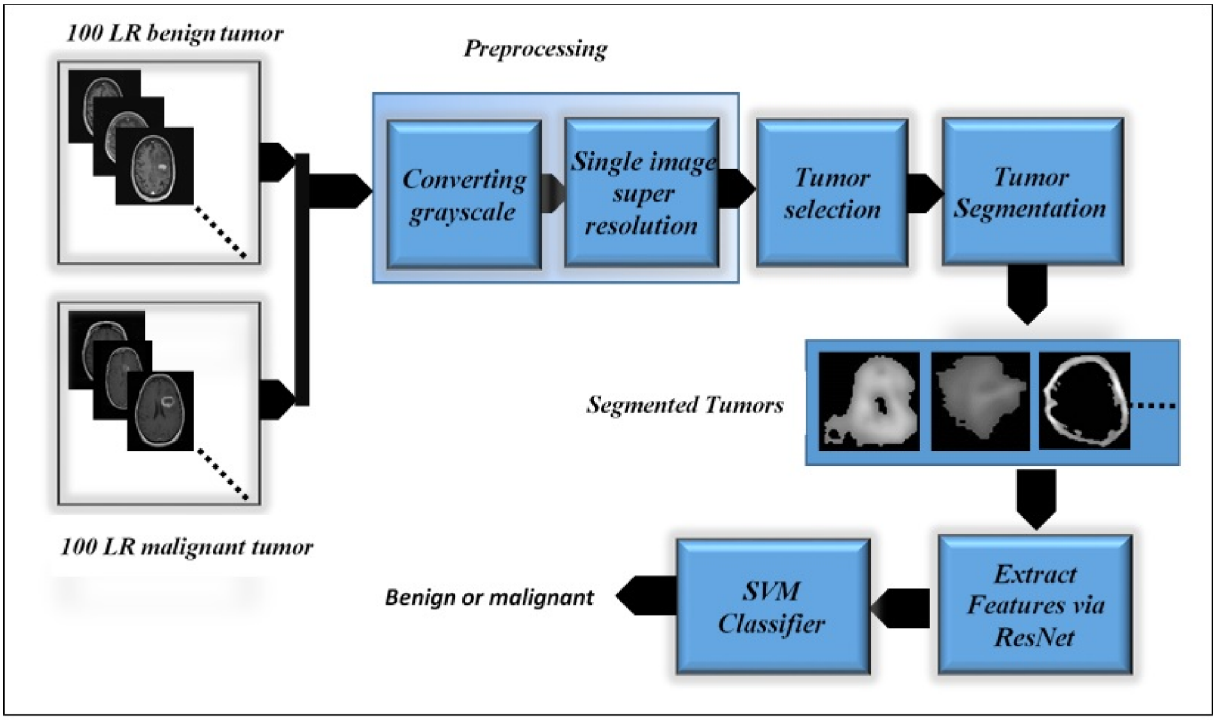

Fig. 3. The general structure of the proposed method.

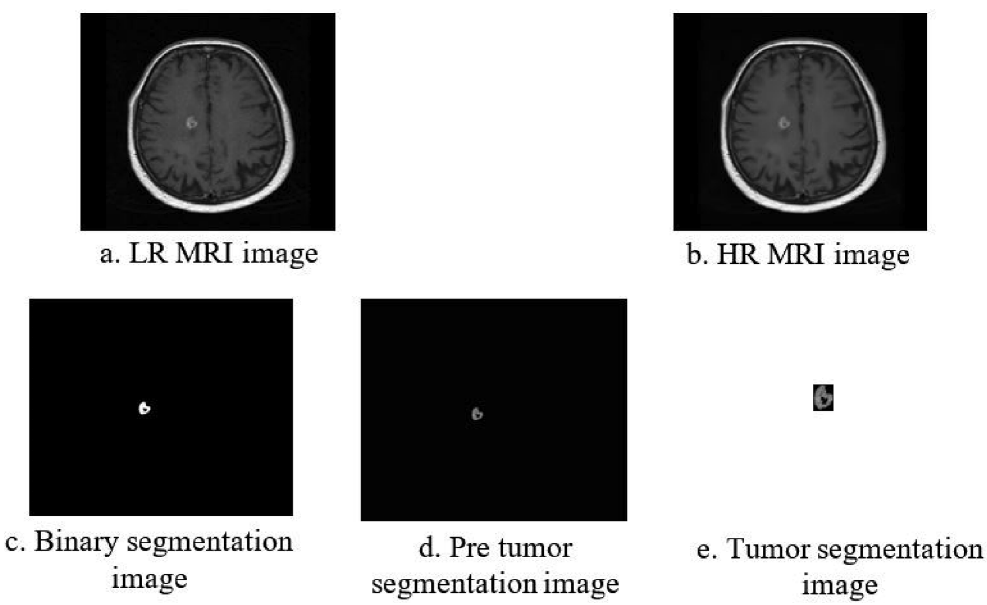

Fig. 4. Test results.

images are extracted using ResNet architecture and classified using SVM method. Each step of the proposed method is described in Algorithm-1.

The image preprocessing is shown in Step 1–3 of Algorithm 1.. MRI images obtained from Step 2 and 3 are shown in Fig. 4a and b, respectively. The optimal threshold value for SR MRI Image is calculated using MFES [30] in Step-4, and MRI image is converted to binary format. The image shown in Fig. 4c is obtained following Step-5. In Step 6, points corresponding to the coordinates of the white points in *binary segmentation image* can also be found in *LR MRI image*, and only these points are left in *LR MRI image*. Thus, pre-tumor segmentation image shown in Fig. 4d is obtained. In Step-7, tumor image in pre-tumor segmentation image is cropped, and tumor segmentation process is thus completed. The image obtained at the end of Step-7 is shown in Fig. 4e. The process by which binary segmentation image and *LR MRI image* are combined to obtain pre tumor segmentation image and tumor segmentation image is visually described in Fig. 5. In Step 8, the features of the segmented images are obtained using the last FC layer of ResNet architecture. In Step 9, they are given to SVM classifier to classify brain tumors as benign or malignant.

Algorithm 1. Algorithmic process of the proposed method

Step-1: original MRI image ← Obtaining ***low resolution MRI*** image in DICOM format

Step-2: LR MRI image ← Converting ***Original MRI image*** to grayscale

Step-3: HR MRI image ← Apply SISR [32] to ***LR MRI image*** and increase resolution

Preprocessing

Step-4: binary image ← Calculate the optimal threshold value for HR MRI image using EMFSE [33] approach and convert MRI image to binary format

Step-5: binary segmentation image ← Remove skull and residual images in ***binary image***

Tumor selection

Step-6: **pre tumor segmentation image** ← Match ***binary segmentation image*** and ***LR MRI image*** for tumor segmentation

Step-7: **tumor segmentation image** ← Crop tumor image in **pre tumor segmentation image**

Tumor segmentation

Step-8: ***Features*** ← *extraction of features in the last FC layer of ResNet architecture*

Step-9: Give the ***features*** to SVM classifier

Step-10: *Classification of benign and malignant brain tumors using SVM classifier*

Feature extraction & Classification

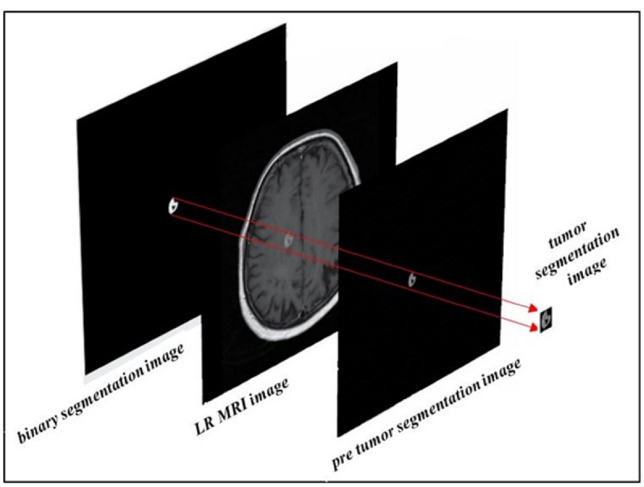

Fig. 5. Obtaining tumor segmentation image.

Experimental results

In the first step, MRI images in DICOM format containing 100 LR benign tumors and 100 LR malignant tumors were converted to grayscale. Later, Step 4–10 in Algorithm 1 were applied to these images without any SISR. In this process, 1000 features were extracted from the last FC layer of ResNet pre-trained CNN architecture. These features were analyzed by SVM classifier using 5 k-fold cross validation method, and an accuracy rate of 87.5% was obtained. Confusion matrix and ROC graphs obtained from this process are shown in Fig. 8. This first approach used for the experimental study was called brain tumor diagnosis system: maximum fuzzy entropy segmentation and convolutional neural network (MFES-CNN).

In the second step, Step 1–10 in Algorithm 1 were applied to MRI images containing 100 LR benign tumors and 100 malignant tumors. Thus, MRI images were converted to HR MRI images using SISR [29] approach developed by Zhang et al., which aimed to increase the segmentation performance. LR MRI images and HR MRI image obtained at the end of 5 test processes are shown in Fig. 6. It can be understood from zoomed images that the resolution of HR MRI images is evidently higher compared to LR MRI images. binary segmentation image, pre tumor segmentation image, tumor segmentation image obtained from the first 5 test MRI images are shown in Fig. 7. 100 benign tumor segmentation images and 100 malignant tumor segmentation images obtained at the end of this process were given to ResNet pretrained CNN architecture, and 1000 features were extracted from the last FC layers. These features were analyzed by SVM classifier using 5 k-fold cross validation method. The process yielded an accuracy rate of 95% and a ROC of 0.98. Confusion matrixes and ROC graphs related to the segmentation performance are shown in Fig. 9.

The classification performance of the proposed SISR-MFES-CNN approach in terms of brain tumor segmentation was compared with that of MFES-CNN approach. It can be observed that SISR-MFES-CNN approach increased segmentation performance by 7.5%. In addition, ROC graphs used in both steps were also analyzed. Because there is a wide area below ROC graph, it can be stated that the proposed model displayed a high performance in terms of benign and malignant tumor segmentation. The area below ROC is 0.98 in the proposed method,

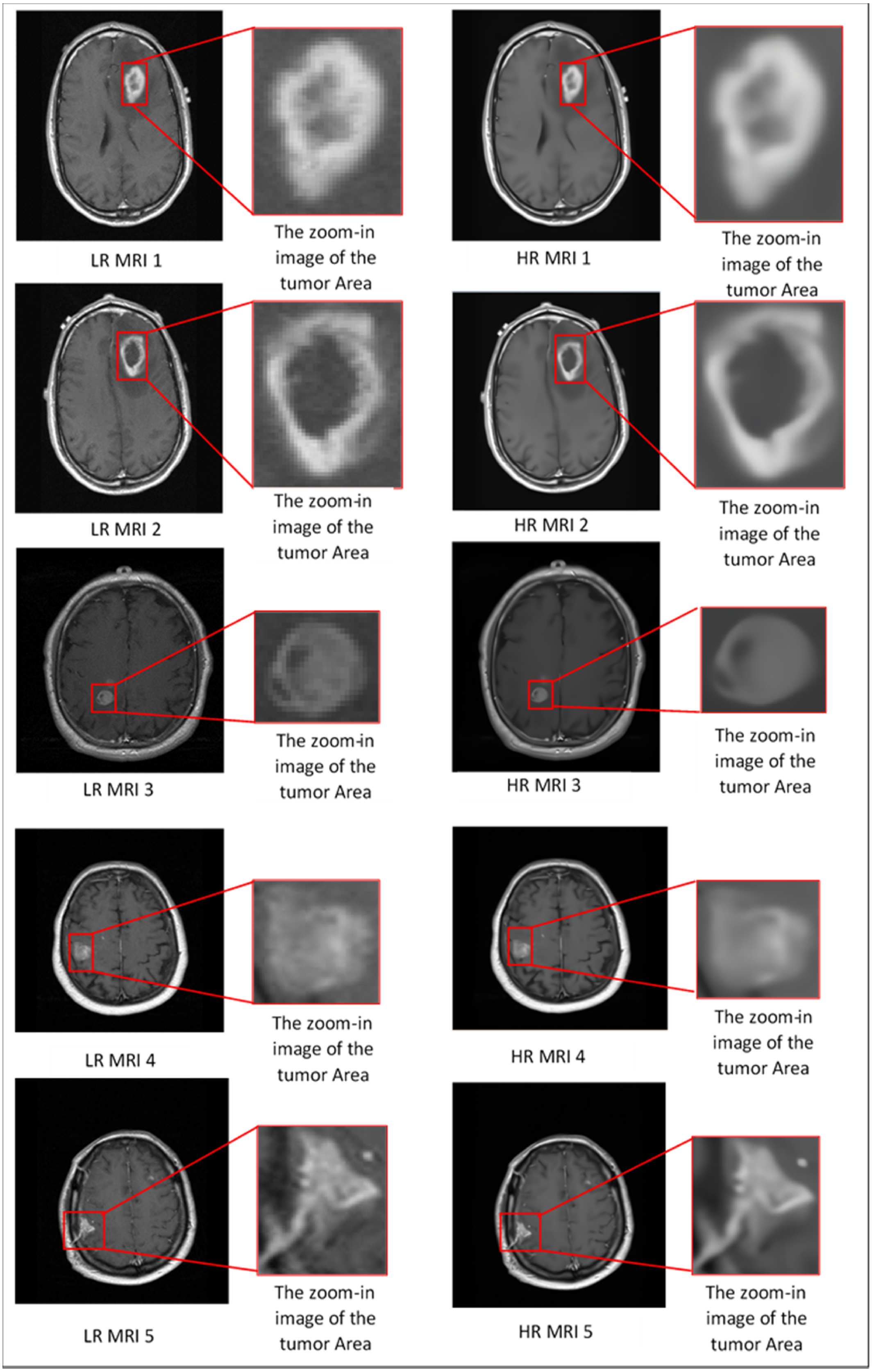

Fig. 6. MRI images following the application of Super Resolution to MRI images.

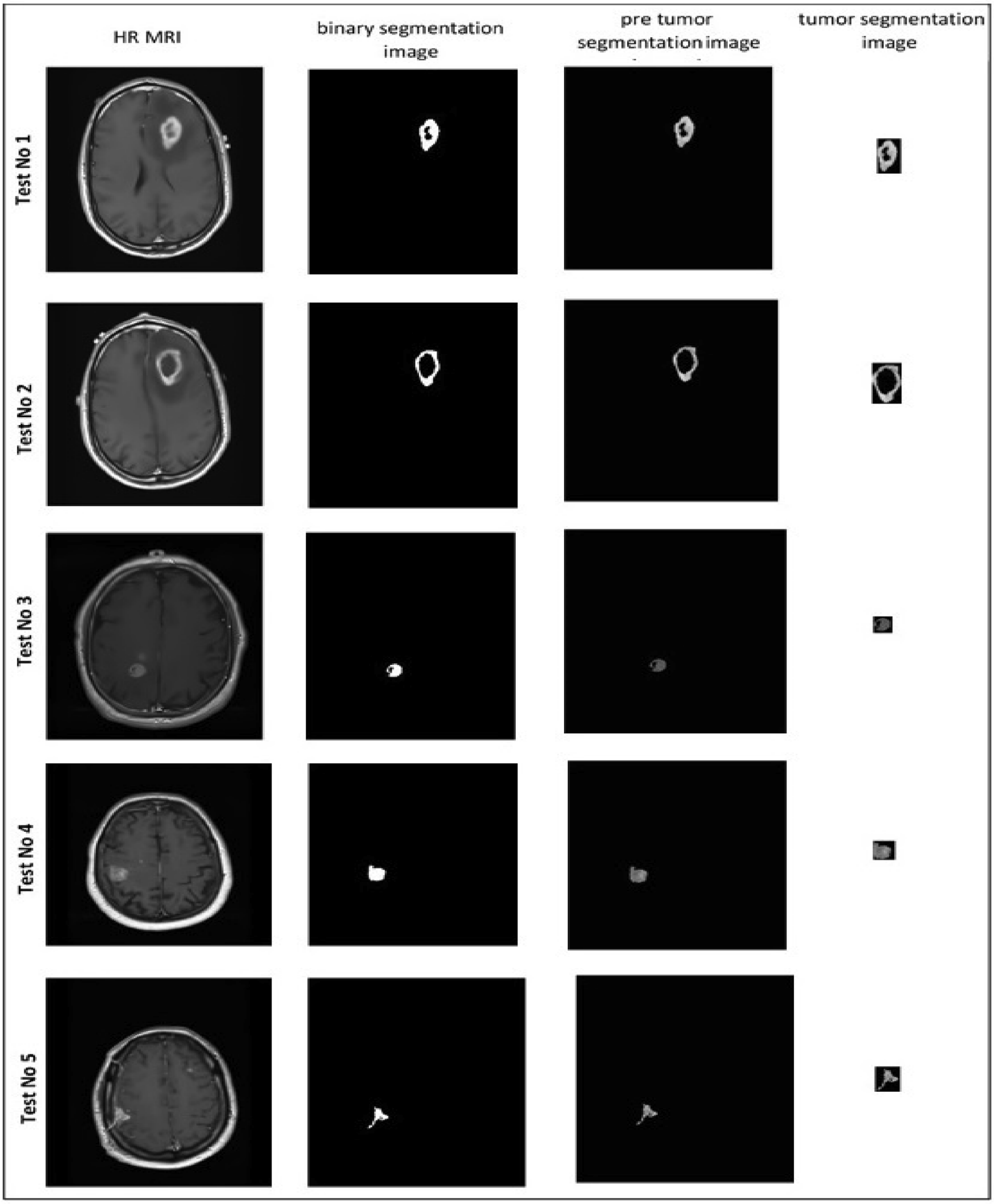

Fig. 7. HR MRIs and segmentation results.

which is 0.4 higher compared to the other method. Thus, it is evident that the proposed SISR-MFES-CNN approach displays a higher performance in terms of benign and malignant tumor segmentation.

Conclusion

In the present study, SISR-MFES-CNN approach is proposed in order to increase the classification performance in terms of benign/malignant brain tumors in MRI images. The proposed method consists of 10 steps. Each step of the proposed method is described in Algorithm-1. Tumor tissues were detected more accurately using SISR and MFES. ResNet, which is a popular CNN architecture, was used for feature extraction. Finally, features extracted for tumor recognition process were classified using SVM. The experimental studies demonstrated that ROC values of the proposed method were significantly higher compared to normal values. In this study, a new classification approach which is not in the

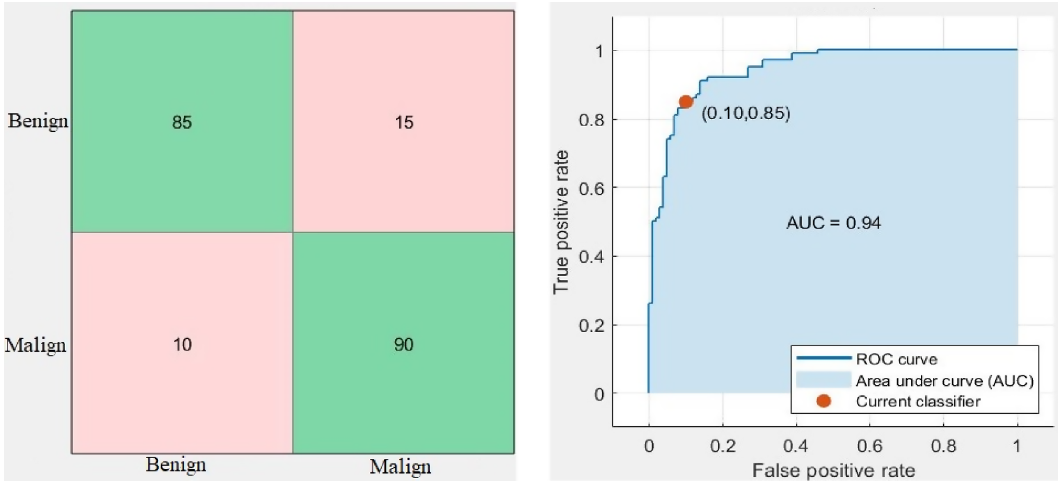

Fig. 8. Confusion Matrix and ROC of LR Images.

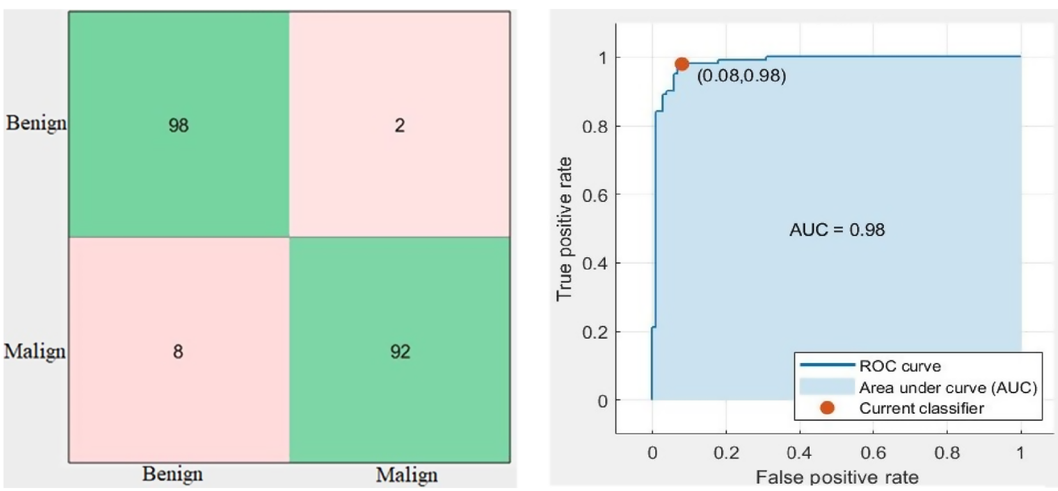

Fig. 9. Confusion Matrix and ROC of HR Images.

literature is proposed by using SISR, MFES and CNN together.

The SISR-MFES-CNN approach proposed in this study uses supervised learning technique. The biggest disadvantage of supervised learning technique is that their performance changes depending on the training dataset.

Although the proposed study is a rapid and accurate study for the detection of brain tumors, further research is needed in this area. SR methods that can better segment the tumor region in brain images can be investigated. Various CNN architectures related to the feature extraction stage of the segmented fields can also be tried.

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.

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