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Master's Degree Thesis

Automated Brain image Segmentation from Magnetic Resonance Image Using SVM and Watershed transform

Graduate School of Chosun University

Department of Computer Engineering

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SVM과 Watershed 변화을 이용한 뇌영상 MRI 이미지의 자동 세그멘테이션 연구

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Automated Brain image Segmentation from Magnetic Resonance Image Using SVM and Watershed transform

Advisor: Prof. Jeong-A Lee

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ABBREVIATIONS

AD : Alzheimer’s disease

CAD: Computer Aided Diagnosis

FCM: Fuzzy C-means

CNN: Convolutional Neural network

GLCM: Gray Level Co-occurrence Matrix

SVM: Support Vector Machine

LGG: Low Grade Glioma

HGG: High Grade Gliomas

MRI: Magnetic resonance imaging

DCT: Discrete cosine transform

GA: Genetic Algorithm

K-NN: K Nearest Neighbor

ANFIS: An adaptive neuro-fuzzy inference system

ABSTRACT

Automated Brain image Segmentation from Magnetic Resonance Image Using SVM and Watershed transform

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The development of the health care computer assist systems provides better and early diagnosis of the patients suffering from a brain tumor. A brain tumor is categorized as two major kinds named as benign or malignant. Benign brain tumors have a uniform structure and do not contain active cancer cells. On the other hand, malignant cancerous tumors have a heterogeneous structure and contain active cells. The automated brain tumor segmentation and classification from magnetic resonance images (MRI) is a high-level priority for computer-aided health care systems. Accurate brain tumor segmentation is an essential step for further brain tumor analysis and classification of tumor types. In our proposed scheme to improve final tumor classification accuracy, we have applied several image processing techniques. First, noise removal and image enhancement steps were taken to increase segmentation accuracy. Afterward, the texture-based Gray Level Co-occurrence Matrix (GLCM) algorithm was applied for tumor texture feature extraction. Ultimately, the support vector machine (SVM) was applied for final brain tumor classification. We evaluated the performance of our algorithm in terms of final tumor classification accuracy and compared it with a genetic algorithm (GA), adaptive neuro-fuzzy inference system (ANFIS) K-Nearest Neighbor (KNN) classification algorithms. Experimental results indicate that the proposed method has been able to provide the best accuracy compared to other methods by using appropriate filters and GLCM-based texture feature extractor along with SVM-based machine learning. The experimental results show a 97% segmentation accuracy and 94% tumor classification accuracy while the tumor classification accuracy is GA(**91.11**%), ANFIS (**89.76** %), KNN, (**93.79**) methods.

한글요약

SVM 과 Watershed 변화을 이용한 뇌영상 MRI 이미지의

자동 세크멘테이션 연구

시아막 로샨자드흐

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건강 관리 컴퓨터 보조 시스템의 개발은 뇌종양으로 고통받는 환자에 대한 더 나은 조기 진단을 제공한다. 뇌종양은 양성 또는 악성이라는 두 가지 주요 종류로 분류된다. 양성 뇌종양은 균일한 구조를 가지며 활성 암세포를 포함하지 않으며, 악성 뇌종양은 이종 구조를 가지며 활성 세포를 포함한다. 자기공명영상 (MRI)은 종양 구조에 대한 자세한 정보를 나타낼 수 있는 뇌종양의 영상 및 분석에 사용되는 주요 영상 시스템 중 하나이다. 컴퓨터 보조 건강 관리 시스템의 정보처리 중 하나로 요구되는 것이 자기공명영상 (MRI)의 뇌종양 영상의 자동 분할과 분류 작업이다. 정확한 뇌종양 영상분할은 뇌종양 분석 및 종양 유형 분류를 위한 필수 단계이다.

본 논문에서는 최종 종양 분류 정확도를 향상시키기 위해 몇 가지 이미지 처리 기술을 적용했다. 먼저, 노이즈 제거 및 이미지 향상 단계를 수행하여 분할 정확도를 높였다. 이후, 텍스처 기반 그레이 레벨 동시 발생 매트릭스 (GLCM) 알고리즘을 종양 텍스처 특징 추출에 적용하고, 서포트 벡터 머신(SVM)이 최종 뇌종양 분류에 적용되었다. 본 논문에서 제안된 방식의 성능을 최종 종양 분류 정확도 측면에서 평가하고, 이를 유전자 알고리즘 (GA), 적응 신경 퍼지 추론 시스템 (ANFIS), K-Nearest Neighbor (KNN) 분류 알고리즘의 성능과 비교하여, 기존의 방식에 비해 보다 높은 정확도를 달성 할 수 있음을 보였다. 실험 결과에 의하면, 본 논문에서 제안하는 SVM 기반 머신 러닝과 함께 적절한 필터와 GLCM 기반 텍스처 피처 추출기를 사용하는 방식은 97 %의 분할 정확도 및 94 %의 종양 분류 정확도를 달성한 반면에, 기존 방식의 종양 분류 정확도는 GA (91.11 %), ANFIS (89.76 %), KNN, (93.79) 이였다.

1. Introduction

A. Overview of magnetic resonance imaging (MRI)

MRI or magnetic resonance imaging is a relatively new technique used since the beginning of the 1980s.MRI scans are used for magnetic and radio waves or for any other non-toxic X-rays, and therefore the person is not exposed to harmful forms of radiation. How to work the MRR scanner: In this method, the patient is placed inside a tube magnifier, then the radio waves are sent 10,000 to 30,000 times more powerful than the magnetic field of the earth. These waves affect the atoms of the body, so that the nuclei of the atoms are in a different position. By returning to the first state; the nucleus of the atoms emits its own radio waves. The scanner received these signals and a computer picks them up as a picture. The basis of these images is the location and strength of the input signals. We mainly contain water and water contains hydrogen atoms.

B. Motivation

Medical image segmentation is a complex task and crucially important for the farther analysis in clinical probe using computer-aided systems. The human brain has a complicated structure which needs additional attention for accurate extraction of different ROIs of the image. Whole brain extraction from MRI image can facilitate farther analysis of brain-related disease in early stages of disease detection. Many imaging techniques are used for brain imaging-based analysis. MRI images normally include noise due to different imaging equipment and environmental conditions. Many image processing techniques have been proposed for brain MRI segmentation including most notably thresholding, region- growing, and clustering. The watershed transform segmentation method is one of the most powerful and widely used image segmentation method. As the advantages of this method, we can refer to the simplicity, speed. One of the major disadvantages of the watershed transform method is the high rate of over-segmentation.

Many of the machine learning based algorithms have been applied to solve the over-segmentation problem of watershed transform method. Machine learning methods are supervised algorithms which they need lots of training and corresponding labeled data to have accurate segmentation results for test images. In the majority of cases, the amount of training and test data is not enough. Therefore, the unsupervised methods which need no labeled data can perform better in case of data shortage for training machine learning methods. On the other hand, we cannot always guarantee the image quality to be similar to the training image. In addition, in the case of deep learning based methods, they demand a large amount of training data to prevent network overfitting which is undesirable in medical image processing. SVM method needs no training and corresponding labeled data and can automatically group a similar data point to the same cluster.

SVM and fuzzy C-means (FCM) are the most famous unsupervised clustering methods applied for clustering data in a variety of field. Many different extensions for both methods have been developed yet the original form of both algorithms shown promising results in case of medical image segmentation. In the case of MRI, due to the image accusation techniques and environmental conditions, they normally include wrong regional minima causing over-segmentation of watershed transform [1].

Manual segmentation is time-consuming for a radiologist, so automatic/semi-automatic techniques are needed to accurately diagnose a tumor. Nowadays, fully automatic methods aimed at classifying tumor types in MRI images are common for clinical and research studies. These methods could further help to analyze the tumor area, which has developed rapidly in recent years. Therefore, the diagnostic capabilities of radiologists have improved based on automatic machine learning methods. But despite more efforts and promising results in the analysis of medical images, repetitive and correct segmentation, along with the identification of abnormalities due to the variety of position, shape, and size are a challenging activity in diagnosing brain tumors [2].

Several factors are involved in the accurate treatment of the brain tumor including the type and growth grade [3-5]. A brain tumor is categorized as two major kinds named as benign or malignant. Benign brain tumors have a uniform structure and do not contain active cancer cells on the other hand Malignant cancerous tumors have a heterogeneous structure and contain active cells. Magnetic resonance imaging (MRI) is one of the main imaging systems used to image and analysis of the brain tumor which can represent detailed information about tumor structure [6-8]. Nowadays, fully automatic methods for automatic classification of tumor types in MRI images are common for clinical and research studies [9,10]. Brain tumor MRI image segmentation plays an important role in early diagnosis and structure analysis such as tumor type, location, and size [11,12]. However, effective and accurate image segmentation methods should be able to preserve detailed information of the tumor structure which can lead to improving early diagnosis and further analysis. Manual segmentation is a time-consuming and tiresome process. Therefore automatic/semi-automatic techniques are needed for accurate tumor detection and subsequent classification. These methods could further help to analyze and classify tumor types. Brain tumor segmentation is an intrinsic part of unsupervised tumor classification [13-15]. Accurate brain tumor identification segmentation from MRI images is a challenging task due to the variety of position, shape, and size. Several methods have been reported for automatic segmentation and classification of brain tumors [16]. Despite many efforts and promising results, many of the proposed methods are semi-automatic based on the user manual identification of the tumor area on the MRI image [17]. Therefore, providing a fully automated, user-independent image segmentation leading to improve the unsupervised tumor classification way can substantially help brain tumor diagnosis in early stages [18]. The watershed algorithm is an unsupervised, efficient image segmentation method, mainly applied to grayscale images which are based on the water movement line separate each region in the topographic surface [19, 20]. This method has been widely applied for medical image segmentation which gives a promising result [21]. On the other hand, the support vector machine (abbreviated as SVM) is a powerful supervised machine learning method by finding the optimal hyperplane in an N-dimensional number of features to distinguish the classification of the features.

The motivation for this is to provide an automatic way to increase tumor detection functionality. This article is organized into several sections. Existing research on the diagnosis of brain lesions is presented in Section 2. The proposed approach for the diagnosis of a tumor is suggested in Section 3, and Section 4 shows the original results of the evaluation. The conclusion of the proposed approach is also stated in Section 5.

1. Challenges of MRI image segmentation

Due to the development of medical imaging methods, the problems of special classification of new programs are emerging and new methods are constantly being explored and introduced. Choosing the most appropriate technique for a particular program is difficult. In many cases, a combination of several techniques may be needed to achieve the division goal. Often, integrating multitasking information (obtained by different methods or over time) can help structure sections that cannot otherwise be identified in single images.

The most popular methods for segmentation of MRI brain image segmentation is used, the division process is often more complex and time-consuming debate. Future research may not only affect the development of more accurate and noisier but will focus on improving the speed of computation segmentation methods. The computational efficiency, especially in the real-time processing applications such as computer-guided surgery is very important.

MRI images, they always contain noise caused by different operating equipment and environmental situation. However, the performance of the watershed transform depends on the converges of numerous local minima on the image. Wrong regional minima on the image cause a high rate of over-segmentation of the watershed transform method. To address this problem, in this paper we propose a modified watershed transform method to prevent over-segmentation using SVM method. Our modified watershed transform utilizes the SVM method for region classification to remove wrong regional minima on image and provides a guideline for watershed transform to prevent the over-segmentation problem. Experimental results on brain MRI images evaluations (Dice coefficient: 95.12%) demonstrate that the proposed method can substantially prevent the over-segmentation problem of conventional watershed transform method.

2. Standards

MRI is an advanced medical imaging technique that provides a lot of information about the anatomy of human soft tissues. This technique is often used in radiology to illustrate the structure and function of the human body. MRI can produce a body image with much detail in every direction. MRI is particularly useful in neurological (brain), musculoskeletal and gastrointestinal (cancer) imaging, since it provides better contrast between computerized cut-offs (CTs) and soft tissues of the body. MRI differs from CT, in this way ionizing radiation is not used, but it uses an effective magnetic field to adjust the magnetized nuclei of hydrogen atoms in the water.

Most studies in developed countries have shown that the mortality rate of people with brain tumors has increased over the past three decades. Today, one of the deadliest cases among children and adults is brain tumor. The tumor is an aggregate of tissues that grow beyond the control of the usual forces that regulate their growth. Tumors can directly destroy all healthy brain cells. The tumor can also indirectly damage the normal cells by compressing other parts of the brain and causing inflammation and swelling and the pressure of the brain inside the skull. Brain tumors have different sizes, locations and situations. They also cause pressure on the tissues because of their texture.

The tumor can be benign or malignant and can occur in different parts of the brain and may be among the primary tumors or not. The most common primary tumors are glioma tumors, meningioma, pituitary adenoma, and tumors. Identifying and categorizing brain tumors in MRI is very important in medical diagnosis because its precise categorization is very important for finding tumors, swelling and dead tissues.

Some practical applications for image segmentation are as follows:

- Content-based image retrieval
- Computer vision
- Medical imaging including image rendering volume of scintigraphy and magnetic resonance imaging.
- Determining the location of the tumor and other diseases
- Tissue volume measurement
- Diagnosis and study of the descriptive structure
- Planning for surgery
- Simulation of virtual surgery
- Positioning in surgery
- Object recognition
- Pediatric Diagnosis
- Face Recognition
- Light brake detection
- Placing objects in satellite images (roads, forests, crops, etc.)
- Recognize tasks
- Fingerprint recognition
- Diagnosis of iris
- Traffic control systems
- Video monitoring
- A large number of general algorithms and techniques have been developed to segment the image. To be effective, these techniques typically need to be combined with specific

area knowledge to be able to effectively solve area segmentation problems. The main function of the contrast is to create the clarity of the image. I do not know if you noticed that the previous two-dimensional displays now create all three-dimensional objects using colors and shadows, and the more the ability to split between colors and shadows, the image also increases. Hence, the greater the contrast between the colors (contrast), the separation between the different objects and the three-dimensional simulation of the range with the highest possible quality. That's why the display companies make all their high-contrast displays on their displays. There are currently two trade-offs of contrast, which are known as static contrast and dynamic contrast. It also said that the contrast calculation is typically done in quite dark and standard rooms. A standard darkroom is a room that absorbs all absorbed in the room. There are more LCD monitors in the room, which, if all the light sources are cut off, still reflects a significant amount of exposure by the screen, which reduces the contrast.

C. Thesis contributions

This thesis prposes an automated method for brain tumor segmentaion and classification. In our proposed schema, First, the noise removal steps were taken to increase the accuracy and efficiency of the segmentation, as well as feature extraction. The image enhancement process was carried out using Gaussian techniques. Afterward, the image segmentation is applied using an optimized Watershed transform method. Subsequently, the texture-based Gray Level Co-occurrence Matrix (GLCM) algorithm was applied for tumor texture feature extraction. Ultimately, the support vector machine (SVM) was applied to the extracted features for automated brain tumor classification. We evaluated the performance of our algorithm in terms final tumor classification accuracy with a genetic algorithm (GA) (93.79%), adaptive neuro-fuzzy inference system (ANFIS) (91.11%), K-Nearest Neighbor (KNN) (89.76 %) classification algorithms based on collective intelligence to evaluate efficiency. Experimental results indicate that the proposed method has been able to provide the best accuracy compared to other methods by using appropriate filters, carrier naturalization, and also GLCM-based texture feature extractor along with SVM-based machine learning. The experimental results show a 97% segmentation accuracy and 94% tumor classification accuracy.

2. RELATED WORKS

In this section, we provide a brief review of brain MRI segmentation methods. In this study, a framework for accurately dividing the intensity of the growing brain from infant's preterm delivery to its equivalent in 50 regions of the brain is provided [1]. The proposed method has been compared and improved with Atletico-based techniques and has been proven using comparable results.

The main goal of the study in [2] is to simultaneously select informative features and to determine the uncertainty of an excellent allocation for the segmentation of brain tissues. Experiments on two sets of MRI data have proven the effectiveness and effectiveness of the proposed method. Authors in this study [3] propose an automatic division method based on Convolutional Neural Networks (CNN), to have a positive effect against the limit of the small number of weights. Also, the use of severity normalization as a preprocessor stage, which is based on techniques THG, is accompanied by an increase in very effective data for the diagnosis of brain tumors in MRI. The study in [4] aims to provide a summary of deep-seated segmentation methods currently performed brain MRI. First, they examine current deep learning architecture used to divide the brain's structure and brain lesions. Then, the function, speed, and properties of the deep learning methods are summarized and discussed. Finally, they present a critical assessment of the current situation and identify future developments and trends.

In this study [5], proposed improved watershed for segmentation which is generally provided by the F-weighted synthesis (C-Means) (FCM). The relative position and features of neighboring pixels greatly improve division performance. Simulated MR images of the brain with different noise levels are divided to demonstrate the superiority of the proposed technique compared to other FCM-based methods. This division method is a key component of the MR image-based classification system for brain tumors. In this paper [6], the authors provide a simple and scalable diagnostic algorithm. Their approach combines two ideas: (1) high-capacity convolutional neural networks (CNN) for localization and separation of objects; and (2) when labeled data is scarce. Under the supervision of the pre-training for the auxiliary task, followed by the specification of the specific domain, which yields a significant performance.

2.1 Threshold-based technique

The simplest method of image segmentation is called thresholding. Based on the threshold level, this method converts a gray image to a binary image. There is also a type of threshold based on a balanced histogram. The key point in this method is to select the threshold value (or threshold values for the case where several levels are desired). Several well-known methods such as maximum entropy, maximum variance, and k-mean clustering are used in industry.
Recently, methods have been developed to set the threshold for quality scan images. The key point is that, unlike the maximum variance method, the threshold values are derived from the radiographic image instead of the reconstructed image.The new methods are based on the use of multi-layered fuzzy nonlinear threshold values. In these methods, based on the membership assigned to each pixel, as well as the concepts of fuzzy logic and evolutionary algorithm, they perform the act of forgiving.

This group of lights is one of the oldest solutions in the field of image segmentation. In these methods, we try to determine the optimal size for the pixel array in different groups, which determines the optimal setup using different methods. In some of these methods, the image histogram information is used, while others based on specific features in the image, such as the mean and local deviation, or local gradients, have provided a method for determining which details are given in the reference of these methods of determining the baseline. Reviewed. When only a histogram is based on the image for the whole image, this method is called global determination. If the site has local properties in different areas, then this method is called a local locality setup.

At the threshold of each pixel, the image is displayed as an object or object It is possible.

The two most commonly used threshold methods are thresholds Global and local threshold. In the global threshold method, select the value Threshold using a visual image histogram and the value determination threshold is done. The image contains light objects in the dark background. One method for selecting the appropriate threshold is to use the trial and error method select different values of the threshold and the image obtained by applying this threshold by the viewer is judged. Another way is to choose the right threshold using it. This method is an effective way to automatically select the optimal threshold, Otsu method by maximizing non-group variance and ambushing intra-group variance Pix Leh. The global threshold for anonymity is clear the image is difficult. To remove the heterogeneous effect, the local threshold can be used. Finally, if local communities are determined completely independently of each other, then we will have an institutionalization or adaptation.

2.2 Region-based technique

Today, with the increasing expansion of various methods for discrete information such as scanners and digital cameras, image processing has been widely used. The images obtained from this information have always had noise levels. In some cases, there is a problem with the fading of the borders of the samples inside the image, which reduces the input of the received image. To solve this problem, image processing is used.

Image processing techniques from two areas can be considered: hardware aspects such as imaging, radiography and image display, and other software aspects such as extracting information from image signals and processing them such as de-duplication, retrieval, and zoning. In medical images, especially brain images, due to the close proximity of the levels of light intensity, the tissues and edges and the boundaries between the tissues are ambiguous and not well understood, but in many cases, different regions of the tissue must be clearly identified to diagnose the disease by MRI. Therefore, the division of brain images and the separation of their tissue is one of the most important needs in the images.

The image area consists of two steps: extracting the proper attributes of the image and then classifying these features using a suitable method. The zoning is one of the low-level processing operations of the image with the aim of dividing the image into distinct and homogeneous regions, or equivalently finding the boundaries of these regions. So far, many regionalization methods such as binary morphology and Marcantorrar method have been proposed. The method presented in this study is a graph-based approach. The graph advantage of the graph method is similar to that in that spatial information is generated concurrently and at high speed in the graph, and this method is implemented spatially on pixels and can be reduced to a small percentage of error, causing the area of MRI images of the brain and improves previous methods. This method can be used in medical diagnostic and imaging centers.

2.3 Region Growing

While focusing on focusing on the difference in the brightness of image pixels, this method, although based on the same as the previous method, is different from the implementation nail.
The region's growth methods are largely based on the assumption that neighboring pixels in a region have similar values. The usual way is to compare a pixel with a neighbor. If you agree with the similarity criterion, the pixel can be assigned to the same cluster as one or more of your neighbors. The choice of similarity criterion is significant and the results are affected by noise in all cases.

The method of merging the statistical area (SRM) begins by constructing a pixel diagram using 4 connections with weight edges with an absolute value of intensity difference. Initially, each pixel forms a single pixel area. The SRM then sorts those edges into the prioritization queue and decides whether to use a statistical proposition to merge the current areas belonging to the edge pixels.

In this method, the similarity of the brightness of the pixels is used to segment them. The key to implementing this method is that firstly, the designated sections are considered to be the start of the algorithm, which can be manually selected and can be selected automatically. Further, starting with these points and examining adjacent pixels with the mean values available. In each section, the algorithm is set when there are no other points with the conditions of addition to the growth region. The first problem of this sensitivity method is to choose from different points. The second problem is that there may be no areas or spots in the area where there is no right for any of the departments.

2.4 Previous works

A. Genetic algorithm (GA)

In this study [26] the author used different segmentation techniques and compared the using their segmentation score and selected the best one. Afterward, the relevant features were extracted and the area size of each tumor was extracted. Finally, the genetic algorithm was employed for final brain tumor classification. The overall schema of the proposed method in above mentioned is shown in figure 1.

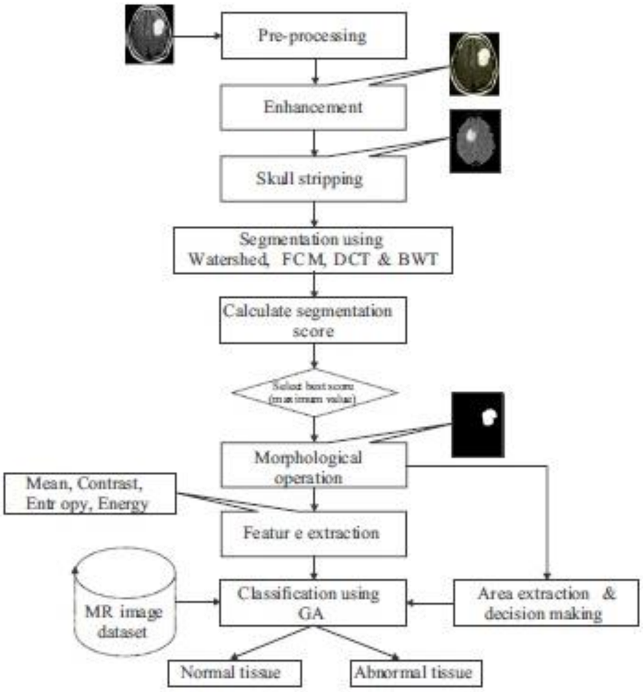

Figure 1. The overall scheme of brain tumor segmentation and classification using GA algorithm.

B. K-nearest neighbor (K-NN)

The author in the paper [27] proposed a method that consists of four phases Preprocessing, Feature extraction, Classification, and Post-processing. The statistical texture feature set is derived from normal and abnormal images. They used the K-NN classifier for classifying images. The detailed method is explained in figure 2.

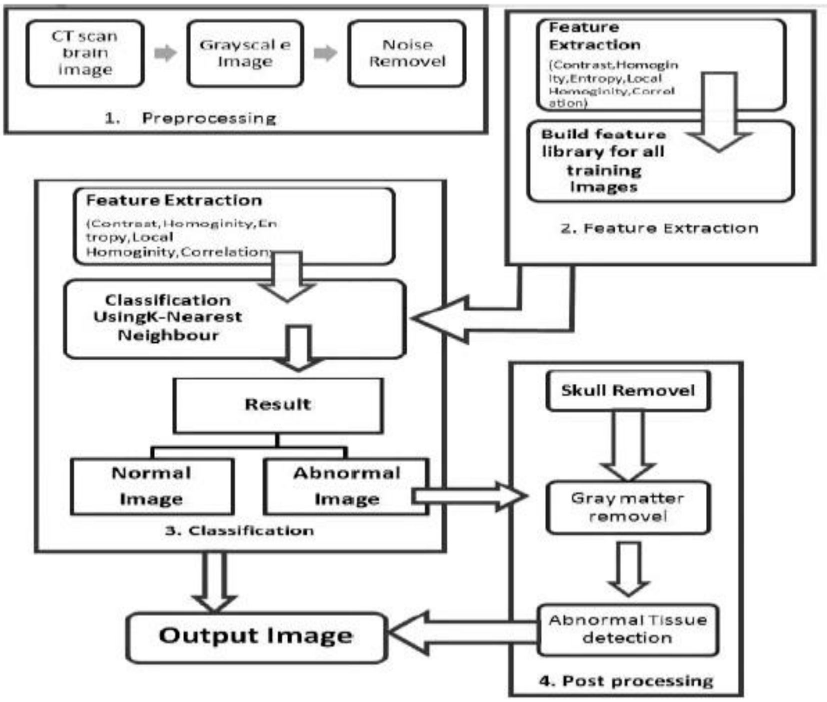

Figure 2. the overall flowchart of the proposed method for brain image classification using K-NN method

C. Adaptive Neuro-Fuzzy Inference System (ANFIS)

The Process of the proposed method in [28] begins with pre-processing the MRI Images by disposing of the noises of the images, like labels and X-Rayy marks. The feature Extraction process eliminates the high-frequency components using a Discrete Wavelet Transform (DWT). Thus derived coefficients make use of a primary couple of DWT coefficients used for classification of Normal, Mild cognitive Influence Alzheimer's disease using Adaptive Neuro-Fuzzy Algorithm (ANFIS). The detailed method is explained in figure 3.

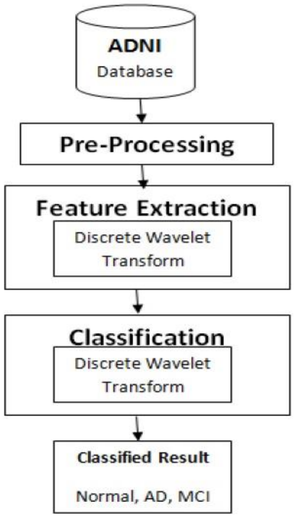

Figure 3. Steps for the proposed method for brain image classification using ANFIS method

The main difference between our proposed method and the GA algorithm [26] is that the classification is different in GA based on the genetic algorithm, but we did it based on SVM. we proposed a learning-based strategy. The other two solutions (K-NN, ANFIS) perform most of the categorization operations.

Adaptive Neuro-Fuzzy Inference System (ANFIS) has been utilized for the brain tumor classification [28]. The author proposed a method to classify the types of tumors only based on feature extraction. In the first step, the MRI image is given to the system as input and normalized. Then the feature extraction method extracts features from each tumor type. The key difference between this method and our proposed method can be expressed as the segmentation section. Segmentation is an intrinsic part of our method which allows extraction of the feature related to tumor morphology including size and area. These features are crucial for accurate tumor classification. Thus, our proposed method reported higher accuracy for final tumor classification results. Also, the proposed method in [27] is based on the feature extraction only. The steps of the proposed method are including preprocessing and subsequent image classification using the KNN algorithm. The proposed method skipped the segmentation process which is a crucial part of tumor classification. The classification is based on the extracted features. Before the tumor classification, feature extraction has been performed and the extracted features are feed to the KNN classification method. Skipping the segmentation process causes the removal of some intrinsic features which leads to low accuracy in the final classification.

3. PROPOSED METHOD

MRI segmentation, as well as brain tumor diagnosis and classification, are among the most important concerns for physicians. The precision of tumor diagnosis and classification by the radiologists depends on their experience. Meanwhile, computer technology can be very important and beneficial to help radiologists. Therefore, in this study, an efficient method based on the watershed segmentation technique is proposed to increase tumor detection performance. Besides, the GLCM algorithm is used to extract features in the tumor detection images. Detection and classification operations are performed by extracting the features contained in images from brain tumor datasets. In this method, instead of combining several different techniques and selecting based on the type of technique, a set of algorithms and effective strategies in increasing image quality, segmentation, as well as extracting its feature and classification have been used. For example, in the article selected for evaluation, it is required that for each image run each time by using several different algorithms, the desired image is segmented, and with several different algorithms, the features are extracted and then by scoring each. In this case, in addition to the need to implement various solutions several times, due to the lack of use of several techniques, the type of scoring is also impaired. While in our method, the best techniques have been used with the most accuracy on the images each time, and by using it, in addition to reducing the execution time and the need for lower memory and hardware, the accuracy is also higher. The method presented in this article consists of the following four basic steps:

- Pre-processing
- Image segmentation
- Feature extraction

- Image classification

The quality of raw MRI images is improved using the preprocessing stage. Also, preprocessing helps to improve certain parameters of MRI images, such as improving the signal-to-noise ratio, eliminating inappropriate noise and undesirable parts in the background, smoothing the internal parts of the area, and maintaining its edges. In the proposed approach, Grayscale and Gaussian filter techniques have been used to improve the signal-to-noise ratio and, therefore, the clarity of raw MRI images and to improve contrast. The block diagram of the proposed method that includes these four phases is shown in Figure 4.

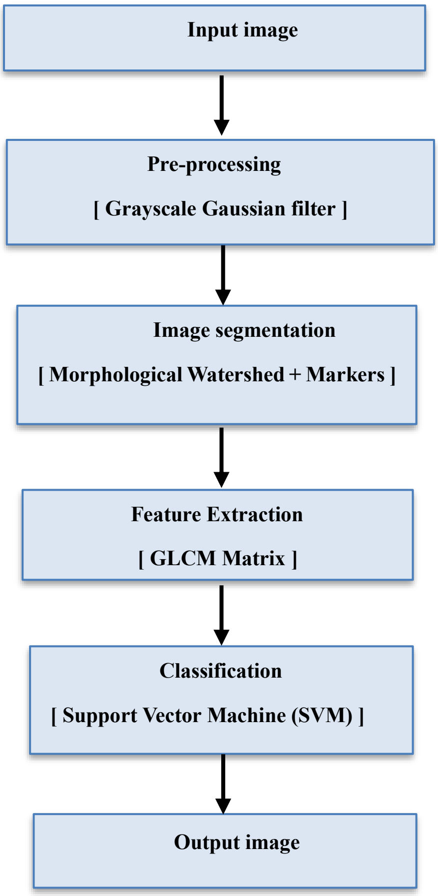

Figure 4. Block diagram of the proposed method.

3.1 Pre-processing

The existence of noise in images is inevitable because the quality of an image is affected by many factors. Therefore, noise removal or reduction can have better results in the segmentation process as well as the classification of images [29]. Accordingly, various filters that are used in the pre-processing phase improve the quality of MRI. Pre-processing can improve various parameters, such as signal to noise ratio, removal of background images, smoothing of image edges, and other parameters in MRI. In the solution presented in this study, to optimize the noise to signal ratio and thereby increase the quality, using the Grayscale filter, the raw MRI is converted to a full- black and white image and then the Gaussian filter is used. With this filter, the image fading and brightening are done so that the neighboring pixels contribute to the operation result [30]. For this purpose, the Median filter can also be used in which the average pixels within the kernel are determined as the final pixel value. In the evaluations carried out in [31], it is concluded that the Gaussian filter will have a better final quality that the results of which are shown in Figure 5.

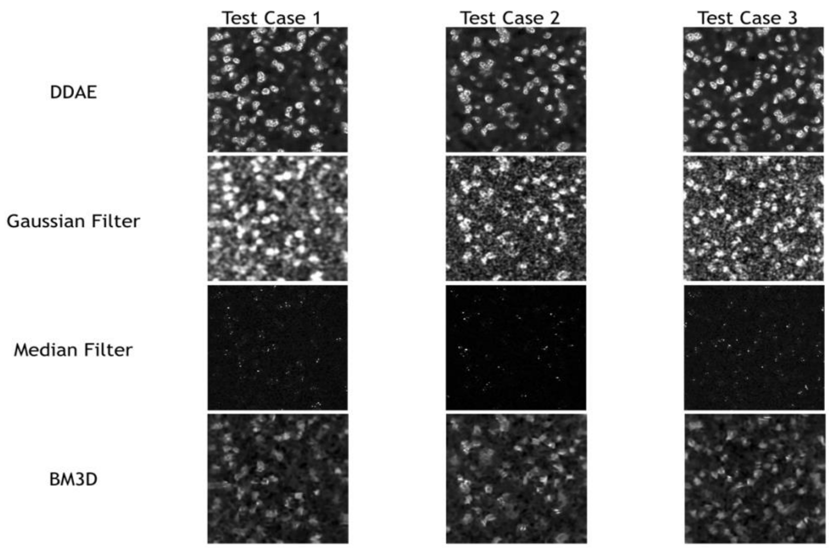

Figure 5. Results of noise filtering using different filters.

The general steps of the pre-processing are as follows:

- Resizing the input image to 215 * 160
- Applying the Grayscale filter to the converted image
- Adjusting the histogram to further improve image quality
- Converting the image to binary format and then considering the pixels with the value as black and the rest as white

3.2 Image Segmentation

At this stage, the morphology filter is applied to the image to obtain the best results from image segmentation, and the improved watershed technique segments the desired images. This operator is used to sharpen image regions and fill in the gaps in the image [32]. Therefore, at this stage, the morphological operator is used to optimize the pixels in the image. The process for the morphological operation is illustrated in Figure 6.

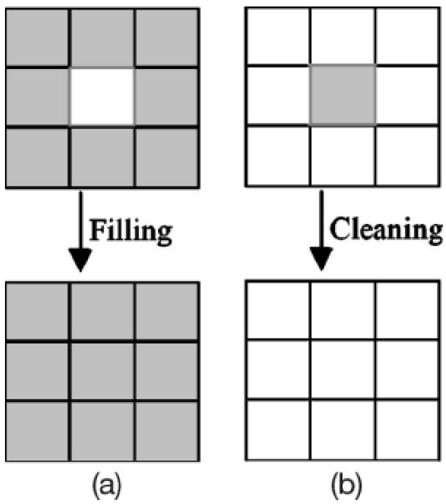

Figure 6. A morphological operator on a 3 * 3 area

(a) Filling operation (b) Cleaning operation

3.3 Watershed Transform

After pre-processing, the segmentation is done to determine the homogeneous image segments. Accordingly, the watershed technique is used. The watershed transform method is one of the most powerful and common image segmentation methods. Some of the advantages of this method are its simplicity, speed, and precision [33]. In geological, the watershed line is a section that separates two boundary catchments and the rain falling on either side of the edge heads to the same side of the lake. This idea is used in digital image segmentation. The image-processing region in this method is the image gradient. In an MRI, uniform textures usually have low gradient values, so these points represent the valleys, and image boundaries are known as peaks. The Watershed technique uses two principles of edge detection and mathematical morphology (pixels with uniform illumination gradients) to segment the MRI. Figure 7 demonstrates the schematic of the watershed segmentation.

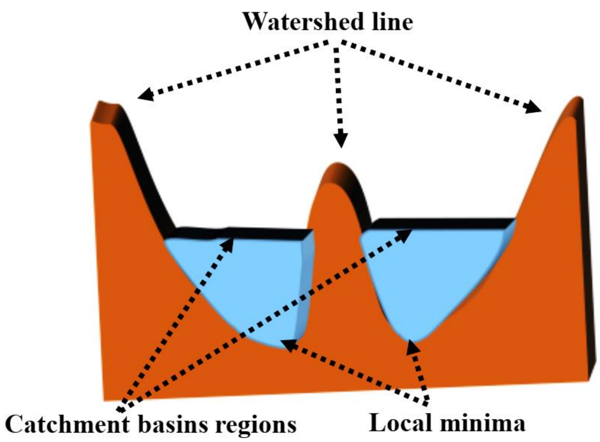

Figure 7. Representation of the watershed transform method

One of the major disadvantages of the watershed transform is that the wrong regional minimum can have a high impact on the segmentation performance, which causes over-segmentation in the image and can produce inappropriate results. Usually, the watershed conversion is applied to the image gradient. In the image gradient, the foreground and background have the lowest value while the edges have the highest value. Therefore, the possible noise in the image will have a profound effect on the image gradient and create a large number of local minima. As a result, the local minima created by noise will increase image over-segmentation [32]. Accordingly, this article solved this problem with markers. The markers pre-process the image, and by performing interactive segmentation, they eliminate the sensitivity to the uneven illumination of the image, which results in the elimination of inaccurate local minima. Thereafter, the gradient yields a new image with a minimum number of inaccurate local minima, which improves the watershed transform performance significantly.

Feature extraction is a process by which the features of an image are identified and used for subsequent processing. Feature extraction is a way to capture the visual content of an image. The purpose of image extraction is to reduce the original data set by measuring certain features. The extracted features are considered as inputs for classification. There are several techniques for extracting features; In this study, the texture-based Gray Level Co-occurrence Matrix (GLCM) method is used [33]. This matrix specifies the relation between specific pixel intensities at a given distance and direction, and then a P(i,j) matrix is generated from the neighboring window of each pixel. This matrix indicates the probability that there are points with the assumed brightness levels at a certain distance and angle from each other in the image. GLCM functions, [34] determine the texture of an image created by a GLCM by calculating how many times the pixel pairs occur with certain values and in a special space relation and then extract statistical values from this matrix. The following parameters are extracted using GLCM:

1- The number of objects: Indicates the number of objects in the image.
2- The area of objects: shows the area of objects, based on the intensity of the image.
3- Energy: A measure of the irregularity or information contained in an image.
4- Entropy: Entropy is a statistical measure of randomness that can be used to determine the texture of the input image.
5- Standard Deviation: The secondary moment of an angle is called the standard deviation.
6- Coverage.

GLCM is a two-dimensional histogram in which the component (x, y), is the frequency of the x event that occurs with y. (d) is the relative distance between the pair pixels, θ is the angle (it is horizontal at zero degrees, vertical at 90 degrees, in line with the positive diameter in 45 degrees, and line with the negative diameter in 135 degrees), and y is the grayscale; By which, computers determine how many times a pixel with an intensity of x occurs concerning another pixel, namely j, at a certain distance of (d) and the direction of θ. The most widely used feature extraction of tissue is GLCM. In this process, GLCM is calculated, and statistical tissue features of contrast, correlation, entropy, homogeneity, and energy are preprocessed from the above cases and enhance the hierarchical converted brain images.

Figure 8 shows an example of how to calculate the matrix G for distance 1 in the zero degrees direction. In this figure, for the 4 × 4 matrices of an image, its GLCM matrix is composed of five color levels. The value of the element (i, j) in the GLCM matrix means that in the image matrix there are several pixels of color i with the right pixel with value j.

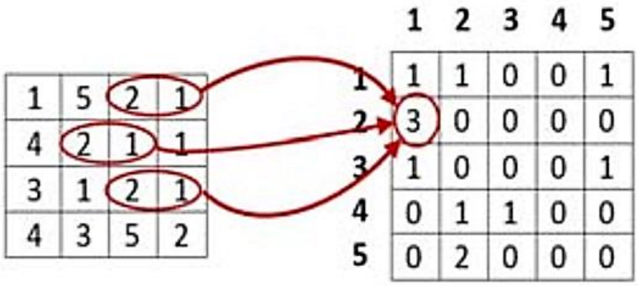

Figure 8. Calculate GLCM matrix for interval 1 in zero-degree direction

Accordingly, the GLCM matrix is used to extract features or identify any part of the image that can be used for testing and learning. The feature extraction flowchart by GLCM matrix is shown in Figure 9.

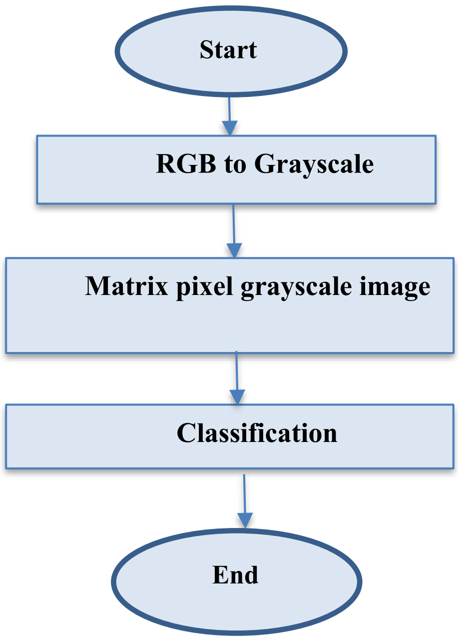

Figure 9. Feature extraction flowchart with GLCM matrix

Four main features of "entropy, contrast, homogeneity, and energy" have been used on the GLCM matrix concerning equations (1) to (4) [11]. Eq.1 shows calculating the entropy feature. When an image does not have a uniform texture, the entropy increases, therefore, the GLCM elements will have small amounts. Complex textures tend to be highly entropic. Entropy is also inversely related to energy.

$$Entropy = -\sum_{i=1}^{M}\sum_{j=1}^{N}(log\big(g(i-j)\big) \times g(i,j))$$

Eq.2 shows calculating the contrast. Using the spatial frequency contrast, an image is estimated. It specifies the difference between min and max of a consecutive set of pixels.

$$Contrast = \sum_{i=1}^{M}\sum_{j=1}^{N}((i-j)^{2} \times p(i,j))$$

The image homogeneity is also calculated by Eq.3. The value will increase in pairs of elements with a slight difference in their gray color. It will also have the highest value when all the elements in the image are uniform.

$$Homogeneity = \sum_{i=1}^{M}\sum_{j=1}^{N}(\frac{p(i,j)}{1+|i-j|})$$

Eq.4 shows calculating energy. The energy detects the irregularities in the texture of the image and its maximum value is equal to one. The maximum amount of energy occurs when the gray area distribution is fixed or has a periodic form.

$$Energy = \sum_{i=1}^{M}\sum_{j=1}^{N}(p(i,j)^{2})$$

3.4 Classification

In this research, the support vector machine (SVM) based classification method is used to classify the extracted features of the MRI. The SVM method is a supervised non-parametric statistical method and operates on the assumption that there is no knowledge of how the dataset is distributed [12]. The main advantage of this method is its high ability to use fewer training samples and achieve higher precision than other classification methods. Figure 7 shows two classes and their support vectors. It is assumed that the data consist of two classes and the classes have x_i (i=1,…,L) training point where x_i is a vector. These two classes are labeled with yi = ± 1. Since it is intended to divide the tumors into two types of low grade and high-grade glioma, the two classes are considered as completely separate and the optimal margin method is used to calculate the decision boundary of two completely separate classes. In this method, the linear boundary between two classes is calculated as follows:

- All +1 class samples are located on one side of the boundary line and all -1 class samples are located on the other side
- The boundary of a decision should be such that the distance between the closest training samples of both classes is maximized in a perpendicular direction to the decision boundary as far as possible.

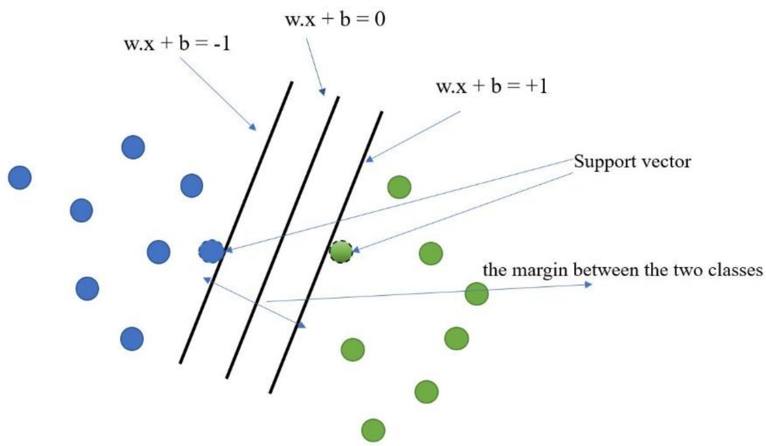

Figure 10. The optimal linear boundary for the case where the two classes are completely separated

A linear decision boundary can generally be written as follows:

$$w.x + b = 0$$

Where x is a point on the decision boundary and w is an n-dimensional vector on the decision boundary. b is also the distance from the source to the decision boundary, and w.x represents the internal multiplication of two vectors w and x. Since multiplying both sides by a constant does not disturb the equation, the following conditions apply to them for defining the unit value of b and w.

If x_i is a support vector $\quad y_i(w.X_1 + b) = 1$

If x_i is not a support vector $\quad y_i(w.X_1 + b) > 1$

The first step in calculating the optimal decision boundary is to find the nearest two-class training examples. In the next step, the distance of those points is calculated perpendicular to the boundaries separating the two classes. The boundary of optimal decision-making is the one with the maximum margin. The optimal decision boundary is calculated by solving the following optimization problem.

$$\max_{\mathbf{w},b} \min_{i=1,\dots,L} \left[y_i \frac{(\mathbf{w}.\mathbf{x}_i + b)}{|\mathbf{w}|} \right]$$

Figure 11 explained a block diagram how to apply the SVM algorithm to the GLCM.

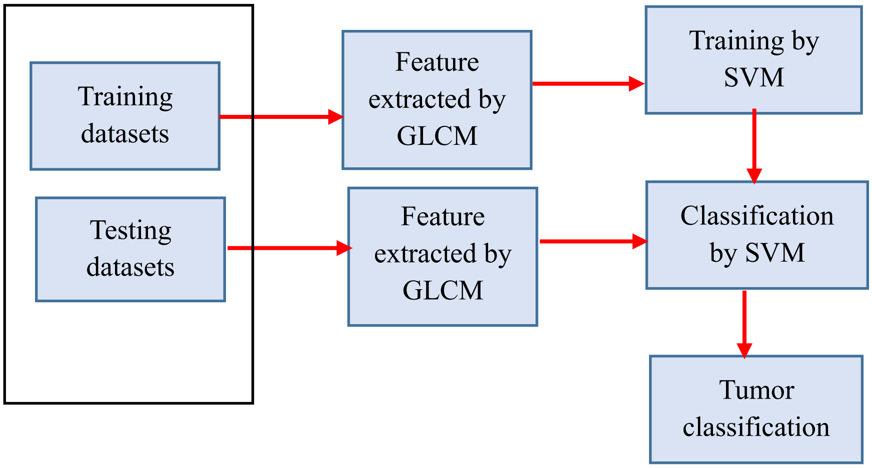

Figure 11. Block diagram on how to use GLCM and SVM algorithms.

In this section, the proposed solution is evaluated. Implementation is done in Python environment using CV2 and SimpleITK modules. The BRATS 2019 dataset has also been used for the learning process and consequently the classification of tumors into low-grade glioma (LGG) and high-grade glioma (HGG) groups. The BRATS is a large dataset of brain tumor magnetic resonance scans that have been developing since the year [13]. The applied dataset consists of two sections LGG and HGG, each containing four different samples T1, T2, T1C, and Flair. These samples are in the 'MHA' format. To this end, the data falls into two categories of learning and test data. 12 LGG and 15 HGG samples were selected for learning. The reason for this choice is that the LGG samples are less in the data set. T1 and T2 samples have been used in this evaluation. Five LGG and five HGG samples were selected for testing. At the beginning and before the feature extraction stage for classification, the gaussian, morphology, and finally, watershed filters are applied for image optimization and segmentation.

The GLCM technique then extracts the tumor features by which learning is conducted by training images and the type of tumor is specified. Finally, the SVM-based classification will be used to classify the tumor into two LGG and HGG groups.

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The GLCM technique then extracts the tumor features by which learning is conducted by training images and the type of tumor is specified. Finally, the SVM-based classification will be used to classify the tumor into two LGG and HGG groups.

3.5 Performance evaluation and comparison

There is some error rate depending on detecting or not detecting HGG and LGG tissue in all brain tumor MRI in the dataset. These can be measured based on the value of true positive, false positive, true negative, and false negative. In this paper four criteria of precision, accuracy, and recall based on Table 1 were used to compare the solutions

Table 1. Evaluation criteria

		Predicted class	
		Positive	Negative
Real class	Positive	True- *positive* (TP)	False-ne*gative* (FN)
	Negative	False-*positive* (FP)	True-*negative* (TN)

The above table specifies the possible states of operation of a category for each class of true negative (TN), true positive (TP), false negative (FN) and false positive (FP).

Specificity criterion: equals the number of true positive cases compared to the total true cases.

$$Specificity = \frac{\mathrm{TP}}{TP+FP}$$

Sensitivity: Includes the number of true positive cases compared to the total positive cases.

$$Sensitivity = \frac{\mathrm{TP}}{TP+fN}$$

Accuracy: equals the number of true positive cases compared to the dataset. Since this criterion is the only criterion in which in addition to true positive cases, the true negative cases are evaluated, it is one of the important criteria for evaluation.

$$Accuracy = \frac{\mathrm{TP+TN}}{TP+TN+FN+FP}$$

Average Dice's Coefficient: This parameter indicates the overlap of the two separated image areas and can be calculated through the following equation.

$$\text{Dice's Coefficient} = \frac{2\mathrm{TP}}{2TP+FN+FP} \tag{10}$$

Our proposed method has been compared and evaluated with the approach presented in [7].

The reason for this comparison is the novelty of the approach, as well as the closeness of the performance and goals of this article with our proposed approach. The method presented in [7] consists of several steps, which include MRI image preprocessing, improving contrast and brightness using image enhancement, skull banding operations, segmentation, feature extraction, selection of related features, as well as classification based on genetic algorithms. Accordingly, various segmentation schemes were initially applied using Watershed segmentation, FCM segmentation, DCT segmentation, and BWT segmentation for use in classification, and the best option was selected based on segmentation score. The fuzzy clustering method (FCM) divides the whole data set into many smaller groups. The FCM algorithm simplifies hard C-method clustering to identify data that partly belongs to several clusters. Discrete cosine transformation (DCT) also helps to divide the image into parts of different importance based on the visual quality of the image, resulting in efficient segmentation. Finally, through the use of genetic algorithms and GLCM, useful features are selected to diagnose the tumor. First, Figure 12 shows an example of the application of filters and segmentation to extract the tumor area by the proposed approach.

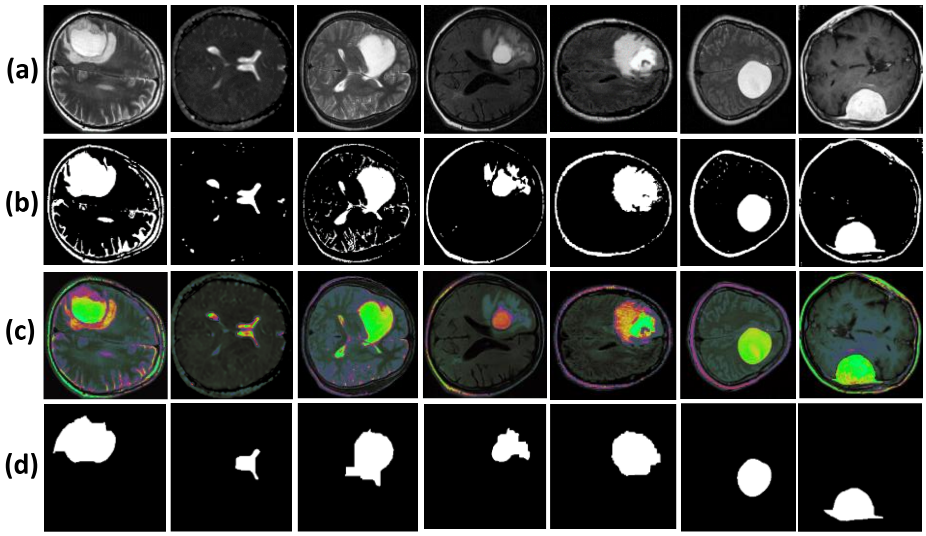

Figure 12. An example of the step-by-step application of filters by the proposed approach on the image to extract the tumor a) Original image by applying Grayscale filter b) Gaussian filter application c) Watershed + filter application d) Extracted tumor region.

The sensitivity, specificity, accuracy coefficient, and dice coefficient with GA, ANFIS, and K-NN efficiency methods have special validity. Table 2 summarizes the comparison results.

Number of test images (201)				
Parameters	**ANFIS Roy S,et.al [28]**	**GA Nilesh Bhaskarrao,et.al [26]**	**K-NN Ramteke, R. J et.al [27]**	**Proposed method**
True negative	60	64	61	72
False positive	9	6	12	2
True positive	118	121	114	117
False negative	14	10	14	10
Specificity (%)	86.95	91.42	83.56	97.30
Sensitivity (%)	89.39	92.36	89.06	92.13
Accuracy (%)	88.55	92.03	87.06	94.03
Average dice coefficient index (%)	91.11	93.79	89.76	95.12

Table 2. Comparison of accuracy in different methods.

The main difference between our proposed method and the GA algorithm [26] is that the classification is different in GA based on the genetic algorithm, but we did it based on SVM. One of the main problems with the GA algorithm is the need for high memory to run the algorithm because there is a need to maintain several hundred chromosomes and thousands of generations, which will be much higher in the images, so the need for memory and error probability will be higher. But our strategy is based on learning, so it will be easy to implement. The other two solutions perform most of the categorization operations. They are not considered a hybrid solution, and the purpose of comparing them is to examine the proposed hybrid method with other methods that are not hybrid and operate only based on a classification algorithm.

Adaptive Neuro-Fuzzy Inference System (ANFIS) has been utilized for the brain tumor classification [28]. The author proposed a method to classify the types of tumors only based on feature extraction. In the first step, the MRI image is given to the system as input and normalized. Then the feature extraction method extracts features from each tumor type. The key difference between this method and our proposed method can be expressed as the segmentation section. Segmentation is an intrinsic part of our method which allows extraction of the feature related to tumor morphology including size and area. These features are crucial for accurate tumor classification. Thus our proposed method reported higher accuracy for final tumor classification results. Also, the proposed method in [27] is based on the feature extraction only. The steps of the proposed method are including preprocessing and subsequent image classification using the KNN algorithm. The proposed method skipped the segmentation process which is a crucial part of tumor classification. The classification is based on the extracted features. Before the tumor classification, feature extraction has been performed and the extracted features are feed to the KNN classification method. Skipping the segmentation process causes the removal of some intrinsic features which leads to low accuracy in the final classification.

Also, in the following, in Figures 13 to 15, the comparison obtained from the evaluation of the proposed solution with other solutions and based on the Accuracy, Sensitivity, Specificity criteria have been evaluated.

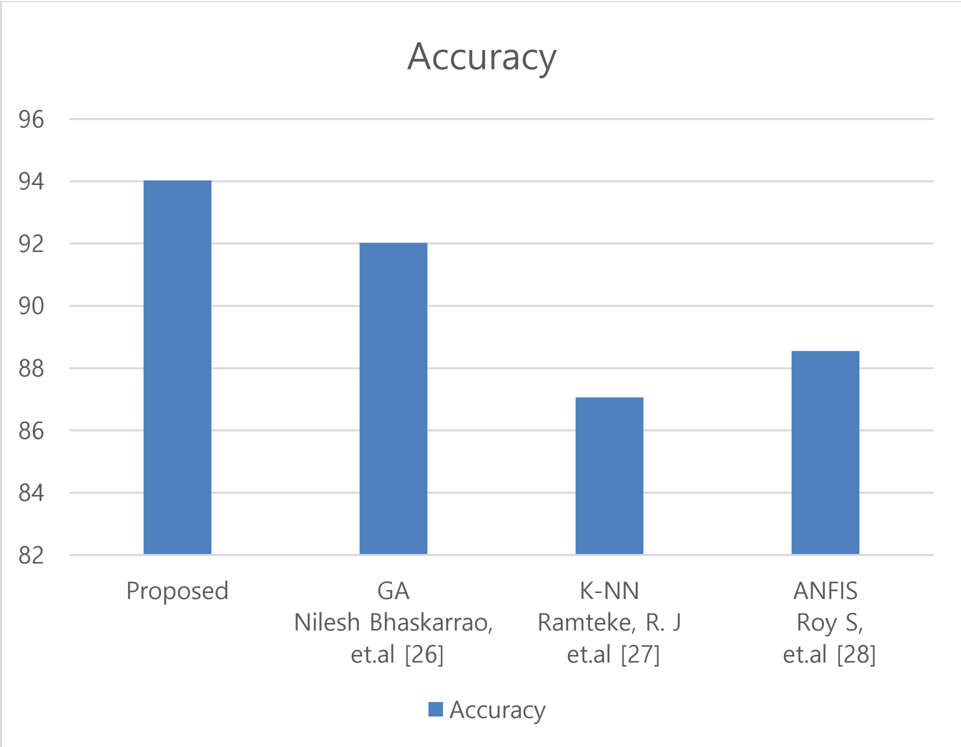

Figure 13. The accuracy rate in the performed evaluation of the approaches.

As shown in Figure 13, the proposed approach is more precise in terms of the operation accuracy compared to the other three methods, which in fact, indicates that the approach is more accurate in diagnosing the type of tumor. The reason why the proposed method is more efficient is the employment of different techniques in each stage of the approach. First of all, the quality of MRI images for processing is improved through preprocessing; In fact, this step is one of the most important steps in the classification operation, and the choice of filter type has a more favorable effect on the accuracy of the segmentation and feature extraction. Besides, preprocessing helps to improve certain parameters of MRI images, such as improving the signal-to-noise ratio, eliminating inappropriate noise and undesirable parts in the background, smoothing the internal parts of the area, and maintaining its edges. In the proposed approach, Grayscale and Gaussian filter techniques have been used to improve the signal-to-noise ratio (SNR), and therefore the clarity of raw MRI images and to improve contrast, the obtained results also show the correct use of these filters. Of course, the use of proper segmentation along with extracting important features has also had a great impact on this level of optimality. In the following figure 14, the Sensitivity parameter is examined.

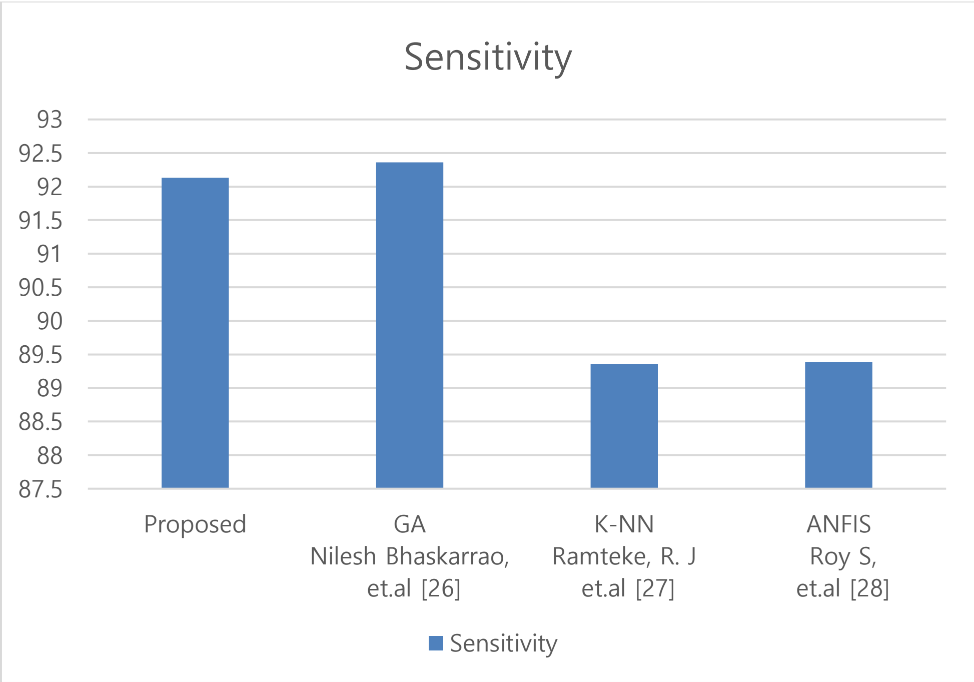

Figure 14. The sensitivity rate in evaluation of the approaches.

As shown in figure 14, the proposed approach and the genetic algorithm-based approach are more efficient than the other two; In fact, the accuracy of their operations is significantly higher, which is due to the use of the GLCM algorithm in both approaches. However, in our proposed approach, the SVM algorithm has been used instead of genetics; By using it, in addition to increasing the sensitivity rate, we have been able to increase the accuracy and precision of the approach.

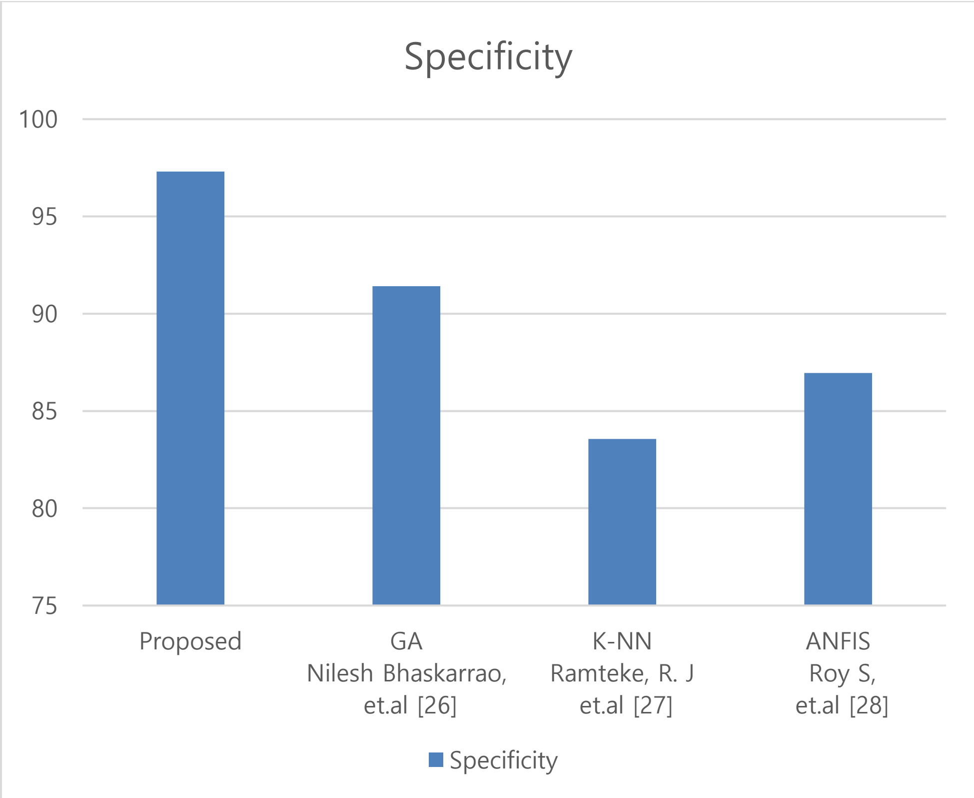

Figure 15. The specificity rate in the evaluation of the approaches.

As shown in Figure 15, our proposed approach has a higher specificity rate compared to three other methods. In fact, with the help of the functions in the GLCM algorithm, we have been able to extract the best features from the images optimized by the preprocessing and accurately categorize the tumors with high accuracy through a Support Vector Machine-based approach. Compared to the genetic algorithm that like our approach used GLCM functions to extract features, as can be seen, we have been able to achieve a higher level of accuracy. This is due to the use of appropriate filters as well as the use of the optimized watershed technique; In a way, the approach has performed better than the genetic-based algorithm in the segmentation phase, and as a result, a precise segmentation has been performed for the processing. Although both approaches use the same technique to extract features, other parameters that also affect tumor diagnosis are better selected in our proposed approach; In a way that, besides GLCM, which is dependent on the quality of the used images, the proper preprocessing, better segmentation, and more efficient classification have been used, and the results of the evaluation indicate this.

4. CONCLUSION

MRI segmentation, as well as brain tumor diagnosis and classification, are among the most important concerns for physicians. Meanwhile, computer technology can be very important and beneficial to help radiologists. Therefore, in this study, a solution based on the improved Watershed algorithm along with the GLCM matrix as well as SVM classification is presented. Usually, the Watershed conversion is applied to the image gradients and noise in the image will have a profound effect on the image gradient resulting in a large number of local minima that will increase image over-segmentation. To solve this problem, the markers technique is added to the Watershed method. In this thesis, an automated segmentation and classification system based on the improved Watershed algorithm along with the GLCM matrix as well as SVM classification is presented. In the first step, the image enhancement and noise removal were performed to prevent local minima that will increase image over-segmentation.

To solve the over segmentation problem, the markers technique is added to the Watershed method. Using the markers, interactive image segmentation is performed on the image to eliminate the uneven illumination of the image. Then, the GLCM matrix extracts useful features to detect and classify the tumor type by the SVM algorithm. Finally, to evaluate the proposed method, the recall, accuracy, and precision parameters were calculated and was compared with GA, KNN, ANFIS methods. The results of the evaluation indicate that the proposed method is more accurate and precise than other methods and therefore it can be very useful in diagnosing the tumor type.

Using the markers, interactive image segmentation is performed on the image to eliminate the uneven illumination of the image. Then, the GLCM matrix extracts useful features to detect and classify the tumor type by the SVM algorithm. Finally, to evaluate the proposed solution, the recall, accuracy, and precision parameters were calculated and the proposed method was compared to some of the states of the art methods. The results of the evaluation indicate that the proposed method is more accurate and precise than other methods and therefore it can be very useful in diagnosing the tumor type.

PUBLICATIONS

A. Conferance:

Modified Watershed Transform for Automated Brain Segmentation from Magnetic Resonance Images

Publication: ICCCV 2019: Proceedings of the 2nd International Conference on Control and Computer Vision -June 2019 https://doi.org/10.1145/3341016.3341028

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