Study on Capabilities of Different Segmentation Algorithms in Detecting and Reducing Brain Tumor Size in Magnetic Resonance Imaging for Effective Telemedicine Services

Jide J. Popoola, Thompson E. Godson, Yekeen O. Olasoji, and Michael R. Adu

***Abstract*—Over the past decade, different image segmentation algorithms have been developed and employed in segmenting or analyzing brain magnetic resonance imaging (MRI) scans in the clinical applications for the detection of brain tumor. However, accurate detection, compression and transmission of brain tumor data remain parts of the challenging tasks militating against brain tumor telemedicine services due to the complex nature of brain tumor MRI scans. In overcoming this challenge, five different brain tumor segmentation algorithms were developed for this study. The algorithms were developed using MATLAB scripts. The developed algorithms were evaluated using patients' data retrieved from Mayfield website. The result of the comparative performance compression rate efficiency evaluation test carried out shows that the developed hybrid threshold-watershed segmentation algorithm outperforms others in terms of compression efficiency. The result implies that the usage of the developed hybrid threshold-watershed segmentation algorithm in transmitting brain tumor patients' data transmission over wireless communication system will require limited bandwidth resource.**

***Index Terms*—Tumor; Brain Tumor; Telemedicine; Medical Imaging Techniques; Segmentation Algorithms.**

I. Introduction

Human body is made of numbers of well-coordinated cells that cooperatively work together for human growth and survival. In achieving these fundamental functions, each cell in the body performs specific and distinct function(s). Ideally, when required, majority of these body cells divide in an orderly manner to produce new cells in order to ensure healthy and functional body system. On the other hand, failure of these body cells to manage their growth as well as controlling their division in an orderly manner usually results in production of a mass of tissue being referred to as a tumor. As reported in [1], [2], a tumor is defined as a collection of tissue that grows uncontrollably beyond the natural forces that controls normal cells growth. Thus, the tumor of the brain is an abnormal growth of unrestrained tissues in the brain [3]. The brain tumor as an abnormal mass of tissue growing in the brain can be either malignant or benign. Basically, the benign tumor usually originates from cells within or surrounding the brain. It does not contain active or cancer cells. Malignant brain tumor, on the other hand, contains active or cancer cells. Irrespective of the type, brain tumor can influence people at any age. Moreover, it has been observed to be one of the primary causes of current rise in the mortality rate among people [4].

In the last two decades, the rapid use of computers and communication technologies being referred to as information and communication technologies (ICT) has given birth to a plethora of ideas on wireless services and applications designed for people's benefits. One of such wireless service and applications is on the usage of ICT on health services commonly referred to as telemedicine. Telemedicine, as reported in [5], is a health care delivery services offered to patients over a certain distance by means of electronic system. It can equally be defined as any health care delivery model whereby patient care is provided at a distance using information technology such as computers, cell phones and/or any other electronic devices. Series of health services deliver to patients via telemedicine includes patients' diagnosis, treatment, prevention of disease and injuries, research and evaluation and education of health care providers in order to improve people's health. According to [6], telemedicine is a health delivery system with high capability for revolutionizing the traditional physician-patient physical relationship or contact.

According to [7], one of the advantages telemedicine has brought into medical service is that, it has helped significantly in managing the problem of insufficient medical facilities and personnel. Another observed benefit of telemedicine according to [8] is its inherent capability of delivering health care service to hard-to-reach regions, especially in developing countries. This is because terrain effects that make hard-to-reach regions inaccessible have no negative effect on wireless or ICT system accessibility in any location. Thus, usage of telemedicine via ICT has potential of delivering the required information through wide geographical locations at the right time in the right form. These benefits and more are all that the health practitioners in developing nations of the world observed that make them to tap into the power of ICT in reducing both the morbidity and mortality rates in their rural regions for the benefits of the rural dwellers and underprivileged populations. Interestingly, use of telemedicine is unrestricted to only the developing nations of the world. For instance, [9] stated that telemedicine had started in Japan as

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far back as 1996 when their government gave approval for telemedicine in conjunction with the associated deregulation policies. Similarly, [10] reported that the first phase of telemedicine had begun since late 1960s and early 1970s in the United States of America. Likewise, [11] revealed that telemedicine had commenced in Spain since late 1960s.

Generally, telemedicine adoption is considerably increasing worldwide. According to surveyed literature, telemedicine has currently been adopted in treating patients with diverse diseases such as hyperthermia, hypertension, hypothermia, hypotension, cardiac diseases and diabetes [7]. This shows that the real-time monitoring of these chronic diseases or illness through wireless communication system has contributed immensely to health services delivery system across the world. Also the two-way communication between the patient and medical personnel over long distances with high fidelity, which allows the transmission of diverse data such as patient medical records, audio, videos, images and physical examination through different devices through telemedicine platforms has made available high-quality and cost-effective medical care to people irrespective of their locations.

Transmission of these patient data over wireless communication system requires large bandwidth. However, recent observations have shown that only limited bandwidth are available because of proliferation of diverse kinds of wireless systems and applications as well as the current radio spectrum scarcity [12]-[15]. Thus for efficient patient data transmission and effective telemedicine health service delivery, it is imperative that patient data be small in size to enhance their efficient transmission over wireless channel. Also, compared to other health challenges, a dearth of literature has been observed on telemedicine application in brain tumor disease. In order to contribute to knowledge in this area, this study was embarked upon with two objectives. The first objective is to develop some segmentation algorithms for segmenting or detecting brain tumor in magnetic resonance imaging (MRI). The second objective is to compare the brain tumor size reduction capabilities of the developed algorithms in order to determine a particular algorithm that can enhance efficient brain tumor image size uploading and/or downloading in wireless communication system. In enhancing logical presentation of the study reported in this paper, the rest of the paper is organized as follows. In Section II, brief reviews on image segmentation and related works on image segmentation algorithms for brain tumor detection in MRI scan were carried out. Section III explains in details the method used to carry out the study presented in this paper. The results obtained were presented and discussed in Section IV while the paper was concluded in Section V with summary of our findings and future work to be done.

II. Image Segmentation and Related work Reviews

Medical image segmentation technique or algorithm for brain tumor detection in an MRI scan is a significant procedure for determining suitable therapy at appropriate time for brain tumor. According to [16], image segmentation is technique usually employed in detection of infected tumor tissues from the brain MRI. The technique involves processing pictures of a body part to extract the explicit information. In addition, it plays an essential role in the surgical planning as well as in monitoring tumor growth or shrinkage during brain therapy. Basically, prior to the application of any brain tumor treatment, tumor segmentation is important to safeguard healthy tissues while destroying tumor cells in the course of the therapy. Thus, brain tumor segmentation must involve diagnosing, delineating and separating tumor tissues from normal brain tissues. Therefore, segmentation is defined as digital image segregation method by which an image is divided into multiple portions with the aim of changing the representation of an image in order to be more meaningful and easier to analyze.

Various medical imaging techniques such as single-photon emission computed tomography (SPECT), computed tomography (CT), magnetic resonance spectroscopy (MRS), position emission tomography (PET) and magnetic resonance imaging (MRI) are usually employ in providing essential information regarding brain tumor location, size, shape and metabolism during its diagnosis. According to [17], while all these medical imaging techniques are used together to offer comprehensive information about the brain tumors; MRI technique is being considered as the standard technique because of its wide availability and its effective soft tissue contrast. Thus, as reported in [18], MRI has become the main medical imaging technique in studying brain tumor. It is an advanced medical imaging system that is usually employed in producing high quality images of the parts of the human body. Also, it is an essential technique that helps in determining ideal therapy at right stage for tumor-infected patient.

Generally, MRI has a multidimensional nature of data provided from different sequential pulses. Thus, as reported in [16], the extraction of the brain tumor requires the separation of the brain magnetic resonance images (MRIs) to two regions. The first region will contain the tumor cells of the brain while the second region will contain normal brain cells. Image segmentation is the primary machine learning process usually used in extracting the particular region of interest from an input image. Various machine learning based segmentation algorithms or approaches have been proposed in literature. However, according to [19], there is no benchmark or standard segmentation technique or algorithm that can provide satisfactory results for all imaging applications. For instance, as reported in [20], while threshold-based, region-based and pixel classification algorithms are usually employed in two-dimensional (2D) image segmentation, model based segmentation algorithms are commonly employed in volumetric or 3D image segmentation.

Conventionally, brain tumor segmentation algorithms primarily include the use of standard segmentation algorithms such as threshold-based methods, edge-based method, region growing method, watershed algorithm, morphological-based method, genetic algorithm, fuzzy clustering, K-means clustering, artificial neutral network, atlas-based algorithm, and hybrid method to mention a few. Thresholding method works by comparing pixel intensities with one or more intensity thresholds. This segmentation algorithm has three types: local, global and multiple thresholding. While the global thresholding technique works better for images with homogenous intensity, the local thresholding technique usually works better for images that contain more than one region with different objects. For instance, in [21], global thresholding algorithm was employed to form the binary image before the brain tumor was segmented using morphological operation. The developed algorithms by these authors worked well for homogeneous image [22]. However, due to difficult in selecting optimal threshold, there is possibility of both over-segmentation and under-segmentation, which makes some part of the image look dark while some part may look bright as a result of intensity inhomogeneity across the scene.

Similarly, edge-based segmentation algorithm works by partitioning an image based on rapid changes in intensity near edges. Thus, the segmentation method uses the changes in the intensity of images to detect edges. This segmentation technique was applied in [23] based on Sobel edge detection by combining Sobel method with image dependent thresholding method to develop an improved edge detection algorithm. The developed algorithm when evaluated gave superior performance over conventional segmentation methods. Generally, according to [22], edge-based segmentation methods are simple and easy but sensitive to the threshold. It requires a balance between detecting accuracy and noise immunity [24]. Thus if the level of detection accuracy is too high, noise may bring in fake edges making image outline unreasonable. On the other hand, if the noise immunity degree is too high, some part of the image outline may be undetected leading to error in locating objects position.

Region-based segmentation algorithm, on its own, works by segmenting the image into various regions with similar characteristics. As reported in [25], the segmentation algorithm examines pixels in an image and form disjoint regions by merging neighborhood pixels with homogeneity properties based on a predefined similarity criterion. As reported in [26], there are two basic techniques for implementing region-based segmentation algorithm: namely region growing method and region splitting and merging method. In the region growing based segmentation method, image is segmented into various regions based on the growing of initial pixels or seeds. On the other hand, region splitting and merging based segmentation uses splitting and merging for segmenting an image into various regions. While splitting stands for iteratively dividing an image into regions having similar characteristics, merging stands for combining the adjacent similar regions. In [27], automatic brain tumor segmentation from MRI images using region-growing algorithm was proposed. One of the benefits of the proposed algorithm is its less executable time. Similarly, as reported in [24], split and merge segmentation algorithm is also a fast computational method. However, its drawback is its insensitivity to image semantics [28].

Another segmentation algorithm, which has been widely used in brain tumor segmentation include watershed segmentation. For instance, [29] proposed a robust image segmentation technique to minimize undesirable over segmentation, which is one limitations of conventional watershed segmentation method. The proposed medical image segmentation was developed by combining watershed segmentation and competitive Hopfield clustering network algorithm. The performance evaluation of the proposed algorithm was evaluated through quantitative and qualitative experiments using benchmark images. The performance evaluation result shows significant segmentation results. Other two segmentation methods employ in brain tumor segmentation are fuzzy clustering and K-means clustering. In fuzzy clustering, according to [20], each pixel is allocated a membership function value to the available classes based on its attributes. Fuzzy clustering is a popular segmentation technique in the area of unsupervised image segmentation by pixel classification especially in the case of brain tumor segmentation. The early proof of effectiveness of fuzzy clustering segmentation method for brain tumor segmentation was demonstrated in [30]. The authors visually demonstrated the overlapping intensity distributions for tumor and normal tissues in multisequence data. The result of their study showed the possibility of generating segmentation images that display clinically important neuroanatomic and neuropathologic tissue contrast information from raw MR image data.

Obviously, this brief survey on brain tumor segmentation algorithms has shown clearly that the various segmentation algorithms available have different tumor size detection rate accuracy, therapy efficiency and limitations. Thus, the major contribution of this paper to knowledge will be on how to overcome these observed limitations and drawbacks by developing specifically two hybrid segmentation algorithms to overcome these observed limitations and drawbacks. The idea of hybrid segmentation was to overcome limitation(s) observed in single segmentation algorithm as the hybrid algorithms combine strengths of two algorithms together. The step-by-step approaches involved in developing the five segmentation algorithms, which comprises of three single and two hybrid algorithms, for this study are presented in the next section under methodology.

III. Methodology

This section presents detailed information on materials and method employed in carrying out the study presented in this paper. The section also presents the source of brain MR tumor image dataset used, the algorithms developed and used to perform brain tumor MRI segmentation. Fig. 1 shows the flow diagram of the proposed five segmentation algorithms developed to detect brain tumor on MRI scan of affected patients. While three of the developed algorithms were single segmentation algorithms, two were hybrid segmentation algorithms. K-means, fuzzy c means and threshold algorithms are the three single segmentation algorithms developed. On the other hand, threshold-k means and threshold-watershed are the two-hybrid segmentation proposed and developed in this study. All the five developed segmentation algorithms in this paper follow the four stages in the block diagram shown in Fig. 1. Detailed activities involved in the implementation of the five segmentation algorithms as shown in Fig. 1 are presented in the following sub-sections.

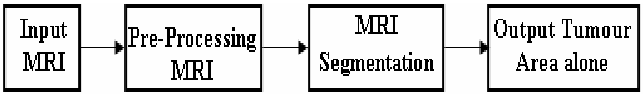

Fig. 1. Block diagram for the developed segmentation algorithms.

A. *Input MRI Stage*

In this stage, which is the first stage in developing the segmentation algorithms for the study presented in this paper, all the MRI scans from affected patients' brains were fed into MATLAB script environment using "imread()" function. Typical MRI samples images of brain tumors used are shown in Fig. 2. The MRI scans samples images used are in "jpg" and "png" formats. They were retrieved or obtained from Mayfield Clinic website.

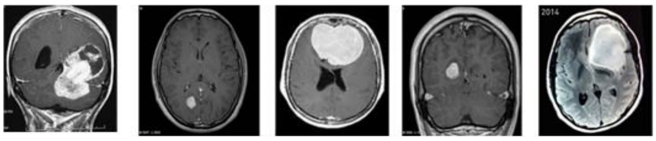
Fig. 2. Typical samples of magnetic resonance (MR) images used.

B. *Pre-processing Stage*

This stage, which is the second stage, entails the removal of noise and other artifacts as well as sharpening of the edges of the images. RGB to BW conversion also takes place in this stage for the image actual segmentation. The five algorithms employed in this study involve different pre-processing schemes in order to prepare the images to suit the respective segmentation process based on uniqueness of each algorithm.

C. *MRI Segmentation Stage*

In this stage, which is the third stage, specific MATLAB function was used to segment the preprocessed image in order to isolate the tumour area alone. For insatnce, watershed algorithm employs "watershed()" in built function; threshold algorithm makes use of "regionprops()" function; fuzzy c means clustering algorithm makes use of "fcm()" function; while k means clustering algorithm makes use of "kmeans()" function. Similarly, each developed algorithm works based on different principle. Detailled information on the procedural steps involved in implementation of each of the developed algorithms for the study are presented as follows.

1) *Thresholding Algorithm*

The development of the threshold algorithm for this study was done by setting a limit or threshold value, τ, which turns a gray-scale image into a binary image. Thus, when τ value is reached, the image will give white colour response otherwise black colour response. This occurs because brain tumour region is thicker than normal brain cell. Hence, any brain cell not as thicker as the tumour's region is not a tumour. Segmentation with this algorithm is therefore achieved by grouping all pixels between thresholds into one class. The mathematical expression employed in determining the threshold value, τ, for segmenting an image, $I(i, j)$, as given in [31] is:

$$I'(i,j) = \begin{cases} 1, \text{ if } I(i,j) > \tau \\ 0, \text{ if } I(i,j) \le \tau \end{cases} \quad (1)$$

where $I'(i,j)$ is a segmented image.

The step-by-step procedures for the developed threshold algorithm for this study are as follows:
Step 1: Select an initial threshold value, τ , ;
Step 2: Segment the image, $I(i, j)$, using τ in (1) to obtain 2 groups of pixels: I_1 which consists of all pixels with intensity values greater than τ and I_2 which consists of all pixels with intensity values less or equal to τ ;
Step 3: Compute average mean threshold or intensity, τ_{mean}, values: m_1 and m_2 for the pixels in I_1 and I_2 respectively;
Step 4: Compute a new threshold value; and
Step 5: Repeat step 2 through 4 until the difference between values of τ in successive iterations is smaller than a predefined paramter $\Delta\tau$.

2) *K-means Clustering Algorithm*

K-means clustering works by partitioning 'n' observations into 'k' clusters in which each observation belongs to the cluster with the nearest mean, which will serve as a prototype of the cluster. The algorithm groups the data by repeatedly finding the statistical mean value for each group after segmenting the image through classifying each pixel in the group with nearest mean. The distance between each pixel to each cluster, centers are computed by using Euclidean function. Single pixel is compared to all cluster centers using the distance formula. The algorithm works by minimizing an objective function known as squared error function given in [24] as;

$$J(V) = \sum_{i=1}^{c}\sum_{j=1}^{c_i}\left\| x_i - v_j \right\|^2 \quad (2)$$

where $\left\| x_i - v_j \right\|$ is the Euclidean distance between x_i and v_j, c is the number of cluster centers, c_i is the number of data points in i^{th} cluster. For a given image, the new cluster center is computed using the mathematical expression given in [24] as:

$$v_i = \left(\frac{1}{c_i}\right)\sum_{j=1}^{c_i} x_i \quad (3)$$

where c_i is as earlier defined.

The step-by-step procedures for the developed K-means algorithm for this study are as follows:
Step 1: Select $X = \{x_1, x_2, x_3, \ldots, x_n\}$ as the set of data points and $V = \{v_1, v_2, v_3, \ldots, v_c\}$ as the set of centers;
Step 2: Randomly choose the c cluster centers;
Step 3: Compute mean or center of the cluster;
Step 4: Compute the distance between each pixel or data point to each cluster center;
Step 5: If the distance is near to the center then move to that cluster. Otherwise, move to the next cluster;

Step 6: Re-compute the center; and
Step 7: Repeat the process until the center converges.

3) Fuzzy means Clustering Algorithm

The algorithm works by allowing one piece of data to belong to two or more clusters. Thus, fuzzy c-means (FCM) is an overlapping clustering algorithm. It assigns membership to each data point corresponding to each cluster center on the basis of distance between the cluster center and the data point. Data point near the cluster center does have more membership towards particular center. After each iteration, fuzzy membership, μ_{ij}, is computed using the mathematical expression reported in [24] as:

$$\mu_{ij} = \frac{1}{\sum_{k=1}^{c}\left(\frac{d_{ij}}{d_{ik}}\right)^{\left(\frac{2}{m-1}\right)}} \quad (4)$$

If d_{ij} and d_{ik} are substituted with $\|x_i - c_i\|$ and $\|x_i - c_k\|$ respectively while $\|*\|$ is any norm expressing the similarity between any measured data and the center. Thus (4) becomes;

$$\mu_{ij} = \frac{1}{\sum_{k=1}^{c}\left(\frac{\|x_i - c_j\|}{\|x_i - c_k\|}\right)^{\left(\frac{2}{m-1}\right)}}, \max_{ij}\left\{\left|u_{ij}^{(k+1)} - u_{ij}^{(k)}\right|\right\} \quad (5)$$

Subsequently, the fuzzy centers, V_j, are computed using the mathematical expression reported in [24] as:

$$V_j = \frac{\left(\sum_{i=1}^{n}(\mu_{ij})^m x_i\right)}{\left(\sum_{i=1}^{n}(\mu_{ij})^m\right)}, \forall_j = 1,2\ldots c \quad (6)$$

where V_j is the j^{th} cluster center, n is the number of data point, c is the number of cluster center, n is the fuzziness index $m \in [1,\infty]$, μ_{ij} is the membership of i^{th} data to j^{th} cluster center, d_{ij} is the Euclidean distance between i^{th} data and j^{th} data cluster center, x_i is the i^{th} of dimensional data. The iteration will converge when there is a termination criterion between 0 and 1 where k is the iteration steps.

The step-by-step procedures for the developed fuzzy means clustering algorithm for this study are as follows:

Step 1: Select $X = \{x_1, x_2, x_3, \ldots, x_n\}$ as the set of data points and $V = \{v_1, v_2, v_3, \ldots, v_c\}$ as the set of cluster centers;
Step 2: Randomly choose the c cluster centers;
Step 3: Compute the fuzzy membership, μ_{ij}, using (5);
Step 4: Compute the fuzzy centers, V_j, using (6); and
Step 5: Repeat steps 3 and 4 until minimum j is obtained.

D. Developed Hybrid Segmentation Algorithm

As mentioned earlier, two different hybrid segmentation algorithms, namely threshold-watershed algorithm and threshold-K means algorithm, were developed for the study by combining together the strentghs of both threshold and watershed algorithm in the first hybrid algorithm and threshold and K-means in the second hybrid algorithm. The hybrid algorithm were also implemented in MATLAB envoronment using MATLAB script. The hybrid algorithms thus make up for the inefficiency of the constituent algorithms. Threshold algorithm was first applied to separate the brain tumour region from the MRI scan in the two hybrid algorithms. Subsequently, watershed algorithm and K-means were applied on the resultant image in order to improve the image output. The sequence of operation of the two hybrid segmentations, threshold-watershed algorithm and threshold-K means algorithm, are shown in Fig. 3. The comparative performance evaluation results obtained when the five developed algorihms were evaluated are presented in the next section.

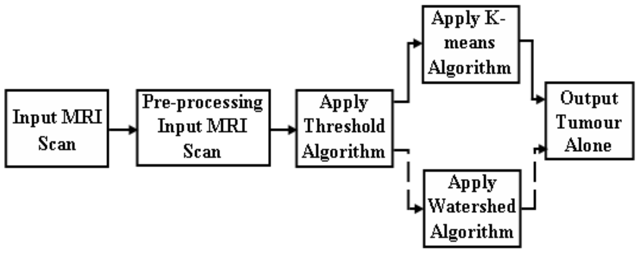

Fig. 3. Sequential operation for the developed hybrid algorithms.

IV. RESULTS AND DISCUSSION

In this section, the comparative performance evaluations results of the five developed segmentation algorithms were presented and discussed using figures. The section is divided into two subsections. In the first subsection, the results of the validations tests carried out on the developed segmentation algorithms were presented. Similarly, in the second subsection, the result of the comparative compression rate efficiency test conducted on the five developed segmentation algorithms was presented and discussed. Details on each of the two subsections as well as their respective importance are presented in the following subsections.

A. Validation Tests

In validating the reliability and accurate detection capabilities of the developed algorithms for this study, two separate validation tests were conducted on the developed algorithms. The results of the two validation tests carried out on the developed segmentation algorithms for this study are presented in this subsection. The essence of the tests is to determine the developed algorithm detection capabilities. In the first validation test, a non-brain tumor MR image, which served as control experiment, was tested with the developed algorithms to determine the developed algorithms false detection rates. The result of the control experiment or test, as shown in Fig. 4, shows that the false detection rate of

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each of the developed segmentation algorithms is zero percent. This implies that the detection capability rates for the five developed algorithms can be classified as true positive outcome. Hence, none of the developed segmentation algorithms gives negative false alarm or false positive outcome. The result indicates that the developed segmentation algorithms have high detection capability rates.

The true positive detection result therefore indicates that the developed segmentation algorithms can differentiate tumor brain tissues from non-tumor brain tissues. In addition, the true positive validation test result shows that if any of the developed segmentation algorithms is coupled with necessary early anti-tumor growth treatment, the resulting system or device will go along way in early detection and treatment of brain tumor. Furthermore, the true positive validation test result implies, according to findings of the studies presented in [32]-[34], that the developed algorithms for this study have high sensitivity and positive predicative values.

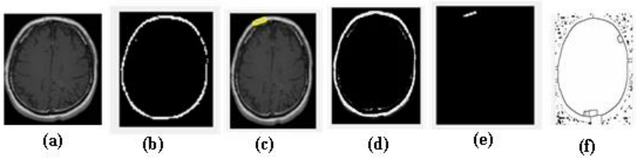
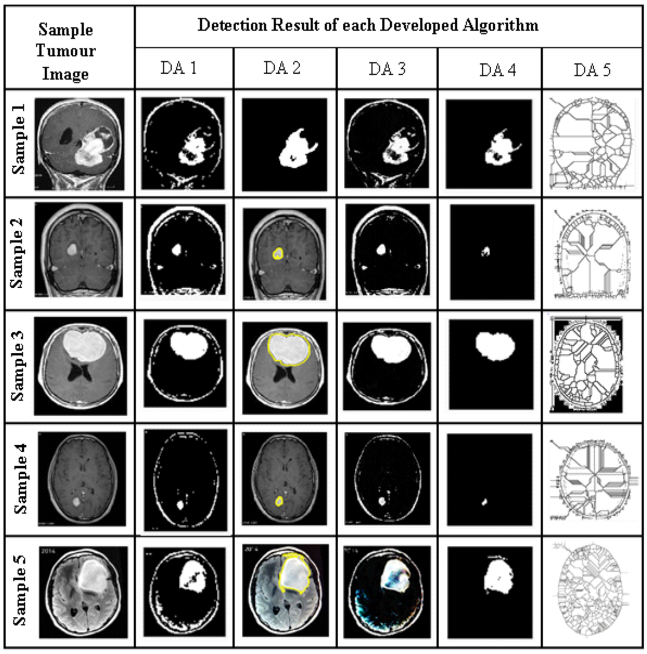


Fig. 4. Control experimental results (a) Original non-tumor image, (b) K means clustering algorithm result, (c) Threshold algorithm result, (d) Fuzzy c means clustering algorithm result, (e) Hybrid threshold-K means clustering algorithm result, and (f) Hybrid Threshold-watershed algorithm result

To further validate the detection capability of the developed segmentation algorithms, five tumor-infected brain tissues patients from a benchmark database were tested with each of the developed algorithms. The respective result obtained from each of the developed algorithms is presented in Fig. 5. The result shows that each developed segmentation algorithms is able to detect tumor-infected tissues in each of the images. This implies that each developed algorithm gives true positive result of each tested samples.

B. *Compression Rate Efficiency Tests*

The essence of this test is to determine the reduction rate capability of each of the developed segmentation algorithms in order to ascertain which of the algorithm has highest compression efficiency rate. This is because the smaller the size of an image or datum, the smaller the bandwidth requires for its transmission using wireless communication system. Thus, for effective brain tumor telemedicine services application, the size of the image needs to be reasonability reduced or small without deforming the brain tumor tissue. The result of the test as shown in Fig. 6 shows that the developed algorithms have different compression efficiency rates. In addition, the result of the compression rate efficiency as shown in Fig. 6 shows that the developed hybrid threshold-watershed (DA 5) algorithm has the highest compression efficiency ranging from 95% to 99% while the developed fuzzy c means clustering (DA 3) is next to it with compression efficiency ranging from 89% to 99% and the developed hybrid threshold-K mean clustering (DA 4) algorithm is the worst with compression efficiency rate ranging from 42% to 88%. Thus, based on DA 5 algorithm outstanding compression rate efficiency result, the algorithm is recommended as the best algorithm to be used for the telemedicine services application in brain tumor segmentation. Furthermore, the successful development of the five algorithms and the discovery of optimal segmentation algorithm ideal for brain tumor segmentation through experimental test have shown clearly that the set objectives of the study reported in this paper have been achieved.



KEY

DA 1:- K means clustering Algorithm
DA 2:- Threshold Algorithm
DA 3:- Fuzzy c means clustering Algorithm
DA 4:- Hybrid threshold-K means clustering Algorithm
DA 5:- Hybrid threshold-watershed Algorithm

Fig. 5. Detection capability of the developed segmentation algorithm

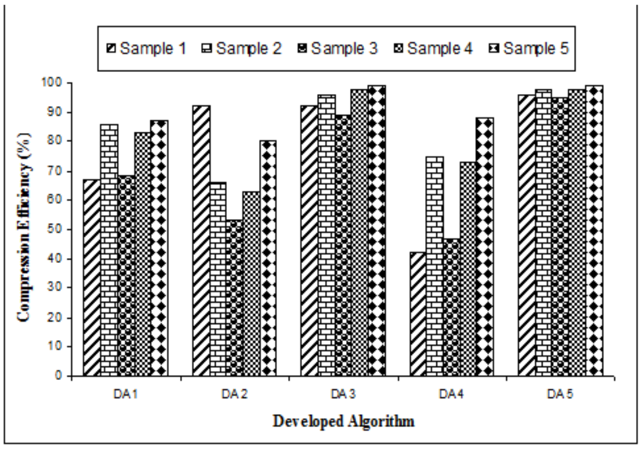


Fig. 6. Comparative compression efficiency of the developed algorithms

V. Conclusion

In this study, five different segmentation algorithms were developed. The developed algorithms when evaluated were able to segment the sampled image used to test them into normal or unaffected brain tumor tissue and abnormal or infected brain tumor tissue respectively with true positive outcomes. Comparative compression rate efficiency result conducted on the five developed algorithms shows that the developed hybrid threshold-watershed (DA 5) algorithm outperforms the other developed algorithms. The developed algorithm, (DA 5), is therefore recommended as the best algorithm to be used for brain tumor telemedicine services or application. The main focus of the future work will now be on how to develop telecommunication modules for the intended brain tumor telemedicine service or application.

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