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BRAIN TUMOR DETECTION BASED ON ASYMMETRY AND *K*-MEANS CLUSTERING MRI IMAGE SEGMENTATION

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Abstract

The brain is one of the largest and most complex organs of the human body. The brain can be a victim of numerous pathologies, including malignant tumours, strokes, infection, head injuries, and diseases. Brain tumour extraction and analysis are challenging tasks for medical image processing due to the complexity of images. Since the growth of tumours causes asymmetry in the affected parts of the brain, the proposed method calculates asymmetry based on the intensity difference between the left and right of a Mid-Sagittal Plane (MSP). One of the problems of this method appears when the brain object is rotated or tilted. A new method is proposed to solve this problem, by locating the Mid-Sagittal Plane in T1-weighted MRI images, based on the low intensity of Inter-Hemispheric Fissure (IF) region. In this paper, we have proposed segmentation of the brain MRI image using *K*-means clustering algorithm followed by a connected component label to determine the location and size of a tumour. The experimental result clearly shows the efficiency of the proposed method in comparison to the traditional systems in terms of computational cost and consumed time.

Keywords: Bilateral symmetry, Brain tumour, Connected component labelling, *K*-means clustering, MRI.

1. Introduction

A brain tumour is a growth of abnormal tissue cell inside the brain that grows by uncontrolled cell division. Normal cells grow in a controlled manner as new cells substitute old or damaged ones. Brain tumours are named after the cell type from which they grow. They are primary when they start inside the brain; those are the most common type occurring in children, or secondary tumours, which are commonly found in adults; these tumours caused by cancer that spreads to the brain from the breast, lung, or other parts of the body. The Treatment methods differ depending on the tumour type, size and location [1]. Medical image processing plays an important role in the detection of a brain tumour. Medical imaging modalities such as MRI (Magnetic resonance imaging), CT (Computed Tomography), Cranial ultrasound, etc. are used to depict the inner distribution of the physical attributes to the human body, which helps the physician to visualize the inner portions of the body. In this paper, the MRI scan is used to implement the system [2]. The MRI, one of the most commonly used tests in neurology and neurosurgery, is more comfortable and less harmful than CT scan for diagnosis. It does not affect the human body. Because it is noninvasive and does not require ionizing radiation such as x-rays, and it is also based on both the magnetic field and radio waves [3]. MRI provides exquisite details of the brain, spinal cord and vascular anatomy, and has the advantage of being able to visualize anatomy in all three planes: axial, sagittal and coronal, as shown in Fig. 1.

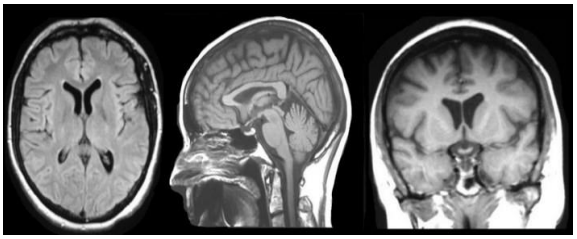
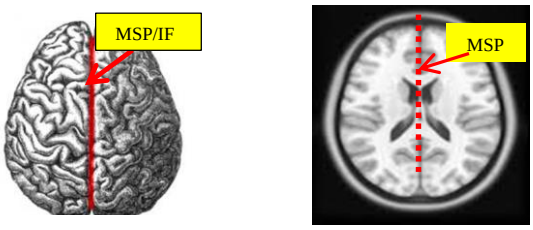


Fig. 1. Brain MRI scan image, from left to right the axial, sagittal and coronal slice images scan.

Healthy human brains tissues are present in an approximate bilateral symmetry. This symmetry is used to describe axial and coronal slices of the MRI brain image. Indeed, neuroradiologists often use the asymmetries of the brain as an indicator of the probability of pathologies and abnormality of the brain image [4]. The MSP for each brain slices provides a centre line for detecting bilateral asymmetries such as mass effects and unbalanced tissues density due to tumour growth or bleeding, etc. [5]. Locating of the mid-sagittal plane is the key for brain asymmetry analysis [6]. The Inter-Hemispheric Fissure (IF), which is the longitudinal dark and deep groove located in the midline boundary between the two cerebral hemispheres, is called MSP as shown in Fig. 2(a). The IF contains Cerebral Spinal Fluid (CSF), the low intensity of the CSF (with T1 weighted MR axial slice) or the intensity differences between the CSF in the IF and the surrounding tissue that gives a weak MR signal on MSP [7] as shown in Fig. 2(b). The brain tissues and the tumour cannot be recognized without image segmentation. Image segmentation, the most significant process in medical image analyses, is used to extract complex information from images [8].



(a) (b)

Fig. 2. The human brain, (a) Medial inter-hemispheric fissure visible in red line, (b) T1-Weighted MRI brain axial slice with indicated the MSP by red dotted line.

Various approaches have been proposed in the field of brain tumour detection, such as [2, 8, 9] these works relied upon the segmentation of the brain MRI image using the *K*-means clustering algorithm. Ahmed and Mohamad [10] proposed the method for the brain tumour detection by using *K*-means clustering, it combines Perona and Malik anisotropic diffusion model for image enhancement and *K*-means clustering technique for grouping tissues that belong to a specific group. Kabade and Gaikwad [3] tried to detect a brain tumour based on the combination of two algorithms: *K*-means and Fuzzy *C*-means; the thresholding is calculated for feature extraction of a brain tumour. Maya and Meenakshy [11] use a segmentation the tumour affected region of the brain by using histogram threshold and *K*-means clustering techniques. Yu et al. [12] tried to detect a brain tumour based on asymmetry comparisons of brain structural, pixel intensity distribution between the left and right sides of a Mid-Sagittal Plane (MSP), 3D Sobel edge operator and multi-scale correlation are computed to extract the optimal MSP. The drawback of this work is due to its sensitivity to image noises and deformations. Pimple et al. [13] tried to analyze bilateral symmetry axis for brain tumour detection by concentrating on segmenting the anatomical regions of the brain, and the number of detected edges (Robert, Prewitt and Canny) are computed to recognize the difference in edges' intensity. Hasan et al. [14] proposed an algorithm for detecting MSP in MRI brain images by using the Principal Components Analysis (PCA) method that is used for orientation detection of brain slice image.

The PCA method essentially attempts to transfer the coordinate of the original brain slice to a new coordinate system. The disadvantage of PCA lies in its inefficiency to distinguishing between the axis of symmetry and axis of orientation. Jayasuriya and Liew [7] proposed a method for extracting the MSP from MRI; this method is based on Computing the pixels intensity score by summing the intensity values along a straight line, keeping a track of the line rotation angle, and, finally, by choosing the angle with the minimum intensity score. Comparing our proposed method with Jayasuriya and Liew [7], the problem is, it is inaccurate in extracting the MSP because in some cases, the brain slice has locations of low-intensity pixels beside MS line, which indicates the presence of tumours or pathologies. Consequently, the score of pixel intensity will be low.

The main contribution of this work lies in locating the Mid-Sagittal Plane in T1-weighted MRI images. The structure of the paper is organized as follows: Section 2 presents the proposed method, which includes pre-processing, tilt estimate, bilateral

symmetry analysis and segmentation. Section 3 describes a proposed algorithm. Section 4 describes the experiments and results. Section 5 concludes the paper.

2. Proposed Method

The proposed method consists of two sections: first, detecting a tumour slice, by using bilateral symmetry to distinguishes a slice that contains tumour area, and second, detecting a tumour region, by applying *K*-means clustering followed by connected component labelling. Figure 3 shows the block diagram of the method system.

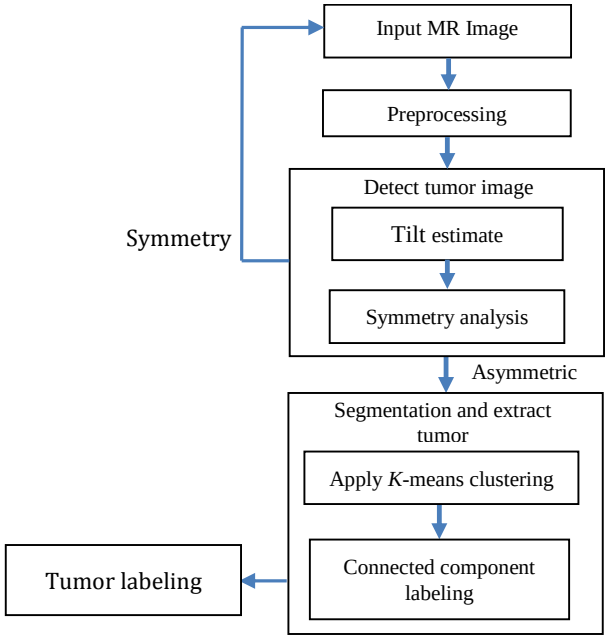


Fig. 3. Block diagram of proposed system.

2.1. Pre-processing

Image preprocessing is an important step in image diagnose. The preprocessing stage will convert the RGB input image to greyscale, remove the noise, and enhances the image. The Preprocessing proposed in this work consists of three steps: histogram equalization, median filter, and sharpening filter. Histogram equalization is a non-linear process uses techniques to improve the degraded image contrast. When histogram equalization is approached, the mean brightness of the processed image will be always the middle grey level regardless of the input mean [15]. The median filter can reduce noise while keeping feature edges intact, especially for salt and pepper noise. The Sharpening process is basically the application of a high pass filter to an image; this process is used for enhancing the intensity of transitions and removing blurring from images and highlighting edges. Image sharpening is to make the tumour edges, contour lines and image details clearer [16].

2.2. Tilt estimate

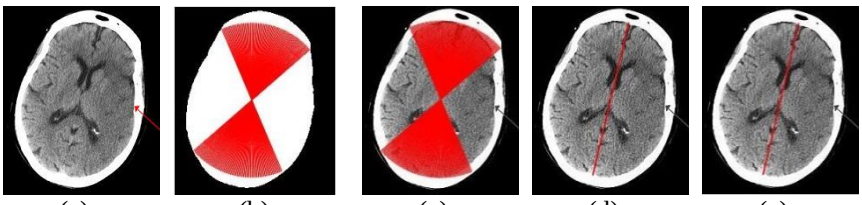
The symmetry axis on each brain slice provides a centre line for detecting bilateral asymmetries such as mass effects and lesions [5]. The proposed system uses a method to detect the rotational angle in the brain slices, by determining the MSP of the brain object. The proposed system is based on properties low-intensity value of the IF region. This paper proposes two stages to detect the MSP of the brain slice; in the first stage, the total intensity values are computed along the plane that passes through the centroid of the brain object's slice by applying several rotations angles from 0° to 180°, i.e., anticlockwise direction as shown in Figs. 4(b) and (c). The following three basic rotation matrices are used to rotate vectors by an angle θ about the *x*-, *y*-, or *z*-axis, in three dimensions [17]:

$$R_x(\theta) = \begin{bmatrix} 1 & 0 & 0 \\ 0 & cos\,\theta & -sin\,\theta \\ 0 & sin\,\theta & cos\,\theta \end{bmatrix} \quad (1)$$

$$R_y(\theta) = \begin{bmatrix} cos\,\theta & 0 & sin\,\theta \\ 0 & 1 & 0 \\ -sin\,\theta & 0 & cos\,\theta \end{bmatrix} \quad (2)$$

$$R_z(\theta) = \begin{bmatrix} cos\,\theta & -sin\,\theta & 0 \\ sin\,\theta & cos\,\theta & 0 \\ 0 & 0 & 1 \end{bmatrix} \quad (3)$$

where the R_x, R_y, and R_z represent the *x-axis* rotation, *y-axis* rotation, and *z-axis* rotation respectively, θ is a rotation angle. In the second stage, the line with mid intensity value is selected among the set of equal intensity lines as shown in Fig. 4(d). Finally, a multi-shift process around selected mid-line is applied as shown in Figs. 4(e) and (f) respectively and an estimate of the best-fit line is determined by taking the minimum intensity score between the left and right sides.



(a) (b) (c) (d) (e)

Fig. 4. Extracted mid-sagittal plane from T1-Weighted MRI brain axial slice. (a) Original image, (b) Binary image with Filling holes, with indicated the set of equal intensity longer lines by red lines, (c) Greyscale image with indicated the set of longer intensity lines, (d) Select midline from set lines, (e) Optimize the position of the plane by applying left and right shifting respectively.

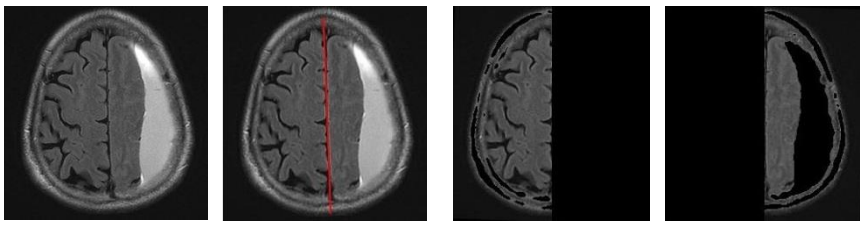
2.3. Bilateral symmetry analysis

The healthy brains are usually bilateral symmetry, i.e., the regions between the MSP are similar in shape and relative location, while areas affected by a tumour or pathology are not symmetrical [18]. The bilateral symmetry features can be extracted from the image based on region [19]. The realization of the symmetry of the object shape is very useful in pattern analysis. In this paper, the Bilateral Symmetry can be calculated by dividing the area of axial, or coronal slices of

objects into two sides according to the MSP, then the intensity value between two sides are calculated. Consequently, the symmetry score indicates the similarity value between the left and right sides of the brain slice image. In an asymmetrical slice, the two sides do not match in size or shape, this is because of the mass effects and imbalances tissues density due to tumour growth or bleeding as shown in Fig. 5. The mathematical formula used to determine the asymmetry value is given by below:

$$Asymmetry = (\frac{\Delta p}{p}) \times 10 \quad (4)$$

where Δp is an intensity difference between the two sides, p is a total intensity count of a brain slice.



(a) (b) (c) (d)

Fig. 5. Brain MRI slice image. (a) Brain haemorrhage, (b) MRI brain axial slice with indicated the MSP by red line, (c) and (d) Illustrates asymmetry between two sides of brain image.

2.4. Segmentation algorithms

Image segmentation involves image partitioning into multiple segments. In this paper, we use the *K*-means clustering and connected components algorithms to detected and determine the location of a brain tumour respectively.

2.4.1. K-means clustering

K-means clustering is one of the popular algorithms in clustering and segmentation; it is an unsupervised clustering algorithm to classify or to group the input data points based on attributes/features into multiple classes (*K* groups). *K* is a positive integer number. The grouping is done by minimizing the distances between data and the corresponding cluster centroid. The purpose of clustering analysis is to collect objects, which are "similar" in one cluster and "dissimilar" to the objects belonging to different clusters. The *K*-means algorithm basically includes the following steps [20]:

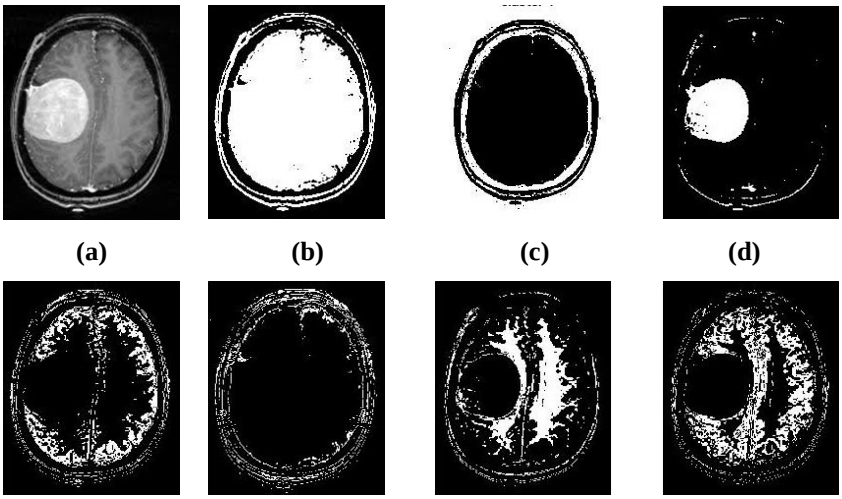
- Initialization: which defines the number of clusters *K*, so-called centroid, and randomly creates the position of the centres for each cluster.
- Assigns each data point of the data set to the nearest cluster centre, by calculating the distance between dataset and cluster centre by applying Eq. (5) and
- The cluster centroid is updated for the new clusters that assigned new data points and other clusters that lost data points. Steps 2 and 3 are repeated until

there is no significant change of data points between the *K* clusters, i.e., when the centre does not move.

$$F = \sum_{j=1}^{K} \sum_{i=1}^{n} (x_i^{(j)} - c_j)^2 \tag{5}$$

where $x_i^{(j)}$ denotes data point, c_j is the cluster centre and n is the number of the data point.

The quality of the final clustering results will depend on the selection of the appropriate number of clusters *K*. According to Rousseeuw [21], in this paper, the Silhouette method see it is used to analyze the clusters' results and to choose the useful *K* cluster. Figure 6(c) through (h) shows the run *K*-means clustering algorithm several times, each time with a different value of *K*. Figure 7 shows the graph of mean silhouette value versus *K*. The range values of mean silhouette lie between 0 and 1. The optimal cluster result is based on the highest peak in a mean silhouette plot, was found at *K* =2. Thus, the cluster of Fig. 6(d) indicates the best result of clustering.



(a) **(b)** **(c)** **(d)**

(e) **(f)** **(g)** **(h)**

Fig. 6. (a) Original image, (b) Output image after thresholding, (c)-(h) *K*-means clustering results from *K* =1 to *K* = 6 clusters.

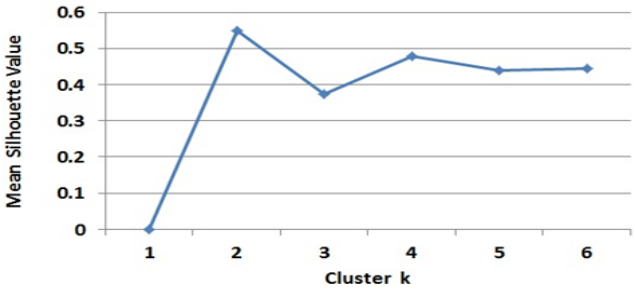


Fig. 7. Cluster *K* vs. mean silhouette value.

2.4.2. Connected component

In image processing, a connected components algorithm detects all the pixels regions in an image which are connected to each other, and have similar pixel intensity values by scanning an image pixel by pixel, *i.e.*, For a binary image all regions of adjacent pixels, that share the same set of intensity values $V = \{1\}$ represents an object and other set values $V = \{0\}$ represent a background of an image. For example, the binary image shown in Fig. 6(a), contains three binary segments of connected components. The extract of the connected components object based on applying the following iterative procedure [22]:

$$X_k = (X_{k-1} \oplus B) \bigcap A, \quad k = 1,2,3,... \tag{6}$$

where A is a test image that contains one or more connected components, B is an appropriate structuring element, X_o is an array that has the same size of A, whose elements are zeros (background), except the points of the connected components in A, which correspond to ones (foreground), as shown in Fig. 8. Connected component labelling is the process of marking each connected component with a distinctive label, and assigning each one, a unique label, then creating a label matrix [23]. The connected component libelling is a fundamental module in medical image processing; it can be used effectively to improve the turn-around time of many medical diagnoses and procedures [24].

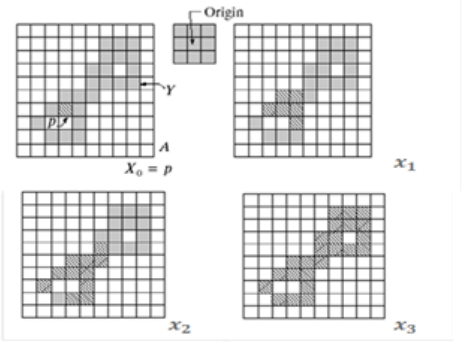


Fig. 8. Extraction the connected components.

3. Proposed Algorithms

The algorithms used in the proposed system are:

3.1. Algorithm of preprocessing image is implemented in following steps:

- Input the test MRI axial brain image from the user.
- The convert RGB colour space into greyscale by applying luma component of YCbCr colour space [25] , where the weighted sum of the R, G, and B components are: $Y = 0.2989 \times R + 0.5870 \times G + 0.1140 \times B$.
- Eliminate noise and improve image quality, by applying the median filter and histogram equalization.
- Enhance the intensity transitions result of the grayscale image, by applying the sharpening filter.
- Calculate the threshold of the grayscale image by applying Otsu's method [26].

- Convert the grayscale image into a binary image based on the threshold.

3.2. An algorithm of detected MSP for tilt estimates the brain object slice:

- Convert RGB image to greyscale and binary images by applying algorithm 3.1
- Fill the holes of the binary image by using an algorithm based on morphological reconstruction [27].
- Compute the centroid of the brain slice object image.
- Generate a straight line that passes through the centroid and rotates from 0°to 180° by 1° degree increment.
- For each rotate angle θ^o do.
- Compute the line intensity score by adding the intensity binary values (one's) along the line and keeping a track of the angle.
- End for.
- Sort the lines intensity scores with angles θ^o in ascending order.
- Choose a set of lines' scores with equal intensity values and maximum repetition.
- Choose the angle θ^o and intensity score that represents the middle value among a set of equal intensity lines.
- On the grayscale image, computer line intensity L1 at angle θ^o.
- On the grayscale image, perform a two-shifting process around θ^o, between -1 to -10 and 1 to 10 and compute the intensity score of these shifting L2 and L3 respectively.
- Estimate the best-fit line by taking the minimum intensity score between L1, L2, and L3.

3.3. Algorithm for K-means clustering segmentation and extract the tumour:

- Convert RGB image to grayscale by apply algorithm 3.1.
- Give the initial no of cluster value as 6.
- Compute the *K*-means clustering by applying the steps in section 6.1 [20].
- Analyses the clusters results and the candidate the useful *K* cluster by apply Silhouette method [21].
- Separate brain objects from the image background by performing the connected components approach by applying Eq. (6).
- Performing connected components label to detect tumour location.

4. Experiments and Results

In this paper, all the stages of the proposed system are implemented in MATLAB R2016A with a set of 30 brains MRI images, all the 30 images are stored in JPEG format in different sizes. The proposed system consists of two stages: first, the detection of tumour slices, by testing the tilt process and bilateral symmetry that classifies the image into two types, tumour and normal brain images, For testing the MSP's detecting

algorithm, Fig. 9(a) shows image brain slice containing tumour, Fig. 9(d) shows the process of locating the rotation angle by using the middle-intensity value. The maximum number of the repetitions for a line with an intensity score value of 192, is 84 times, as indicated in Fig. 9(d), consequently the rotation angle of middle-intensity lines (84/2=42) is 89°. The image is shown in Fig. 9(e), represents the result of the MSP by red a line.

Second, detection of the tumour region, by applying *K*-means clustering and using connected components label to detect tumour location. Figures 9(f) through (k) show the run *K*-means clustering algorithm. The optimal cluster result at the highest peak in a mean silhouette plot is found at $K = 2$. Based on the result of cluster *K* followed by the connected component label the tumour is extracted as shown in Fig. 9(l).

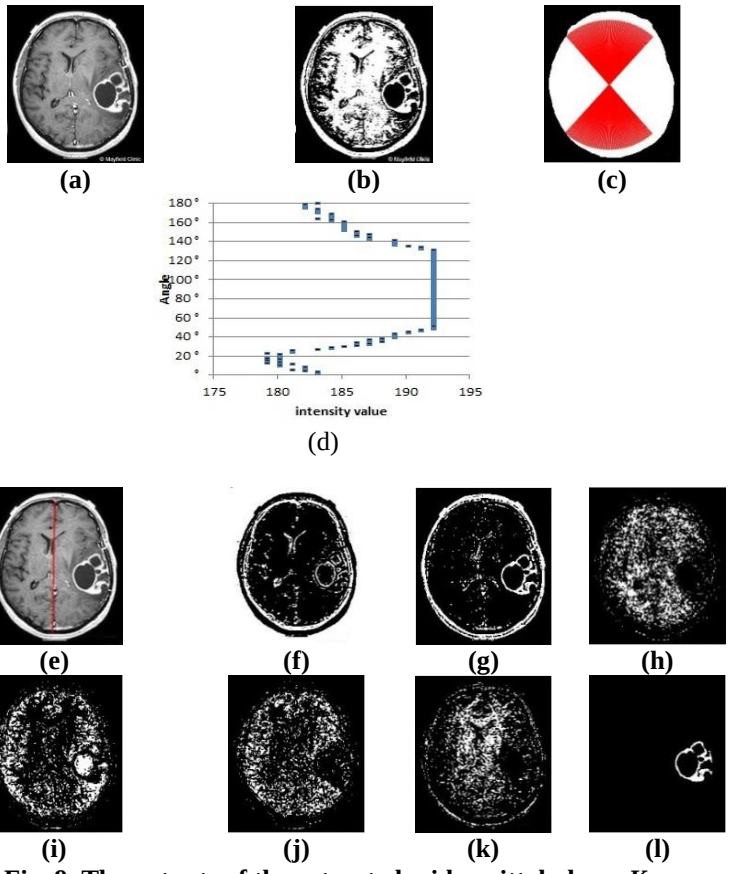


Fig. 9. The outputs of the extracted mid-sagittal plane, *K*-means clustering, and detected tumour lesion, (a) Original axial slice image scan, (b) Output image after thresholding, (c) Binary image with filling holes, with indicated the set of equal intensity longer lines by red lines, (d) Performance analysis intensity values with rotation angles from 0°to 180° by 1° degree increment, (e) Output image with detected MSP (f)-(k) *K*-means clustering results from $K = 1$ to $K = 6$ clusters, (l) Labelling of the detected tumour.

For testing the bilateral symmetry analysis, the intensity difference value between two sides of the MSP is calculated by using Eq. (4). The experimental

results show that the values of asymmetry index of brain tumours fall within the values greater than 0.20, as shown in Fig. 10. Figure 11 shows some examples of the results proposed system. The GUI of the proposed system is shown in Fig. 12.

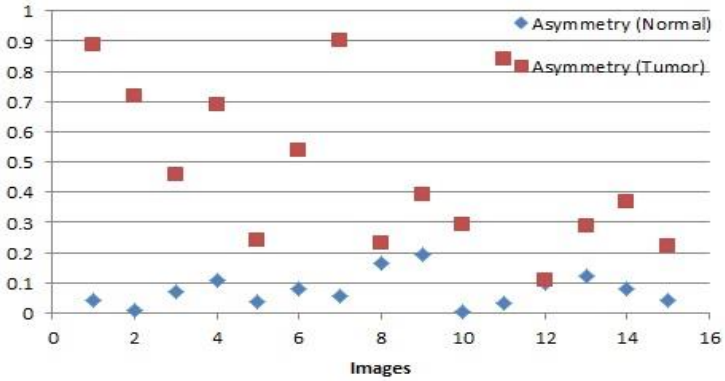


Fig. 10. Asymmetry values for both tumour and normal brain images.

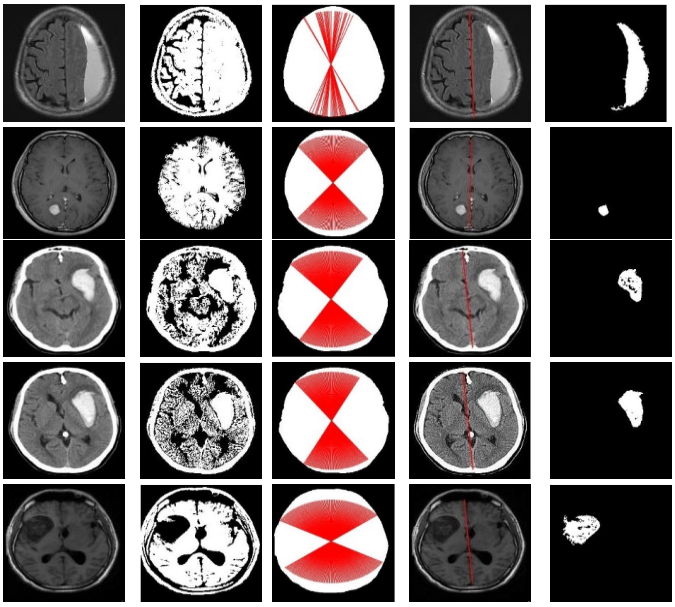


Fig. 11. Examples of Extracted Mid-Sagittal Plane and detected tumor lesion from T1-Weighted MRI brain axial slice, (first column) Original images, (second column) Output images after thresholding, (third column) Binary images with Filling holes, with indicated the set of equal intensity longer lines by red lines, (forth column) Output images with detected MSP, (fifth column) Labelling of the detected tumour.

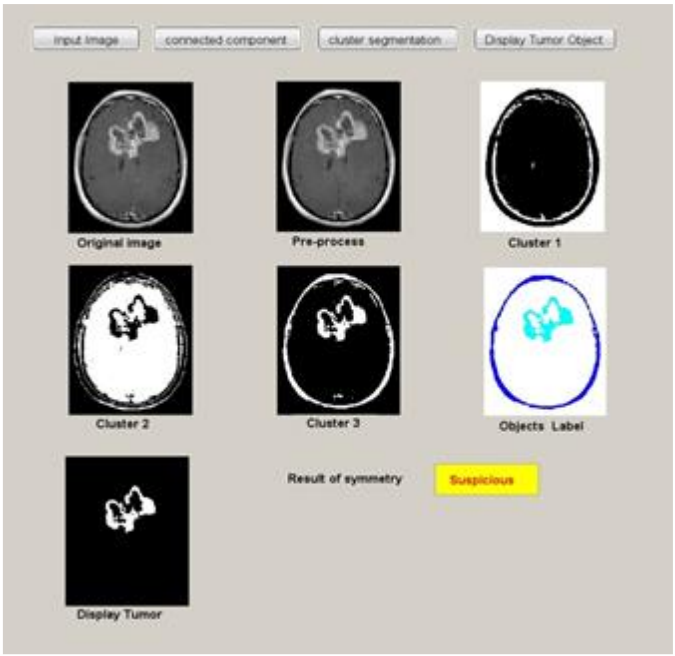


Fig. 12. The GUI of the detection of brain tumour.

5. Conclusions

The objective of this paper is the detection of brain pathologies such as a tumour and brain haemorrhage based on two sections, bilateral symmetry, and *K*-means clustering followed by connected component labelling. The experiments show good results in detecting the asymmetry index, as shown in Fig. 5. There is one disadvantage of this method which appears when the patient's head is tilted during the scanning process; to solve this problem, by detecting the MSP of the brain slice based upon properties of the low-intensity value of the IF region, as shown in Fig. 9. The purpose of converting the original image into the binary image with filling holes as shown in Fig. 4(b) is getting accurate results from the computation of the highest total intensity lines, hence minimizing the differences in intensity values between the brain tissues or areas of tumours. The proposed algorithm gives the best results when applied to pathological images with a mid-plane inter-hemispheric fissure. However, in hard pathological images such as a big tumour, the IF may swerve from its mid-plane and take a curved shape as shown in Fig. 9(a), although to a non-planar of the inter-hemispheric fissure, the asymmetry index score increases. The MRI image segmentation is used to detect tumour location using the *K*-means clustering algorithm. Silhouette analysis is a useful criterion to asses a candidate *K* for clustering. The proposed system provides the best results when the connected component labelling process is applied too. As mentioned by Jayasuriya and Liew [7], comparing our proposed method with the method in the precision of the method is 90% in the normal brain slices and decreased to 83% especially for abnormal brain slice, while in our proposed system has achieved the highest average precision, which is 94%.

Nomenclatures

B	Structure element (Fig. 8) size 3×3, pixels
c_j	Cluster centre
F	Distance between cluster center and the points in the image, pixel
K	Number of Clusters the range values (1,2,..,6)
P	Total intensity of a brain slice
R_x	x-axis rotation
R_y	y-axis rotation
Rz	z-axis rotation
X_k	Iterative procedure (Fig. 8) size n×m, pixels
$x_i^{(j)}$	Data points

Greek Symbols

Δp	Intensity difference between the two sides of brain slice
θ	Rotation angle, deg.

Abbreviations

CSF	Cerebral Spinal Fluid
CT	Computed Tomography
GUI	Graphical User Interface
IF	Inter-Hemispheric Fissure
JPEG	Joint Photographic Experts Group
MRI	Magnetic Resonance Imaging
MSP	Mid-Sagittal Plane
RGB	Red Green Blue

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