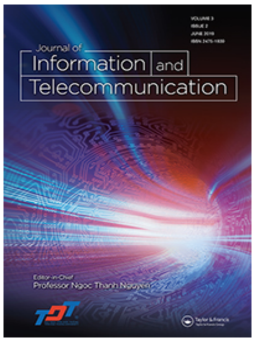

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A Hounsfield value-based approach for automatic recognition of brain haemorrhage

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ABSTRACT
Brain haemorrhage is a critical problem with the high mortality rate that is typically diagnosed based on MRI/CT images. A lot of research is gaining attention recently for its high performance in image recognition of brain haemorrhage. In this paper, we propose a new approach, which can automatically detect, diagnose and classify of brain haemorrhages. Our proposed method focuses on analysing brain haemorrhage regions from images of brain haemorrhage. We rely on HU values to detect haemorrhage regions and determine the bleeding time of brain haemorrhages. It is useful for supporting doctors in timely treatment. Our experimental results show that the accuracy of detection of brain haemorrhages is 100% and the classification of brain haemorrhages achieves the accuracy of 93.33%.

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KEYWORDS
Medical image; DICOM images; Hounsfield value; brain haemorrhage

1. Introduction

In recent years, there are many researchers in Vietnam and other countries in the world related to the medical field, particularly in detecting, diagnosing and classifying disease in humans. During treatment, subclinical results outcome is very important for doctors to detect, diagnose and treat, especially related to the brain haemorrhage. The techniques of computed tomography (CT) (Mayo Clinic, 2016), magnetic resonance imaging (MRI), and digital subtraction angiography (DSA) are very helpful in supporting to detect the brain haemorrhage regions. However, there are about some hundred slices (images) for each case of CT/MRI scan depending on the scan region and the thickness of the slices. Hence, the doctors spend a lot of time looking at all images and finding abnormalities in each CT/MRI image to provide the best diagnosis and treatment. To improve this problem, Bhavna Sharma and K. Venugopalan proposed an automatic segmentation of brain CT scan image to identify haemorrhages. Their method was comprised of three stages: pre-processing performed on the brain CT images, the histogram based centroids initialization, and finally the K-means clustering algorithm was applied on the resultant image to segment the image in different clusters based on the intensity values of pixels (shown in Figure 1).

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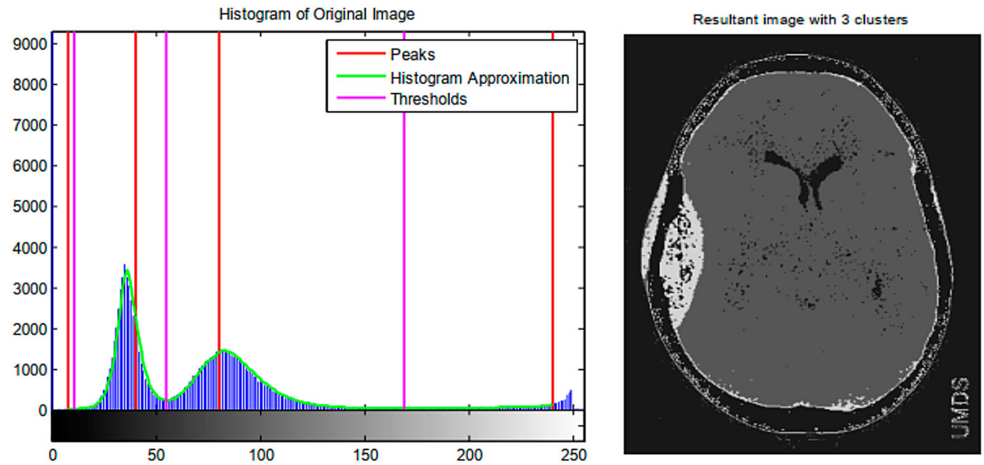

Figure 1. Thresholds of histogram and segmented image (Sharma & Venugopalan, 2012).

Another method is introduced by Sumijan, Harlan, and Wibowo (2017) using the Hybrids Otsu method for feature region and mathematical morphology to calculate volume Haemorrhage Brain on CT-scan image and 3D reconstruction. In this research, the authors extracted the bleeding areas of the brain based on a hybrid of the Otsu algorithm, morphological features algorithm. The 3D reconstruction of the bleeding area from a 2D slice is implemented by a linear interpolation approach (Figure 2).

Al-Ayyoub, Alawad, Al-Darabsah, and Aljarrah (2013) proposed another method of the classification of brain haemorrhages. The authors likewise succeeded with automatically detecting and classification of brain haemorrhages. The implemented system consists of several stages including image pre-processing, image segmentation, feature extraction, and classification. However, the authors used the Ostu method (Otsu, 1975) to detect brain haemorrhage regions. Besides, the classification of brain haemorrhages is based on a number of features such as the haemorrhage dimension (in pixels), the focal point, the area and shape of the haemorrhage region (Figure 3).

From the above methods, we can see that their methods are still limited in the reference of the experienced doctors and medical imaging specialists to determine the duration of bleeding. In additions, their methods are used to the Otsu method, which is a well-known and widely method. However, this method depends on a threshold of the greyscale. To determine this threshold, the authors often convert the CT/MRI images to greyscale images leading to affect image quality and threshold value. Besides, the

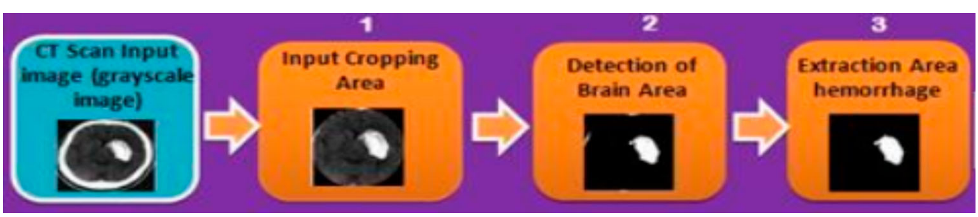

Figure 2. Model of the hybrids Otsu method (Sumijan et al., 2017).

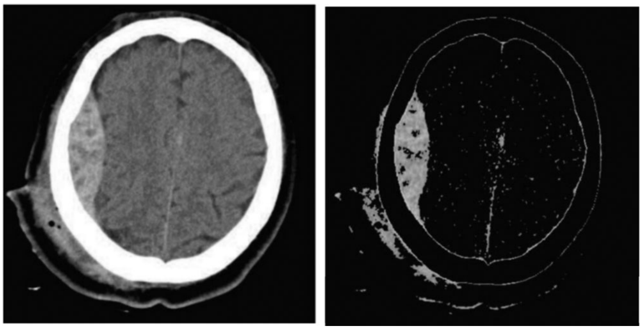

Figure 3. The result of segmentation of brain haemorrhages (Al-Ayyoub et al., 2013).

image is corrupted by additive noise or the sharp valley of the greyscale histogram is degraded leading to a segmentation error. Moreover, the limitation of the Otsu method is its assumption of binary classes. It partitions the greyscale histogram to two classes. If we consider images having more than two classes of segmentation, the Otsu method will not be appropriate.

In order to overcome these limitations, we propose a system that can automatically detect, diagnose and classify brain haemorrhages in patients from CT/MRI medical images. Our method implements a haemorrhaging segmentation based on Hounsfield Unit (HU) (Hounsfield, 1980) without performing image pre-processing. HU is computed easily and quickly from the values of Rescale Intercept and Rescale Slope available in medical image files of DICOM format (Clunie, 2014; Mustra, Delac, & Grgic, 2008). This is also a new contribution to our research. Additionally, the using of HU values is well suited for medical professionals in medical imaging. Furthermore, our method can accurately determine whether there is the brain haemorrhage. In particular, we determine the duration of the brain haemorrhage, which is critical to doctors' decision-making for a patient's treatment. This is a new idea of our approach compared to preceding research.

There are many types of brain haemorrhage such as epidural, subdural, subarachnoid, cerebral, and intraparenchymal haemorrhage … In this work, due to limitations in dataset collection, we focus on the four types of brain haemorrhages namely epidural haematoma, subdural haematoma, subarachnoid haemorrhage and intracerebral haemorrhage (Johnson, 2006; Ngoc Hoa & Van Phuoc, 2010; Josephson, White, Krishan, & Al-Shahi Salman, 2014) as shown in Figure 4. These considered haemorrhage types have many differences in aspects of visual features such as the size of the haemorrhage region, its

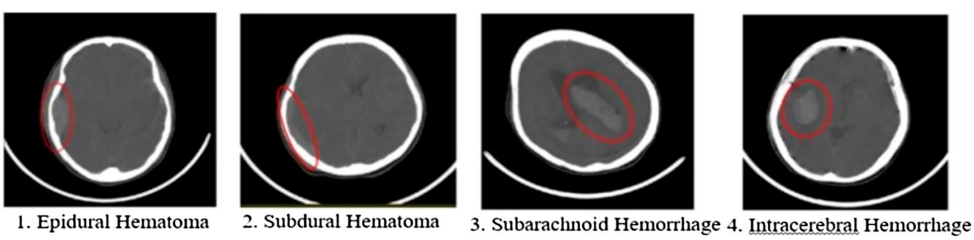

Figure 4. CT images of the four types of brain haemorrhages.

shape, and its location within the skull … We also collect opinions from experienced doctors and specialists in the field of medical imaging in CanTho Medicine University Hospital to help us identify and distinguish the four popular types of brain haemorrhages from our data sets.

2. Proposed methodology

We used the interactive learning machine to create a training dataset with the help of doctors in classifying of the brain haemorrhages from a set of MRI images with DICOM format. We collect a dataset consisting of MRI images of patients involved in one of the four types of brain haemorrhage. These images are classified and labeled as one of the different types of the brain haemorrhage by experts or specialist doctors from the Cantho Medicine University Hospital in CanTho, VietNam. The set of features extracted from these images together with the labels assigned to them are stored in a training database. From experimental results with the testing dataset, our method can identify and classify the area of the brain haemorrhages. It also determines the bleeding timing of brain haemorrhages. The KNN classifier (Altman, 1992) is applied in the proposed method. Our method is summarized as follows: we first compute HU values to have image segmentation and determine areas of brain haemorrhages. We then extract and save features in the training dataset. Our method was described in Figure 5 including the following stages:

- *Stage 1*: The determination of the HU value: The most valuable feature of the DICOM image data is ability to store a lot of the necessary information for the computation of the HU values. The HU value is computed by Equation (1).
- *Stage 2*: Image segmentation: after computing the HU values of image points, we detect areas of brain haemorrhages by image segmentation based on HU values, which are in the range from 40 to 90 as shown in Table 1.
- *Stage 3*: Determination of brain haemorrhage regions: we remove un-related regions and image regions due to some effects of CT technique such as the cortex.

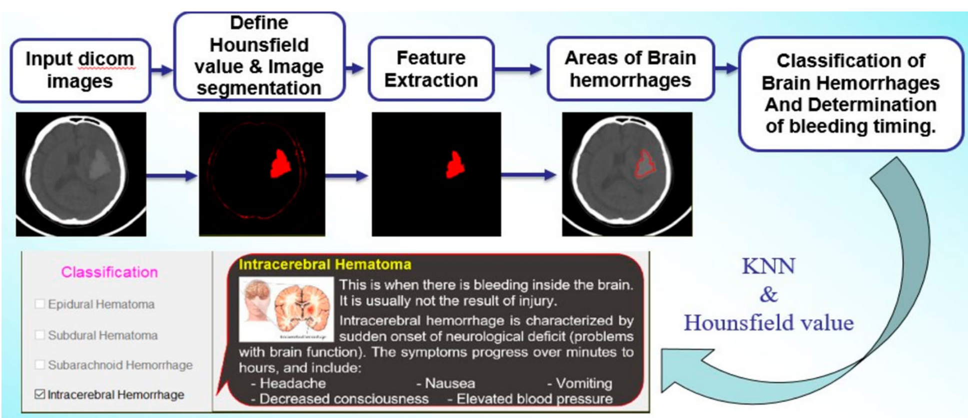

Figure 5. Model of our proposed method of automatic detection and classification of brain haemorrhages.

Table 1. The Hounsfield value (HU) of common substances (Wolfgang, 2010).

Substance	HU
Water	0
Bone	1000
Air	−1000
Grey matter	35–40
White matter	20
Blood	40–90
Calcification	more than 120

- *Stage 4*: Feature extraction: we extract the important features from the areas of brain haemorrhages as shown in Section 2.4. These features consist of HU, the smallest, greatest and average of HU, the centre of the brain haemorrhage, and the size of the brain haemorrhage.
- *Stage 5*: Classification of brain haemorrhages: from the extracted features, we apply the KNN algorithm using the Euclidean distance to identify brain haemorrhages (Figure 10).
- *Stage 6*: Determination of timing of haemorrhage: the bleeding timing was considered to support doctors making timely treatment for patients. Based on the HU values, we estimate the bleeding timing as presented in Section 2.6.

The following is the related work used in our proposed method.

2.1. Determination of the Hounsfield values (HU)

Our method directly processes the source data on medical images formatted according to the Dicom standard (Mustra et al., 2008) without transforming into JPG, BMP, PNG, etc. Therefore, we do not need to consider pre-processing these images. It aims at saving useful information from the DICOM images. Therefore, our method can save the useful information to determine the HU for the detection of the brain haemorrhage and bleeding timing. This is a new idea and a contribution to our approach. To compute the HU, we apply a linear transformation by the following equation (Fanning, 2006):

$$HU = Pixel\_value * Rescale\_slope + Rescale\_intercept, \tag{1}$$

where Pixel_value is the value of each image point, the Rescale_slope and Rescale_intercept are the parameter values provided in DICOM images. We used the dicominfo() function in MATLAB (Ferreira, 2009; Smith, 2009) to access these values (Figure 6).

2.2. The image segmentation for detecting a brain haemorrhage regions

After computing HU, we make an image segmentation based on Table 1. The result of the image segmentation based on HU to detect a brain haemorrhage region as shown in Figure 7. The Hounsfield values are in the range of 40–90 (Buzug, 2008; Heymsfield, 2005; Prokop, 2003) to coincide with the Hounsfield values of brain haemorrhages.

Filename: 'D:\Brain_Hemorrhages\2-I150'
FileModDate: '07-Jan-2017 03:41:49'
Format: 'DICOM'
Width: 512
Height: 512
ColorType: 'grayscale'
Modality: 'CT'
Manufacturer: 'Philips'
InstitutionName: 'BV TRUONG DAI HỌC Y DUOC CAN THO'
InstitutionAddress: 'CAN THO, VIETNAM'
StudyDescription: 'SO NAO'
Rows: 512
Columns: 512
RescaleIntercept: -1024
RescaleSlope: 1
…

Figure 6. The information for the computation of HU in CT image by DICOM standard.

2.3. Brain haemorrhage region extraction

After the image segmentation, some extracted features are close to the cortex since they are mapped by X-rays. Therefore, we removed these features such as the cortex and other features outside the brain haemorrhage area as shown in Figure 8. The Hounsfield values are chosen in the range of 40–50 (Gong et al., 2007) that coincide with HU of haemorrhages.

2.4. Feature extraction

In this Section, we extract the features for identification of brain haemorrhages. These features include:

- The image points with HU in the range of 40–90 as represented in Table 1.

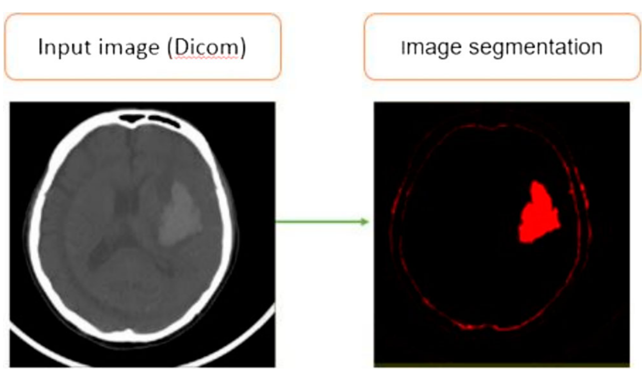

Figure 7. The HU-based segmentation from a DICOM image to detect a brain haemorrhages regions.

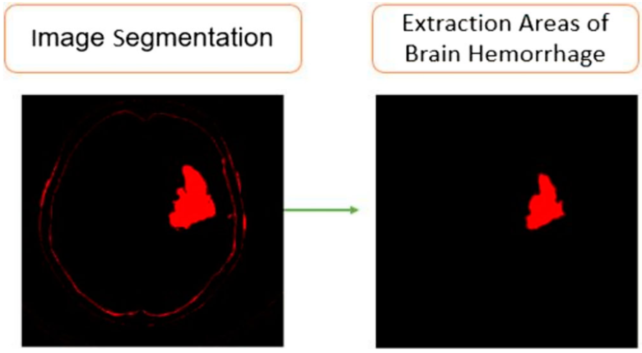

Figure 8. A brain haemorrhage region is determined applying HU-based segmentation.

- The smallest, greatest and average of HU in the haemorrhage region. These values are very important for the determination of the bleeding timing. The determination of the bleeding timing contributes to assisting doctors and medical experts in choosing the proper and timely treatment for patients.
- The centre of the brain haemorrhage: the determination of the centre of the haemorrhage region helps to detect the brain haemorrhage position in the cortex. This makes the classification more accurate.
- The size of the brain haemorrhage (computed by pixel): the size of the brain haemorrhage region is also important since it helps to figure out the size and the seriousness of the brain haemorrhage.

We extract some important features from the regions of the brain haemorrhages and using the Regionprops tool in MATLAB as shown in Figure 9.

2.5. Detection and classification of the brain haemorrhages

After extracting and storing the features from medical images, we compared these features with the features in our training database set. We used KNN algorithm (Deza & Deza, 2009; Altman, 1992) for the classification of brain haemorrhages since it is one of the most widely used classification algorithms. This algorithm is simple and easy to implement. Moreover, it is a supervised learning algorithm and perceived as a simple

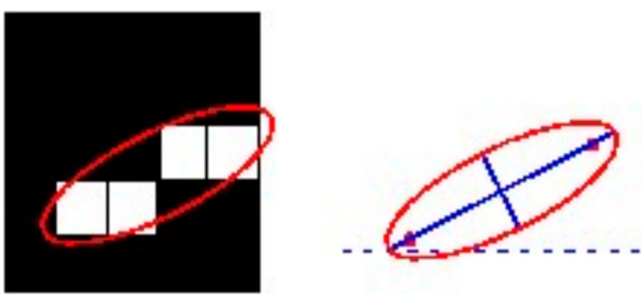

Figure 9. Orientation parameters using the Regionprops tool in MATLAB.

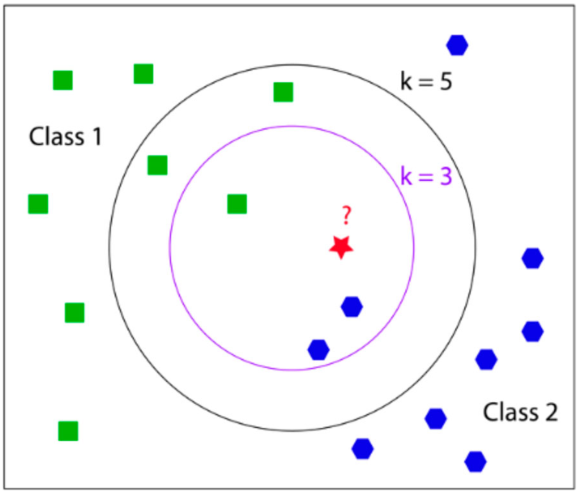

Figure 10. An Illustration of the KNN algorithm.

but powerful classification, even for complex applications, capable of yielding high-performance results (Dzuida, 2010). In this research, the various k-values in KNN classifier are used and compared with each other. Experimental results of accuracy show that the value of K = 3 gives the best classification accuracy (Figure 10).

In literature, there are several other types of distance functions, such as cosine similarity measure, Minkowsky, correlation, … However, there is no a comparative study of examining the distance function effect on the performance of k-NN classifier for the datasets of medical domain. We use the Euclidean distance measurement since it is based on measuring the distances between the test data and each of the training data to decide the final classification output. The distance between two data points is decided by a similarity measure (or distance function) where the Euclidean distance is the most widely used distance function. The Euclidean distance is computed by Equation (2) (Deza & Deza, 2009):

$$d(p, q) = \sqrt{(p_1 - q_1)^2 + (p_2 - q_2)^2 + \cdots + (p_n - q_n)^2} = \sqrt{\sum_{i=1}^{n} (p_i - q_i)^2}, \qquad (2)$$

where p and q are the two typical vectors; p_i and q_i are their elements ($i = 1, \ldots, n$).

The results are represented as in Figure 11.

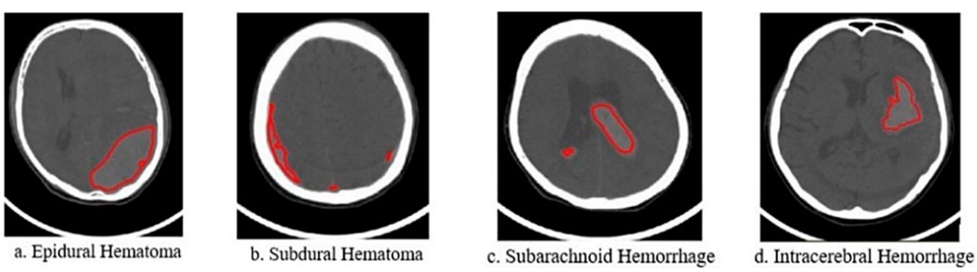

Figure 11. The results of detection and classification of brain haemorrhages.

2.6. Determination of timing of the brain haemorrhages

The determination of the bleeding timing plays a vital role in deciding the proper therapeutics for the treatment. In this research, we estimate the bleeding timing based on the average Hounsfield value of the brain haemorrhage region. The bleeding timing of the brain haemorrhage is divided into three levels (Brant & Helms, 2007; Thust, Burke, & Siddiqui, 2014):

- Hyperacute: the most recognizable hyper attenuating phenomenon (within 3 days) with HU in the range of 50–70 compared to the normal brain's Hounsfield values (HU in the range of 18–30).
- Acute: the dark level is relatively reduced from day 3 to day 14 with HU less than 40.
- Chronic: homogeneity on the region of haemorrhage from the day of 14 to 21 makes the injured region of brain difficult to distinguish due to Hounsfield is a half of the normal region of the brain (HU from 18 to 30).

The bleeding timing was considered to support doctors making timely treatment like surgery, cerebrovascular intervention, or conservative treatment. It is very significant to determine the stage of cerebral palsy such as acute, subacute or chronic stages as described above. This is a new idea of our approach compared to preceding research.

3. Experimental results

Our proposed method is experimented on a system that automatically detects, diagnoses, and classifies brain haemorrhages. We collected 500 CT scanner images by DICOM standard from the patients' skull in CanTho Medicine University Hospital. The training and testing data sets are selected at a 7:3 ratio (Al-Ayyoub et al., 2013). It means that the training set of 350 CT images is classified into four types of brain haemorrhages based on the experience of doctors and specialists of CanTho Medicine University Hospital. This data set includes 95 CT images of Epidural Haematoma, 85 CT images of Subdural Haematoma, 80 CT images of Subarachnoid Haemorrhage, and 90 CT images of Intracerebral Haemorrhage. The files of the training set are 179 Mb. The testing set of 150 images is classified into types of brain haemorrhages and normal brain (no bleeding), which includes 45 normal brain images, 25 images of Epidural Haematoma, 20 images of Subdural Haematoma, 30 images of Subarachnoid Haemorrhage, and 30 images of Intracerebral Haemorrhage.

Our system was installed on MATLAB version R2015a using a computer with CPU i7, 16 Gb RAM, SSD 256 Gb, HDD 500 Gb, Windows 10 Pro 64 bit. The systematic interface for detecting and classifying brain haemorrhages automatically based on the HU is shown in Figure 12.

3.1. Identification and classification of the brain haemorrhages

The brain haemorrhages are classified into four types of the brain haemorrhages: epidural haematoma, subdural haematoma, subarachnoid haemorrhage or intracranial haemorrhage as shown in Figure 13.

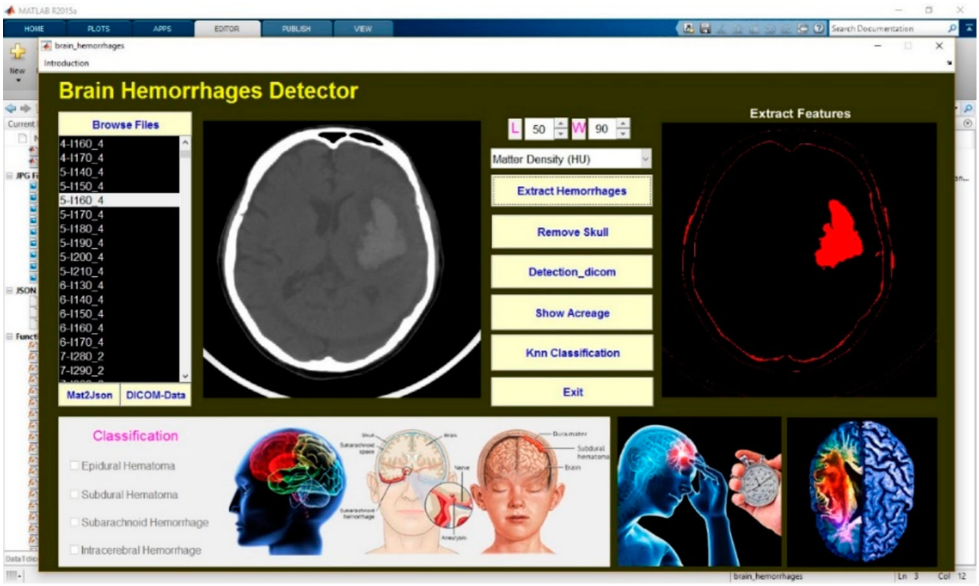

Figure 12. Interfaces of the system 'Automatic detection and classification of brain haemorrhages'.

In order to evaluate the accuracy of our proposed method, we test on a data set of 150 images using the KNN algorithm with the parameter values of K in the range of 1–10. As a result, our method provides the best classification with K = 3. The results are presented in the confusion matrix in Table 2. From the confusion matrix, we can see that in 25 testing images of the Epidural Haematoma, 24 images are correctly identified (96%) and one image is incorrectly identified as Subdural Haematoma (5%). Similarly, in the case of testing 30 images of Subarachnoid Haemorrhage, 27 images are correctly identified (90.00%), one image of the Subdural Haematoma (3.33%) and two images of Intracranial Haemorrhage (6.67%). From the confusion matrix shown in Table 2, the average accuracy is computed

$$\frac{24 + 19 + 27 + 28}{105} * 100\% = 93.33\%. \tag{3}$$

The accuracy from our method achieves 100% based on HU in identifying the presence of brain haemorrhage regions and 93.33% in classifying four types of brain haemorrhages. It gives more accurate identification results than some other research as in (Al-Ayyoub

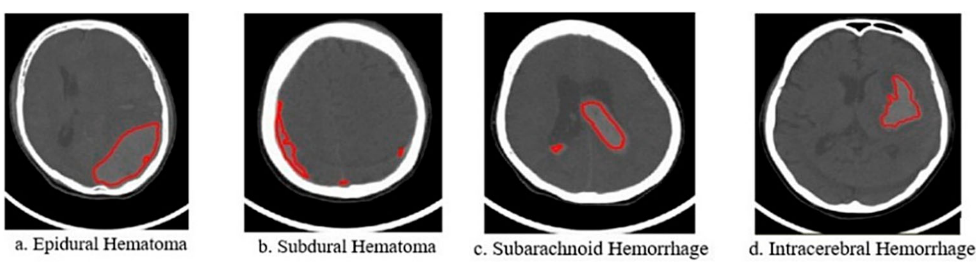

Figure 13. The results of our proposed method in classification of brain haemorrhages based on HU.

Table 2. Table of the confusion matrix.

4 types of brain haemorrhages	Epidural haematoma	Subdural haematoma	Subarachnoid haemorrhage	Intracerebral haemorrhage	No brain haemorrhage
Epidural haematoma (25)	24 (96.00%)	1 (4.00%)	0	0	0
Subdural haematoma (20)	1 (5.00%)	19 (95.00%)	1 (3.33%)	0	0
Subarachnoid haemorrhage (30)	0	1 (3.33%)	27 (90.00%)	2 (6.67%)	0
Intracerebral haemorrhage (30)	0	1 (3.33%)	2 (6.67%)	28 (93.34%)	0
No brain haemorrhage (45)	0	0	0	0	45 (100%)

et al., 2013) with the accuracy of 92%. Their method performs well only on three of four types of lesions of brain haemorrhages. Additionally, our method also determines the bleeding timing of brain haemorrhages to help doctors making timely treatment like surgery, cerebrovascular intervention, or conservative treatment. It is very significant to determine the stage of cerebral palsy such as acute, subacute or chronic stages as described in Section 2.6. This also helps doctors making decisions faster and easier. Moreover, in preceding research, the presence of brain haemorrhage is detected achieving 100% using the Otsu algorithm (Otsu, 1975). Our method uses some available information stored in the DICOM images to determine the Hounsfield values which help us identify the brain haemorrhage regions quickly and accurately. They are our contributions to this research.

3.2. Determination of timing of the brain haemorrhages

After identification and classification of the brain haemorrhages, our proposed method determines the bleeding time of brain to support doctors finding timely and effective treatments. We make a comparison between our method and the Fast Bounding Box method (Fazli & Nadirkhanlou, 2013). The results of this method are represented in Figure 14.

The Fast Bounding Box method applied the Deep Learning technology. The results of the segmentation of brain haemorrhages are not accurate compared to our method. In Figure 14, the Fast Bounding Box method determines the haemorrhage regions by the

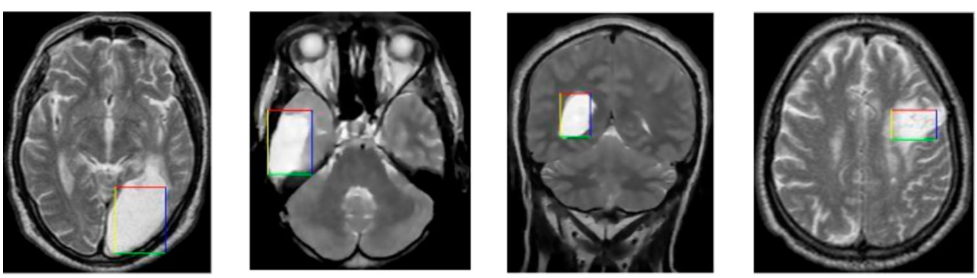

Figure 14. The results of the segmentation of brain haemorrhages based on the Fast Bounding Box Algorithm (Fazli & Nadirkhanlou, 2013).

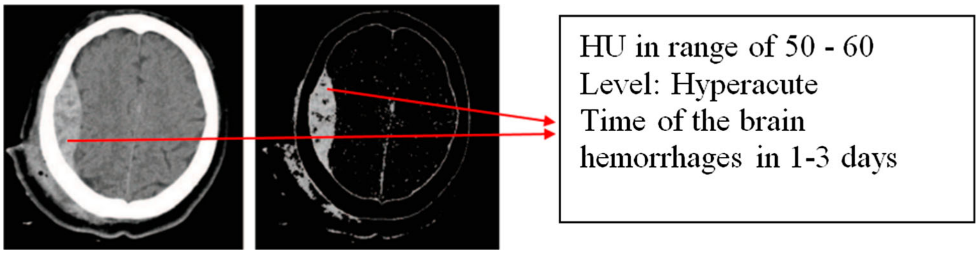

Figure 15. The result of the determination of timing of the brain hemorrhages based on HU.

box shapes while our method accurately determines the regions of brain haemorrhages as shown in Figure 13. These regions have HU values of 40–90. Moreover, HU values are also used to determine the duration of haemorrhage in our proposed method. Figure 15 shows the time of the brain haemorrhage in 1–3 days because HU values are from 50 to 60.

4. Conclusion

There were various techniques developed for effectively detecting the haemorrhage in the brain. A method of automatically classifying brain haemorrhages is proposed in our research based on the Hounsfield Unit. Our proposed method identifies areas of brain haemorrhage better than some well-known image segmentation methods. It also improves the classification accuracy compared to these methods. In this paper, we present a truly automatic image segmentation method because it does not require a user to determine image-specific parameters such as thresholds or regions of interest. The use of the HU analysis leads to an important improvement in the determination of the regions and the bleeding timing of brain haemorrhages to support doctors making timely treatment. Our system can assist doctors in detecting and classifying the brain haemorrhages through medical images (CT/MRI) with DICOM standard, especially the bleeding timing. The four types of brain haemorrhages namely epidural haematoma, subdural haematoma, subarachnoid haemorrhage and intracerebral haemorrhage are considered in this paper.

Disclosure statement

No potential conflict of interest was reported by the authors.

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