An Ensemble Learning Approach for Automatic Brain Hemorrhage Detection from MRIs

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***Abstract*—Brain hemorrhage is one of the conditions that could affect people for several reasons such as high blood pressure, drug abuse, aneurysm, and trauma. Neurologists ordinarily use Magnetic Resonance Imaging (MRI) scan to examine patients for brain hemorrhage. In this study, we have developed an intelligent automatic model to identify MRIs of patients with hemorrhage from intact ones using an ensemble learning approach. Moreover, our proposed model can annotate the affected area of the brain in an axial view of MRI, which helps trainee doctors to improve their reasoning and decision making. In our experimental settings, we have applied a segmentation-based feature texture analysis to prepare MRIs for classification using an adaptive boosting algorithm. Our proposed method has achieved a classification accuracy of 89.2%, with 100% sensitivity in detecting the affected area of the brain.**

Keywords— Brain hemorrhage, MRI, Ensemble learning

I. INTRODUCTION

Magnetic Resonance Imaging (MRI) is a popular technology in the medical field and widely used for brain imaging. MRI employs strong magnetic fields along with radio waves to create detailed images of the inside of the human body. Neurology departments use MRI to detect tissue deformities in the brain, e.g., brain tumor, clots and intracranial hemorrhage that defined as a bleeding within the skull [1]. Using advances in information technology and machine learning methods to detect brain hemorrhage have been widely discussed in the literature. While the use of extracted features from various areas of brain MRI to detect the affected and abnormal area was the main target of several studies.

In the literature, some works have been conducted to detect abnormality in the brain e.g. hemorrhage from MRI images. Kakhandaki and his colleagues in [2] have developed a method to identify the abnormality in the brain using MRI images. In their work, several pre-processing steps were applied on the brain image before extracting the local binary pattern and GLCM features. Those extracted features have been used to train a probabilistic Kernel classification model to identify the abnormal MRIs. Al-Ayyoub and his partners in [3] have proposed to extract some geometric features from CT scans of the brain. They have segmented the ROI of the hemorrhage area to develop a classification model that could identify the type of hemorrhage. Likewise, Phan and others in [4] have followed a similar approach to detect the occurrence of hemorrhage, however, they have carried out extra work trying to determine a potential bleeding time. Balasooriya and Perera in [5] have considered partitioning CT scans into several objects using the watershed method, then extracting features from each object to train an artificial neural network.

In fact, the use of machine learning methods as well as data science technology in the medical field have shown a huge interest for researchers worldwide. Recently, the application of machine learning has been successfully used to help making more accurate medical decisions in several clinical areas and not limited to brain imaging. Aljaaf and others in [6] have tested the effectiveness of different machine learning methods for early prediction of chronic kidney diseases. While predicting the likelihood of heart failure using decision tree algorthim was another successful example of using machine learning in cardiovascular dieases [7]. Robert and his colleagues in [8] have examined 9 machine learning based classifiers to diagnose primary headache disorders using clinical data. Another review was conducted in [9] with the aim of identifying some criterion for best adoption of intelligent methods in the medical decision systems.

Most of research studies that carried out to detect brain hemorrhage were aiming to identify abnormal areas in the brain. However in this study, we propose a new method in which we have annotated the affected areas after detecting the brain hemorrhage. This is a considerable improvement to the body of knowledge and could be beneficial to train junior doctors and specialist nurses. This paper is organised as follows. Section 2 presents our proposed method, including 3 subsections explaining the work process of feature extraction and learning. Section 3 shows the overall results of using ensemble learning method for brain haemorrhage detection. Section 4 discusses our results and finally section 5 concludes the study.

II. PROPOSED METHOD

In this section, our proposed method will be discussed in details. The proposed method consists of three main parts. First, the pre-processing stage, in which we have isolated the area of interest, i.e. isolating the brain area from the skull. Secondly, we have extracted the most representative and relevant subset of features from MRIs to train the adaptive boosting algorithm. Finally, detecting brain hemorrhage and propose a procedure to annotate the affected area.

A. Pre-Processing

In this stage, MRIs will be prepared for classification. The pre-processing stage is essential for valid detection and classification models, where the ensemble learning algorithms cannot differentiate between the texture of the hemorrhage area and the skull bone as shown in figure 1, which might confuse the classification model in later steps. We have observed that the unwanted areas in figure 1 including the skull bone have an intensity of ≥ 250, which is a high intensity that could be employed to distinguish this

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area from the surroundings. Accordingly, we have identified a threshold of intensity '$t = 250$' to discard unwanted areas while keeping the area of interest. Using 't' we have extracted a mask from figure 1, then the mask will be applied to keep only the brain area and mask out other parts as presented in figure 2 (b).

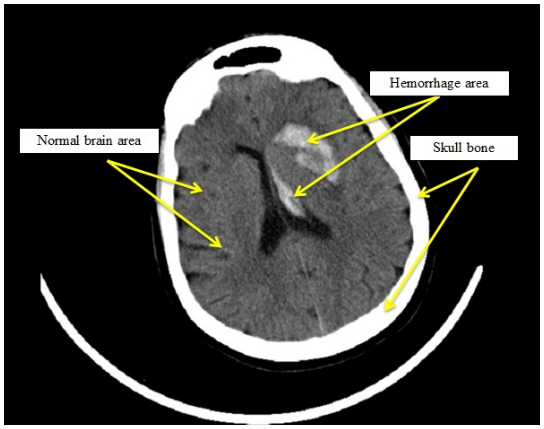

Fig. 1. MRI brain image (axial view), where the image shows normal tissues, the haemorrhage tissues and skull bone.

Fig. 2. (a) Mask of MRI brain image, and (b) Extracted brain area

B. Feature Extraction and Learning

Extracting relevant subset of features from MRI is an essential step to develop a robust detection model, therefore we have applied the Segmentation-based feature texture analysis (SFTA) that has been proposed in [10] to extract features of the hemorrhage cases. The SFTA method has been developed to decompose the greyscale image into a set of binary images using Two Threshold Binary Decomposition (TTBD) technique. Then after, the SFTA feature vector is generated as a resulting binary images' mean grey level, size and fractal dimension boundaries [10].

Our proposed intelligent method collects the positive samples, i.e. hemorrhage area as well as the negative samples, i.e. normal area as follows:

- Annotate different point in the brain MRI (yellow points in figure 3).
- Sample a window of 10×10 pixels dimensions for each point (red windows in figure 3).
- Extract the SFTA feature vector for each window.

The collected features of positive and negative samples were then employed to train our detection model using adaptive boosting algorithm. Adaptive boosting is one of the most popular ensemble learning approaches that considers multiple sequential learners, where for each learner, the adaptive boosting computes the weighted classification error. The weight is then justified accordingly, i.e. increased for the misclassified observations and decreased for the correctly classified observations. The next learner should use the updated weight for the training [11].

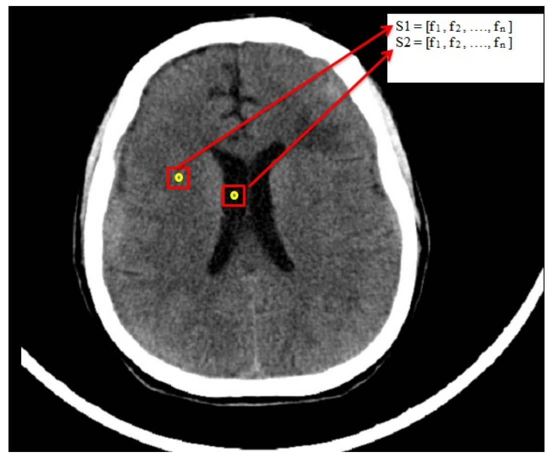

Fig. 3. Feature extraction from normal brain image

C. The Detection and Annotation of Hemorrhage Cases

To detect the brain haemorrhage in the MRI, we have firstly repeated the feature extraction procedure from the whole brain area as shown in figure 2-b. Then, we predicted each sample to see whether it's classified as a positive or negative. Figure 4 illustrates the stages of detecting brain hemorrhage from MRI, where in figure 4-b we can note that the hemorrhage area was detected and anotated with some other not affected area. This is expected because of the complex nature of the brain and the existence of a high intensity pixels in a different area of MRI. Therefore, we have proposed a multistep procedure to check the closeness between predicted/annotated samples to keep the hemorrhage areas and ignore other non-affected areas as shown below.

Using this procedure, we consider only the sample if it belongs to a bigger cluster and ignore any other samples as shown in Figure 4-c. Also, we can annotate the area of the hemorrhage which could be helpful for measurement purposes. Furthermore, the procedure can make a final decision whether the MRI image is normal or abnormal in terms of including hemorrhage area.

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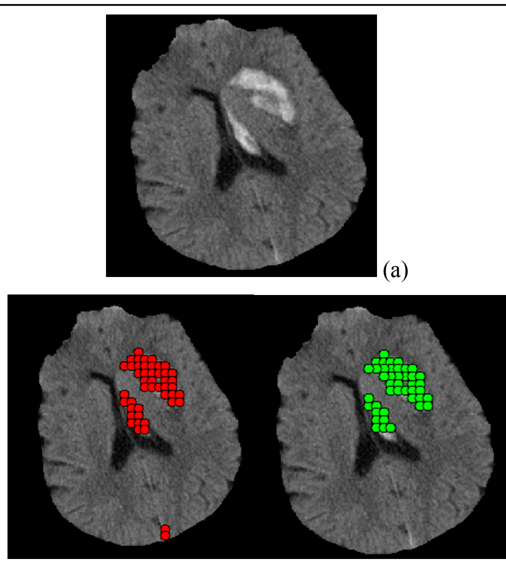
A pseudocode of our proposed multistep
procedure to identify affected area in MRI

Parameters:
  DS = Detected Samples;
  i = Counter;
  M = Euclidean Distance;
  DC = Detected Cluster;


BEGIN
1: Foreach (Samples as DS) Do
2: Initiate Cluster i
3: Add seed sample to cluster i
4:   M = (i, new DS)
5:      If (M < 20)
         Seed sample = new sample
         Cluster i += 1
        Else
          i += 1 and GO to step 2
6: End
End

BEGIN
MRI == 0
1: Foreach (Cluster as DC) Do
2:   If (DC < 6)
       Ignore DC
     Else
        MRI = 1
End

BEGIN
1: If (MRI == 1)
        MRI is Abnormal
   Else
        MRI is Normal
End
```



(a)

(b) (c)

Fig. 4. (a) Abnormal brain image with hemorrhage (axial view). (b) Initial result of prediction (c) Final result after filter out false- positive samples.

III. Results

In this section, the result of applying the proposed method on a limited data set is discussed. Our data sample consists of 32 MRIs of an anonymised patients' brain, with 16 normal images (no hemorrhage) and 16 abnormal images (hemorrhage). This data has been offered by the department of neurology, Al-Ramadi teaching hospital - western Iraq. All patients have signed a consent to share their MRIs with our research team, MRIs and medical report have been provided by a medical team at the department of neurology in an anonymous setting. Authors have no direct or indirect contacts with patients. We used 37.5% of MRIs to train our model, while the remaining MRIs are retained for testing purposes. To evaluate our intelligent detection model, we have employed several statistical performance measures, including sensitivity, specificity and detection accuracy as presented in table 1.

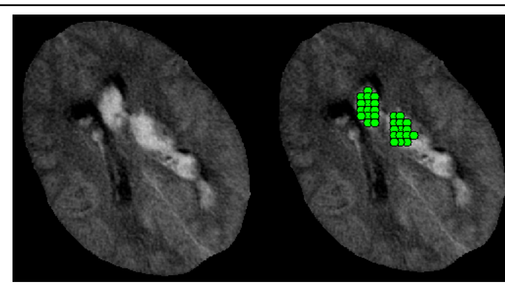
TABLE I. Performance Metrics of Our Model

Algorithm	Performance Measures		
	Sensitivity	***Specificity***	***Accuracy***
AdaptiveBoosting	100%	78.5%	89.2%

Further to the above evaluation, we have also estimated the accuracy of annotation. Our model has achieved an annotation of 78.5%, which indicates that not all the correctly classified MRIs as positive are accurately annotated. This matter will be further discussed in the next section.

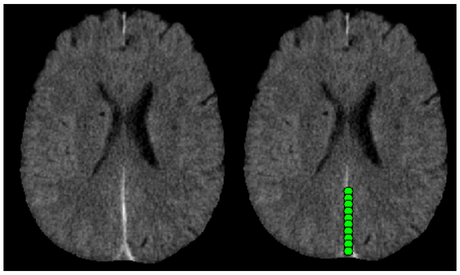
IV. Discussion

Our main goal in this work was to develop an intelligent automated model that able to distinguish between normal and abnormal MRIs in terms of brain hemorrhage. Moreover, we have extended our work to include an annotation to the affected area of MRIs. In the experimental settings, we can see the high accuracy, especially in terms of positive case detection. Although our intelligent model has achieved considerably good results, however, it can be noted that the specificity was lower by about 22% than the sensitivity. We think that this is due to the limited numbers of MRIs that been used for training as well as the existence of some normal texture within the MRI that has a quite similar density to the affected area, which in turn could influence the learner. Figures 5 and 6 explain the presence of false-negative cases and the inaccurate annotation of positive MRIs. In figure 5, the adaptive boosting has correctly classified MRI as haemorrhage case, while the annotation is not accurately covering the affected area.



(a) (b)

Fig. 5. Detecting of normal brain image as abnormal (a) Normal MRI brain image (axial view). (b) Annotation of (a) which shows false positive samples



(a) (b)

Fig. 6. Detecting of abnormal brain image as abnormal, but with inaccurate annotation (a) Abnormal MRI brain image (axial view). (b) Annotation of (a) which shows inaccurate annotation.

V. Conclusion and Future Work

The analysis and classification of medical images gain a huge attention from researchers worldwide. One of the main interesting domains of classifying medical images is the detection brain hemorrhage and annotating the affected area. In this paper, we have proposed an intelligent automated method to detect and classify MRIs with hemorrhage using adaptive learning approach in a combination with an advanced filtering approach. We have also identified a multistep procedure to annotate the affected area. Our proposed method has achieved a considerably high accuracy rate in distinguishing abnormal brain MRIs and annotating affected areas. For future work, we aim to extend to include more MRI samples to the training stage, while extracting a different set of features to decrease the false positive rate and improve detecting the area of interest. Moreover, one of the possible solutions that could be considered in the future is to detect the thin vertical cluster and ignore them as they usually come from the normal texture in the brain.

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