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Assessment of mesial temporal sclerosis through MRI processing

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ABSTRACT

Mesial temporal sclerosis (MTS) is the principal cause of complex epilepsy, is manifested principally by gliosis and hippocampal volume loss. This project aims to develop an algorithm that allows automatic measurement of hippocampal volume and signal intensity in magnetic resonance imaging. The algorithm developed uses preprocessing of the images to reduce the artifacts and for the extraction of the features were used techniques of machine learning (support vector machine) and texture analysis. Results can help to optimize time in the assessment of the mesial temporal sclerosis and can contribute to the best training to the younger neuroradiologists.

Keywords: machine learning, brain MRI, Mesial temporal sclerosis, hippocampal volume, epilepsy

1. INTRODUCTION

Neuroimaging is a highly interdisciplinary field of research in the health and medicine sciences. Different works manifest the fundamental role of the neuroimaging in the determination of neurological diseases and disorders and the support that offer to neuroradiologist in giving an accurate diagnosis, prognosis, and monitoring, due also the neuroimaging has been recognized as a powerful tool to analyze brain changes.¹⁻⁹ Inside of this field, there are different modalities: e.g. for to analyze of the structure of the brain the Computed Tomography (CT) and Magnetic Resonance images (MRI) are the most used; and for to do a physiological analysis was used the Positron emission tomography (PET), single-photon emission tomography (SPECT) and functional MRI for to do a brain analysis of images^{10,11}.

The MRI is widely used in the brain images segmentation and their posterior analysis due it offers high-resolution images of the anatomical structures and is a noninvasive safe method for the patients^{1,3,8}. In this sense, Yamanakkanavar et al.⁸ shows that a detailed analysis of the tissue structures from segmented MRI leads to more accurate classification of specific brain disorders⁸, but at the same time indicates that the manual segmentation is a very laborious and subjective task to that consuming time and also requires a deep knowledge of the brain anatomy⁸. That is one of the reasons that in the last years there are continuous research and advances, especially in the field of machine learning (ML) and deep learning (DL) to develop automatic algorithms for brain segmentation and detection of brain disorders; even though, the automatic medical segmentation continues to be a complex and challenging problem^{6,12,13}.

Among the pathologies and neurological disorders are the epilepsies. According to Raghavendra et al.¹³, the definition of epilepsy is “*a disorder of the brain characterized by enduring predisposition to generate the epileptic seizures.*”¹³ It affects both male and female sexes of all ages.¹³ Magnetic resonance imaging (MRI) is one of the most important tools that permit to determine the syndromic diagnosis and possible etiology of epilepsy¹¹. Concerning the pathological findings in patients with epilepsy are mesial temporal sclerosis (MTS), vascular anomalies, low-grade glial neoplasm, and malformations of cortical development¹¹.

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Nataraja et al.¹⁴ mention that despite epilepsy is well manageable with antiepileptic drugs, there are approximately 30% of epilepsy patients who are not responding to optimal treatment. In this sense, Azab et al.¹⁵ remark that the mesial temporal sclerosis (MTS) is the “most common pathologic entity encountered in epilepsy surgery series”^{11,14,15}.

Mesial temporal sclerosis (MTS) also called Hippocampal sclerosis (HS)¹¹ is “characterized by neuronal loss and chronic fibrillary gliosis on the pyramidal cell layer of the hippocampus”^{14,16}. Yamanakkanavar et al.⁸ and Azab et al.¹⁵ indicate that the MR imaging is the best technique of imaging preoperative that helps to detect and confirm the presence of the MTS, which is due the clinical MRI can detect the gross hippocampal atrophy changes. This changes in the hippocampal are appreciated in a visual way for the radiologists; however, this task is more reliable if is do it by experienced radiologist due to the subtlety of the changes¹⁵.

Silva et al.¹⁶ in their work show that the rate of detection of MTS by visual inspection on MRI is variable between 62 % and 85%¹⁵⁻¹⁷ and this assessment is in the function of the experience of the radiologist and the degeneration of the hippocampal structures. The modalities of MR imaging used to detect these abnormalities and evaluate the shape, orientation, volume and internal structure of the hippocampal anatomy are the high resolution T1-weighted with inversion recovery (IR), T2-weighted, and the fluid-attenuated inversion recovery (FLAIR), especially to assess signal intensity^{11,14,16}.

There are some works^{12,13,15,16,18-25} that use different techniques of machine learning and deep learning such as support vector machine(SVM), artificial neural network (ANN), convolutional neural networks (CNN); illustrate different results to develop an automatic assessment of the volumetry of the hippocampus and the signal intensity of the abnormalities that characterize the MTS. However, for all these authors, like indicate Yamanakkanavar et al.⁸ “the segmentation of the hippocampus, is a difficult task due to its small size and volume, the anatomical variability, low signal to noise ratio(SNR), intensity inhomogeneities.”^{8,19,26}, although it is an important biomarker for the computer-aided diagnosis (CAD) systems.

In this context, the principal aim of this work is to develop an algorithm that will be able to assess the principal features to detect the MTS, hippocampal volume loss, and hippocampal hyperintensity, using especially the coronal images T2 and FLAIR modalities of MRI. The algorithm proposed has different phases: collect images (dataset), preprocessing images, and processing images to determine the principal features and region of interest (ROI) using techniques of machine learning, like support vector machine (SVM), principal component analysis (PCA), and analysis of textures. This paper presents an advance of the algorithm, due that requires the validation of the experienced and experts radiologists and the posterior evolution for uses techniques of deep learning with a larger dataset. The paper is organized as follows: section two indicates the materials (description of the dataset) and the methodology used for the algorithm; in section three present the results and finally the section four gives a brief line of conclusion and discussion of the results obtained.

2. MATERIALS AND METHODS

The schema in the figure 1 illustrates the architecture and the methodology of the algorithm proposed with its different steps: the dataset preprocessing, feature extraction, feature selection, and classification.

2.1 Data acquisition

The collection of images for uses in the algorithm is formed by:

- 30 healthy patients adults (both males and females) and;
- 70 patients with some disorder (45 have findings of mesial temporal sclerosis, 15 patients have other lesions such as ischemia or stroke, and 10 patients have brain tumors)

All studies series have been anonymized before collected from HUTPL and other different hospitals in Ecuador.

The images T1-weighted, T2-weighted, and FLAIR images were acquired by the equipment of RM Philips Medical Systems, model Achieva 1.5 Teslas.

2.2 Preprocessing

In the preprocessing stage, we use python scripts to exclude the possible artifacts presented into the images, especially into the temporal-mesial structures in the coronal FLAIR images²⁵. Figure 2 shows an example of possible artifacts in the FLAIR images in the temporal-mesial structures.

2.3 Feature extraction and feature selection

Feature extraction consists of identifying the brain regions, which will be the principal characteristics of the object of interests²⁷ and in a posterior, the features most relevant will be the input for the classification.

The extraction of features was done in agreement with the expert neuroradiologist. Once that the images are free of artifacts and selected the region of interest (ROI), the anatomical structures that involve the hippocampus (temporal-mesial) will be described according to the features of intensity, shape, and texture analysis. The features to extract after the get the ROIs are in concordance with ²⁷: *Shape Features of the hippocampus*; volume, area, perimeter, irregularity, shape index. *Intensity and signal features*; mean, variance, standard variance, median intensity, skewness, and Kurtosis. *Texture features concerning the hippocampus also*; contrast, correlation, entropy, energy, homogeneity, the sum of square variance.

2.4 Classification

During the feature extraction and feature selection, each image was transformed into a column vector of features, and each value corresponded to a single corresponding voxel intensity. Feature extraction allows the original data to transform into analyzable input data²⁸. In this stage of the algorithm, we use the SVM classifier and combination with the principal component analysis (PCA).

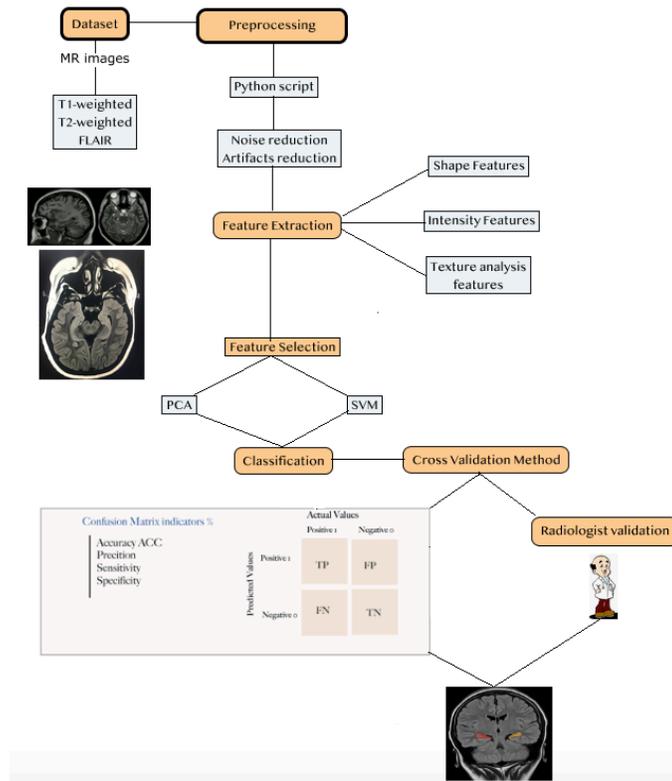


Figure 1. The architecture of the different stages of the algorithm proposed. The first stage consists of the collection of the dataset, preprocessing the images, and feature extraction. The second stage is feature selection, classification, and validation.

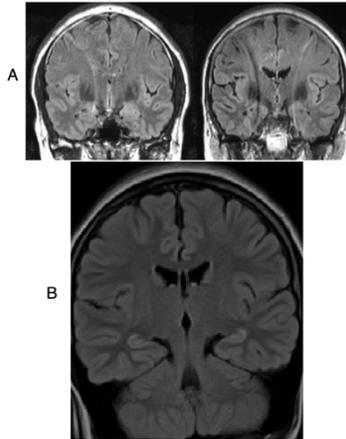
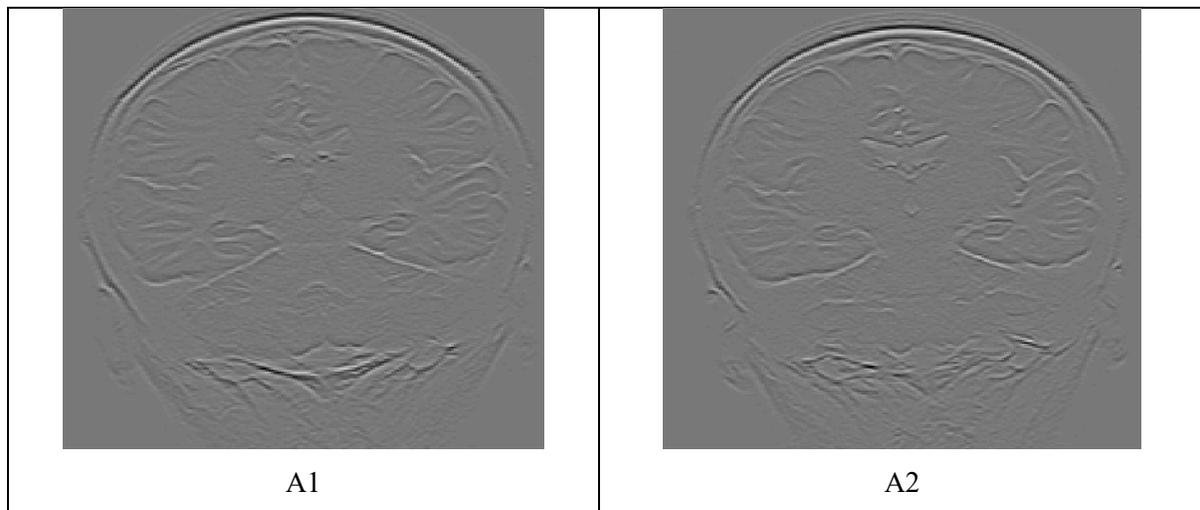


Figure 2. FLAIR coronal images of the structural anatomy of the brain: section (A) shows a couple of images into the zone of the temporal-mesial structures; and section (B) shows an image without artifacts. Figure adapted from Huppertz et al.²⁵

3. RESULTS

In this work only is reported the results derivates from the first stage of the algorithm proposed: the dataset collection, preprocessing and the analysis of the features extraction through the definitions of ROIs and the data for volume hippocampus and intensity signal. In the next work will be reported an analysis exhaustive of the parameters concerning the feature selection and classification.

Figure 3 shows that is possible to do a segmentation of the hippocampus to determine the volume using texture analysis and machine learning techniques. Specifically, in the figure (B1) and (B2) we can see a level of asymmetric in the volume and a hyperintense signal in the lobe on the right side, consequently, these findings show that this patient has mesial temporal sclerosis in a low level. Also in figure 3 in (C), it is presented a segmentation of the hippocampus from a sagittal and cortical view.



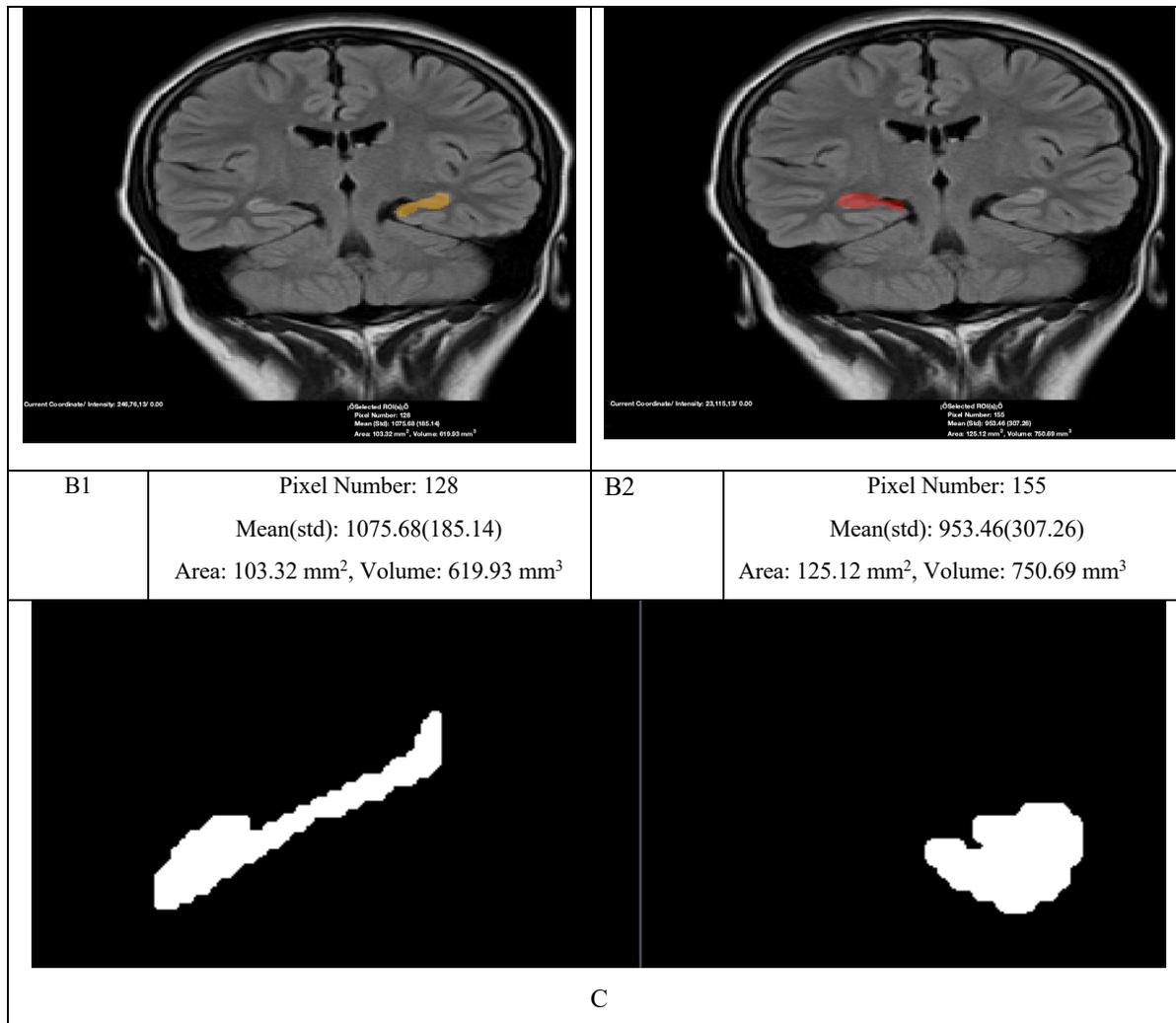


Figure 3. (A1) y (A2) shows the textures analysis of the series for each patient, this analysis allows to us to do a better identification of the anatomical structures that involve the MTS. (B1) and (B2) shows the segmentation and the values of the features of shape from the hippocampus, it is shown the volume for the left and right side of the lobe temporal; we can see a level of asymmetry in the volume and a hyperintense signal in the lobe on the right side, onsequently these findings show that this patient has mesial temporal sclerosis (MTS) in a low level. (C) The structure of the hippocampus segmented from a sagittal and cortical view.

4. CONCLUSIONS AND DISCUSSIONS

The results shown confirm that is is possible to get a good criterion for determining the MTS through the find the automatic volume hippocampus and the variation of the signal and intensity in the anatomical structures. It is in agreement with Huppertsz et al²⁵., Yamanakkanavar et al⁸., Silva et al¹⁶, Nataraja et al¹⁴ and Cendes et al¹¹ in which works present also different methods of segmentation and determination automatic of the hippocampus and the signal intensity. However, the gold standard for determining the MTS is yet the visual analysis and the experience¹⁵; for that reason, in the next work, we will report the analysis of the signal and the volume of the hippocampus with a more rate of training and reliable using deep learning techniques.

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