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MTS Image Analyzer: A Software Tool To Identify Mesial Temporal Sclerosis In MRI Images

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ABSTRACT

Epilepsy is a chronic neurological disorder that causes unprovoked and recurrent seizures which according to WHO affects approximately 50 million people worldwide. Functional magnetic resonance images (MRI) help to identify certain affected areas of the brain, namely, the gliosis and hippocampal volume loss. These losses cause complex epilepsy, and is known as hippocampal sclerosis or Mesial Temporal Sclerosis (MTS). This work presents the development of a Computer Aided Diagnosis CAD system software package) that can be used to identify the characteristics and patterns of MTS from brain magnetic resonance images. The image processing techniques involve texture analysis, statistical features, evaluation of the 3D Region of interest (ROI), and threshold analysis. The software allows the automatic evaluation of the degeneration of hippocampal structures, hippocampal volume and signal intensity. We will describe and demonstrate the software (which can currently be accessed on GitHub). It is expected that this tool will be useful in new neurology/radiology specialists and can serve as a secondary diagnosis. However, it is necessary to validate the software system qualitatively and quantitatively in order to get more effectiveness and efficiency in a real-world clinical application.

Keywords: brain MRI, Mesial temporal sclerosis, hippocampal volume, epilepsy, texture features, 3D ROI, texture analysis

1. INTRODUCTION

According to World Health Organization[1](WHO), epilepsy is a chronic neurological disorder that causes unprovoked and recurrent seizures which affect approximately more than 50 million people in the world and 80% of that live in low and middle income countries. It is estimated that 70% of people living with epilepsy could live seizure free if properly diagnosed and treated[1]. Epilepsy also is associated with hippocampal sclerosis (HS)[2] which is the most common cause of mesial temporal lobe epilepsy[3] as well as other epilepsy syndromes. HS is also referred Mesial temporal sclerosis (MTS) and is found in drug resistant, chronic temporal lobe epilepsies[4,5]. This condition is described by loss and chronic fibrillary gliosis in the pyramidal cell layer of the hippocampus[2].

MTS can be identified by functional Magnetic Resonance Image (MRI), which allows for the evaluation and assessment of hippocampal deformation[6]. The coronal volume and coronal high resolution of T1-weighted with inversion recovery (IR), and T2-weighted, and the fluid-attenuated inversion recovery (FLAIR) modalities of MRI are considered to be the crucial images to best diagnose MTS[7–9]. More specifically , the FLAIR modality allows assessment signal intensity.[4,10,11]

There is great variability in visual inspection of MRI images of MTS in MRI according to Silva et al.[11] The variability

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ranges between 62% and 85%[7,11,12]. For this reason an experienced radiologist is needed to accurately discern the changes of the hippocampal structures and abnormal signals.[7,13,14]

In this context, artificial intelligence, namely Machine Learning/Deep Learning could help analyze and diagnose the MR brain images[15–19] as well as other parts of the human body. There is a need to detect and classify MTS images and the development of systems that could assess, detect and identify the changes of the hippocampal structures like the volume and intensity of signals.[9,11,13,14,20] There is some literature[10,19,21,22] dealing with the automatic detection of the hippocampus. These systems employ the fact that there is hippocampal volume loss which is a principal feature of MTS[14]. Jafari et al.[23]detected the hippocampus through the analysis of signal and texture features in FLAIR images using a machine learning framework. Cantor et al.[24] have proposed the detection of temporal lobe epilepsy in multiparametric quantitative MRI T1 and T2 maps, using Support Vector Machine (SVM), feature selection and, Principal Component Analysis (PCA) method. They reported an accuracy of 88.9%. In addition, using SVM and a large cohort of epilepsy patients with and without mesial temporal sclerosis (MTS), Rudie et al.[25] achieved an automatic classification of MTS using measures of cortical morphology in whole brain T1 MR images.

We describe here a CAD system (software package) that can be used to identify the characteristics and patterns of MTS from brain magnetic resonance images. The image processing techniques involve texture analysis, statistical features, evaluation of the 3D region of interest (ROI), and threshold analysis using the T2 coronal images and FLAIR modalities of MRI. The software, allows the automatic evaluation of the degeneration of hippocampal structures, hippocampal volume and, signal intensity.

2. METHODS

With the automatic detection of the hippocampus in mind, an efficient algorithm has been developed for detection and identification of features of MTS[13]. Figure 1 summarizes the methodology of this process.

2.1 Data and Preprocessing

The data used in this work comes from two sources: (1)Data from public sources, such as Kaggle[26], and Medical Segmentation Decathlon[27] and (2) anonymized data collected from a University Hospital in Loja Ecuador. This dataset consisted of images from 30 healthy patients adults (both males and females) as well as images from 70 patients exhibiting some neurological disorder (45 - mesial temporal sclerosis, 15 - other lesions such as ischemia or stroke, 10 - brain tumors). These T1-weighted, T2-weighted, and FLAIR images were acquired with a RM Philips Medical Systems, Achieva model, with a field strength of 1.5 Teslas. Pre-processing consisted of eliminating artifacts in the images and conversion of the Dicom images to the nifty scheme. The nifty format allows for streamlining of the various training stage.

2.2 Hippocampus Segmentation algorithm

Image Analyzer software allows the user to choose multiple regions of interest (ROIs) in a set of images. That tool is used to determine the feature masks of the hippocampal volume and structures**.**

The segmentation algorithm consists of the extraction of various characteristics from the hippocampal masks. The masks have been previously classified according to the hemisphere to which they correspond, be it right or left. The masks correspond to the axial, sagittal and coronal slices of the MRI images. The three-dimensional grouping of two-dimensional masks allows for recreation of the organ of interest, namely the hippocampus.

Through various post-processing algorithms such as texture smoothing, the volumetric body is reconstructed. The volume is therefore the sum of nonzero voxels within the Tensor space. In addition to this parameter, the signal intensity obtained with the volumetric surface is also added.

For the segmentation,[28,29] well-known networks such as U-Net[28], Unet3D, Vnet3D have been used in versions of PyTorch[29]. The Image Analyzer software uses the U-Net network for each slice of the volumetric images, based on previous work[30,31] (Figure 3). Image masks corresponding to the hippocampus that were previously segmented were taken from the datasets.

After preprocessing the image is input to the 3D U-Net network to segment automatically the hippocampus. The size of input image is 128X128X64. The 3D U-Net parameters used were: batch normalization 64, 32 filters, 1 channel, and max pooling 2X2, up-convolution 2X2, activation function ReLU.

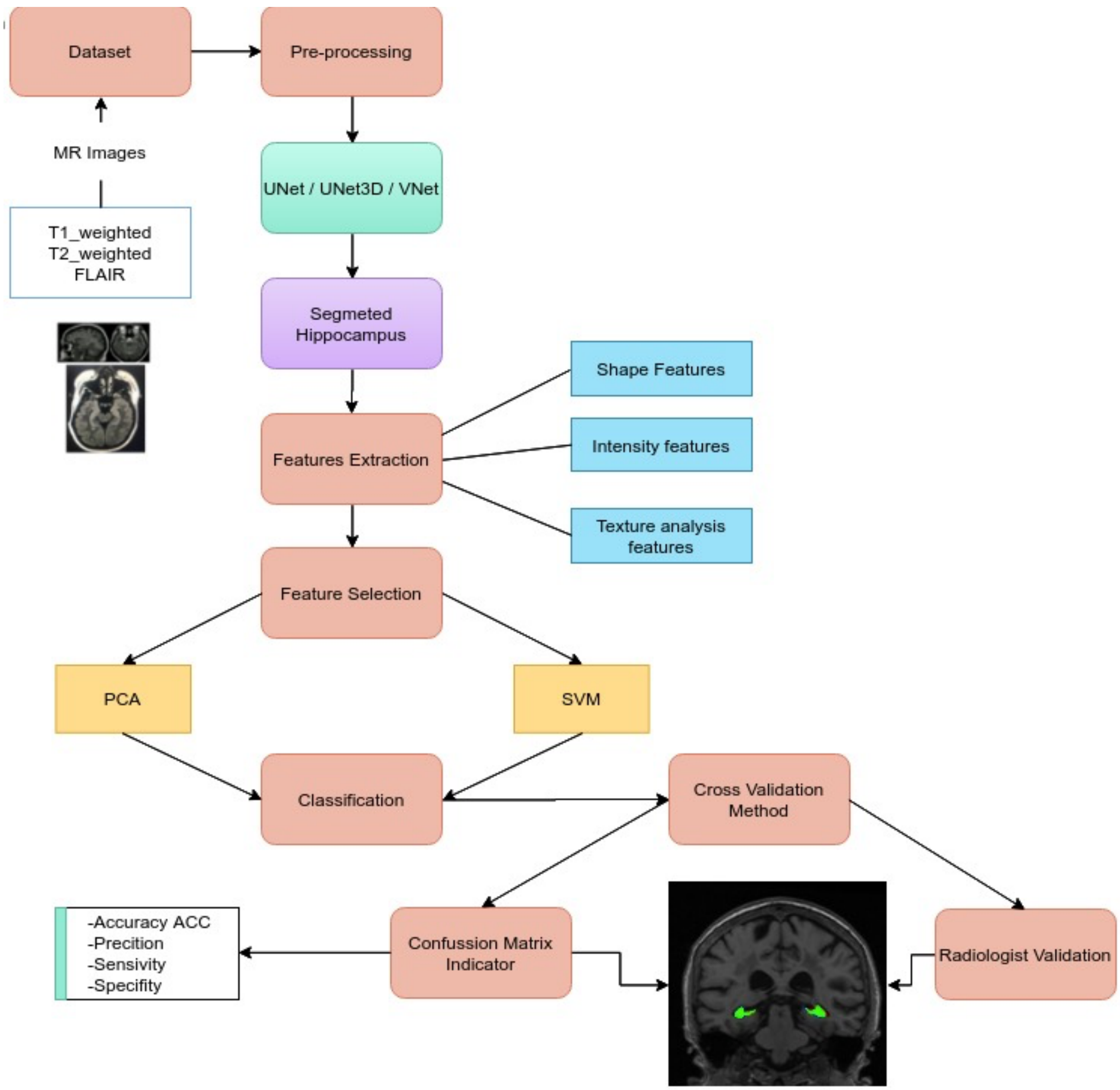

Figure 1. Methodology for segmentation and detection of hippocampus structure in the MR brain images. The algorithm consists of data collection, preprocessing, segmentation, features extraction and selection, classification and validation.

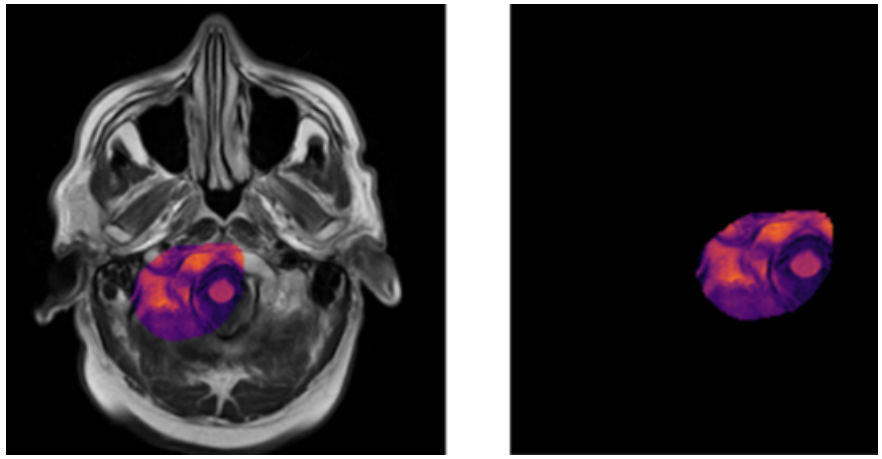

Figure 2. Image Analyzer, manual ROI selection to determine the mask features

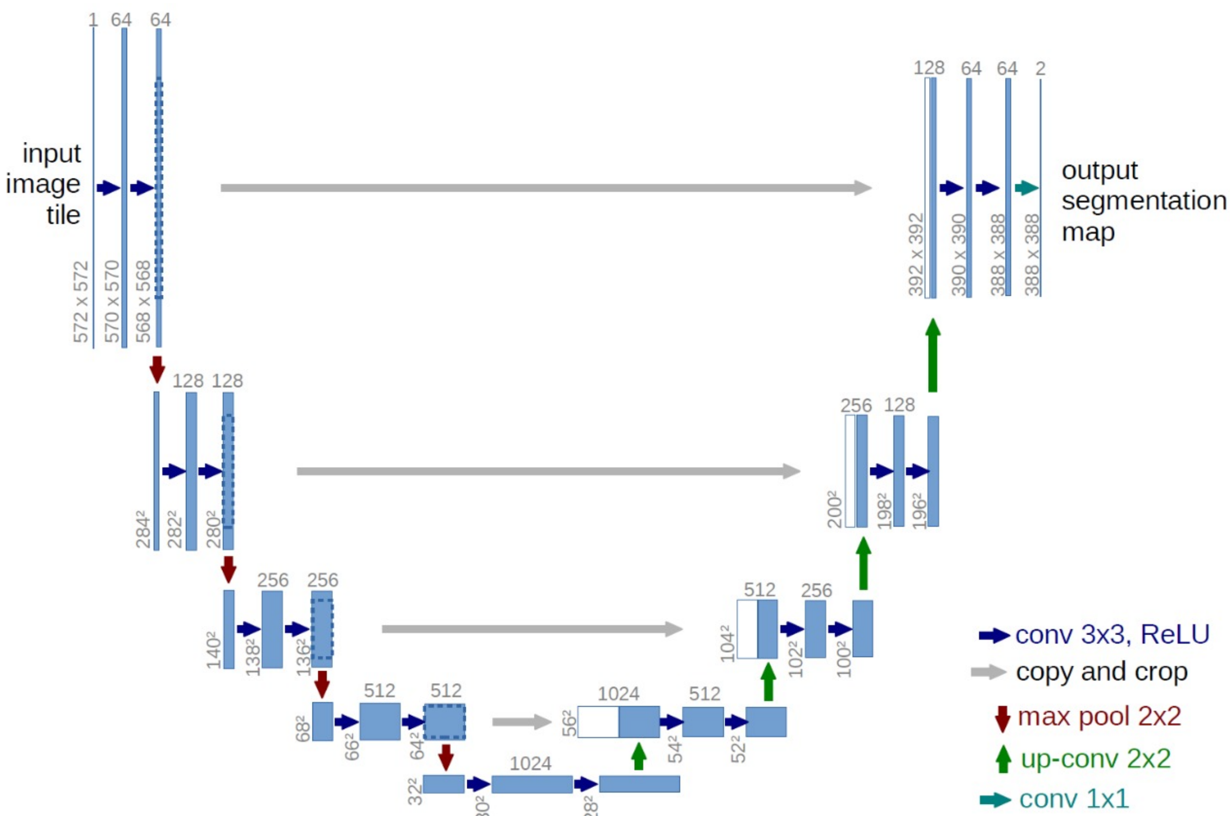

Figure 3. Classic scheme of the U-Net network.[28] This was used in each slice of the volumetric brain image by the Image Analyzer software.

3. RESULTS

The image analyzer software package has been tested and the partial results are provided here. The partial results include the dataset collection, preprocessing and the analysis of the features extraction through the definitions of ROIs and the data for hippocampus volume and intensity signal. The Image Analyzer code is available at the GitHub site (https://github.com/Hikki12/image-analyzer). The user interface is shown in Figure 4.

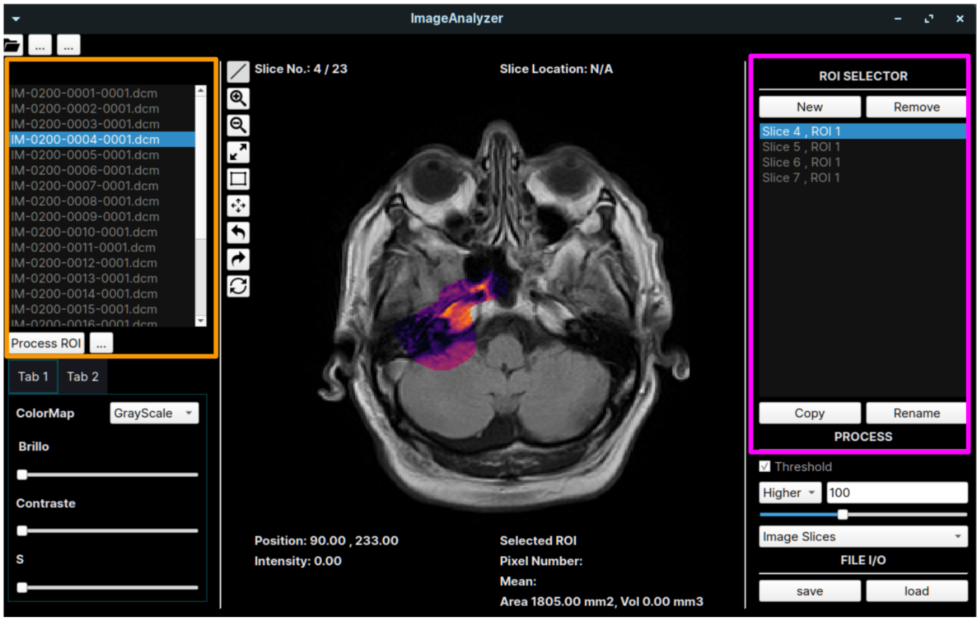

Figure 4. The user Interface of the Image Analyzer software package.

3.1 ROI definition and Segmentation

The Image Analyzer software package allows for manual segmentation using ROI and the automatic segmentation through 3D U-Net. The manual ROI segmentation also allows for determination of which are used to train the U-net network (Figure 5). The manual segmentation allows the ROI selection through the threshold analysis (Figure 5).

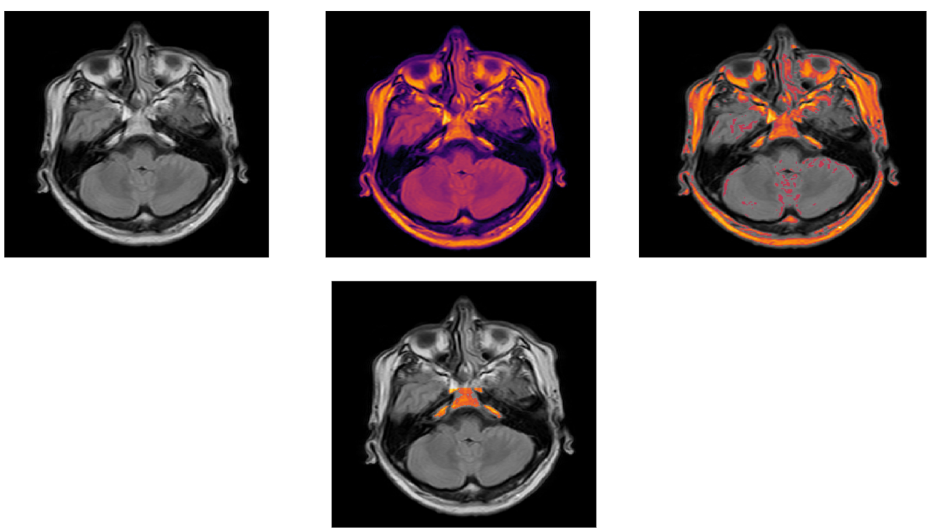

Figure 5. Manual ROI selection. Original image (top left), image with threshold 0-255 (top center), top right with threshold 20 to 250, center bottom image with threshold 80 to 250.

Once we get the segmented hippocampus, feature extraction and selection can be applied to train the SVM classifier in order to determine if the patient has MTS.

The selection and extraction of features is based in the statistical texture analysis[32,33], which consist of the selection of the most relevant features through the intensity histogram of the segmented hippocampus. The texture definition is using the wavelet transform and features parameters like entropy, energy (signal intensity), shape-based (2D), shape-based (3D), and statistical parameters: Gray Level Cooccurrence Matrix (GLCM), Gray Level Run Length Matrix (GLRLM), Gray Level Size Zone Matrix (GLSZM), Neighbouring Gray Tone Difference Matrix (NGTDM)[34]. These parameters allow for characterization of the hippocampus volume and its relation to the MTS.

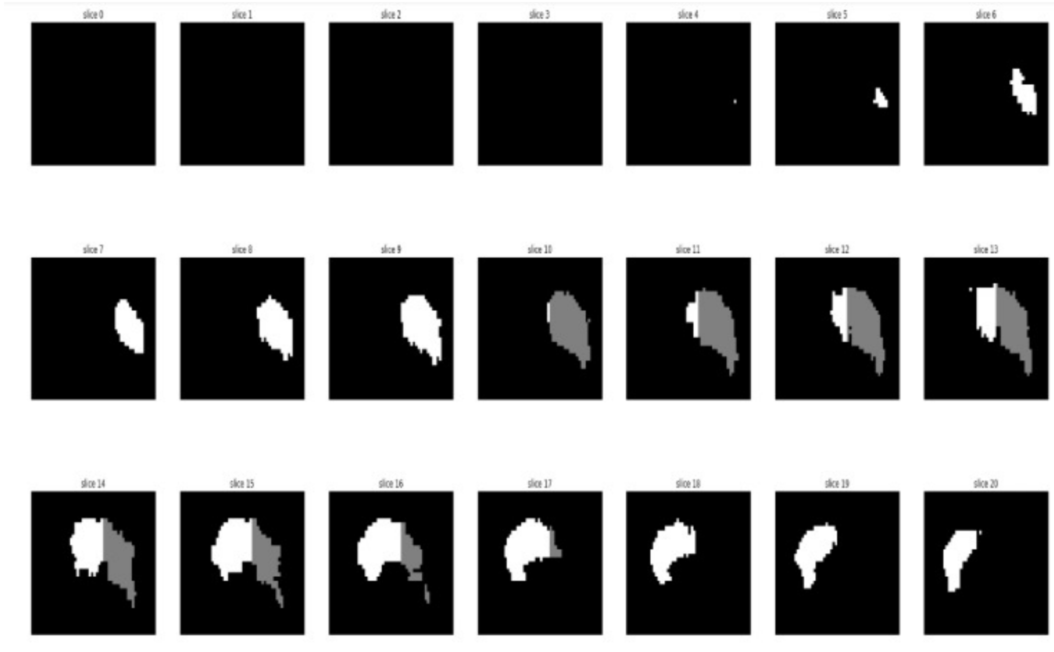

Figure 6. Hippocampal masks in various slices. These were obtained from datasets to train the U-Net 3D network.

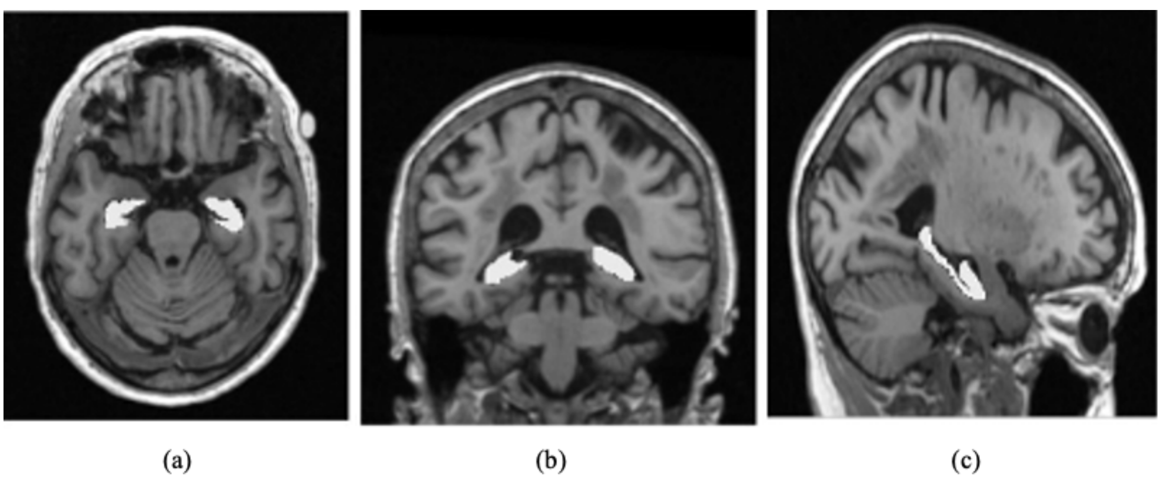

Figure 7. Automatic segmented hippocampus in different planes (a)axial (b)coronal, (c) sagittal.

4. CONCLUSIONS

The partial results show that the use of textures is a good tool for feature selection and segmentation of the hippocampus structure as well as for measurement of the volume employing the U-Net network. The 3D segmentation allows for significant segmentation which allows for determination of a good criterion to finding the MTS volume of the hippocampus and the variation of the signal and intensity in the anatomical structures.

It is expected that this tool will serve to train new neurology/radiology specialists and can be a source of secondary diagnostic opinion. However, it is necessary to validate the software system qualitatively and quantitatively in order to determine the effectiveness and efficiency in real-world clinical applications. This is the subject of future work.

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