Journal of Theoretical and Applied Information Technology
15th January 2024. Vol.102. No 1
© 2023 Little Lion Scientific
ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

DIGITALIZATION AND CLASSIFICATION OF SCANNED ECG USING CONVOLUTIONAL NEURAL NETWORK

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ABSTRACT

The electrocardiogram (ECG) is a non-invasive test that shows and records the electrical activity of the heart. However, the result is given on thermal graph paper which deteriorates rapidly with time. In this paper we work on two objectives, the first is the presentation of a new approach to convert scanned images to extract a good quality signal using computer vision methods. Each image is converted to a gray level, a region of interest is selected, then the bilateral filter method is applied, optimal for preserving the signal contour before binarization by Otsu's method, then we complete with morphological operations. The second objective is the classification of the resulting images from the above method into two categories normal and abnormal. The experimental result of the images collected at the National Cardiology Center of Nouakchott shows the superiority of our approach over the global thresholding and Otsu methods. This ECG digitization approach is an accurate and reliable method for efficient storage and analysis. The results of the binary classification on our test base showed an accuracy of 97%.
Keywords: *Electrocardiogram (ECG), Digitization; Bilateral Filter, Otsu's Thresholding, CNN*

1. INTRODUCTION

Cardiovascular disease (CVD) is a group of heart disorders and is considered one of the leading causes of death in the world with a rate of 32% in 2019 corresponding to 17.9 million people according to World Health Organization [1] . Mauritania is a country located in northwest Africa with a population of approximately 4.6 million (2020), with more than half of the population living in urban areas (53%) (2017) [2]. The country's largest city Nouakchott is the home of the only Cardiology Center. As well as world status, heart disease is one of the leading causes of death in Mauritania with a rate of 14.17% in 2021 [3]. The electrocardiogram is one of the most common and simple tests to record the electrical activity of the heart. It is an important clinical tool for the diagnosis of cardiac pathologies [4]. The graphic representation of heart activity is called electrocardiography, the signals are measured using electrodes on the surface of the body [5][6]. The electrocardiogram remains an essential examination for the recognition of certain cardiological emergencies (rhythm disorders, conduction disorders, acute coronary syndromes), The ECG is collected on a gridded graph paper to have a standardized measurement [7]. In dense populations where the conditions for patient care are expensive and limited, only hospitalized patients have the right to an archive at the cardiology center and the other patients keep their own medical records [3]. In both cases due to the sensitivity of medical images, the noisy thermal paper of the electrocardiogram deteriorates over time [8]. One of the most used solutions nowadays is the scanning and storage of the electrocardiogram graph as an image. The problems with this process are that it requires a large amount of storage and the transmission takes longer [9]. Also, in hospitals with a large number of patients, retrieving the ECG recording from the archives is a laborious and time-consuming task [10]. For these reasons, digitizing ECG paper has become a real challenge for researchers in the field of biomedicine. Converting the ECG paper to digital format will help to solve sharing and storage problems [11], and enables for features extraction [10]. Existing methods of ECG paper digitization generally involve 4 steps: Region-Of Interest detection, grid removal, signal refinement, and vectorization described in [12]. In [13] the author introduced several methods for ECG digitization and concluded that all proposed methods have their own advantages and disadvantages and that there is no single method that is universal. ECG signal preprocessing techniques are being largely explored, but the choice of which method to use is intrinsically linked to the final research objective [14]. we can find in the latter, a list of articles on the preprocessing of ECG signals and the segmentation of heartbeats. The author talks about the importance of these two steps that has a great influence on the final results of classification. In [15], the authors evaluated four pre-processing algorithms to remove the noise components from the ECG signal, The results of their study showed that the Normalized Least Mean Square (NLMS) algorithm can achieve better SNR and Sign LMS compared to other methods. Waits et al. 2017 enumerate a list of different methods of converting ECG papers into digital format in [16]. Various algorithms are used to detect the ECG signal, distinguish it from noise and grid line, and generate a continuous ECG signal. Several algorithms between them present limitations and problems of High frequency noise, salt and pepper noise coming from the suppression of the grid lines, thickness of the signal, we can quote for example [17] [18][19][20]. Aiming at the above problems, the objective of this work is to develop an approach for ECG document conversion and storage using computer vision methods [21] in preprocessing tasks. Bilateral filter and Otsu algorithm are the main methods used in this study. The first one is used before image segmentation to smooth the images, reduce noise and preserve the signal edges. The second is the Otsu thresholding method which separates background and foreground data with an automatic threshold value for each image. These preprocessed ECG images can be used for classification using deep learning (DL) architectures which have shown good results comparable to human experts and other machine learning strategies in various domains, such as speech recognition, image classification, speech recognition, natural language processing and games [22][23]. In addition, DL shows promising results in heart disease classification [12][24][25].

The organization of the paper is as follows: section 1 provides introduction to the research topic. Section 2

presents our approach for converting the ECG paper record and the different methods used. Section 3 discusses the result of this method and finally section 4 presents conclusions and the future work of this research.

2. PROPOSED METHODOLOGY

The present work consists of two parts as follows:

- In the first part, we aim to digitize ECG papers, Firstly, we will describe preprocessing methods adopted in this research to enhance the quality of the scanned images. The format of the scanned image can be PDF, JPEG, PNG. After the process of data reading, all images are saved in PNG format. The next step is the selection of a region of interest (ROI). Then the algorithm is completed by a sequence of image processing methods that perform image conversion, image smoothing, noise reduction and thresholding. Morphological operations will be performed on the binary image, then find the edge of the signal and draw it.
- In the second part, after the process of ECG papers digitalization, we apply a Convolutional neural network model (CNN) with different sizes of convolution, the ECG data sets are taken from the generated database for developing an automatic system able to help the doctors in classifying ECG signals of patients.

The following scheme describes the proposed approach

2.1 Scanned Image

Every patient who visits the National Cardiology Center for an ailment is given an electrocardiogram to see his heart rhythm. The result of this analysis is printed on a millimeter sheet and then scanned. Figure 2 shows different ECG images recorded over different periods.

2.2 Image Reading and Grayscale Conversion

To read the RGB (Red, Green, Blue) color image scanned figure 2, we import the image as a two-dimensional vector, then the image is transformed into grayscale with a range from 0 to 255, where 0 represents black and 255 white [26]. The size and processing time of color images (RGB images) can

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ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

be reduced by converting them to grayscale [27]. The grayscale image is shown in Figure 3. The frequency of each grayscale value was determined using equation (1):

$$f(I) = \frac{\sum_{0 \le i,j \le 255} I(\text{i,j})}{\text{N}} \qquad (1)$$

where N is the number of pixels in the image, $\sum I(i,j)$ the number of pixels with an intensity value equal

to $I(i,j)$ and $f(I)$ is the frequency of the grayscale intensity [28].

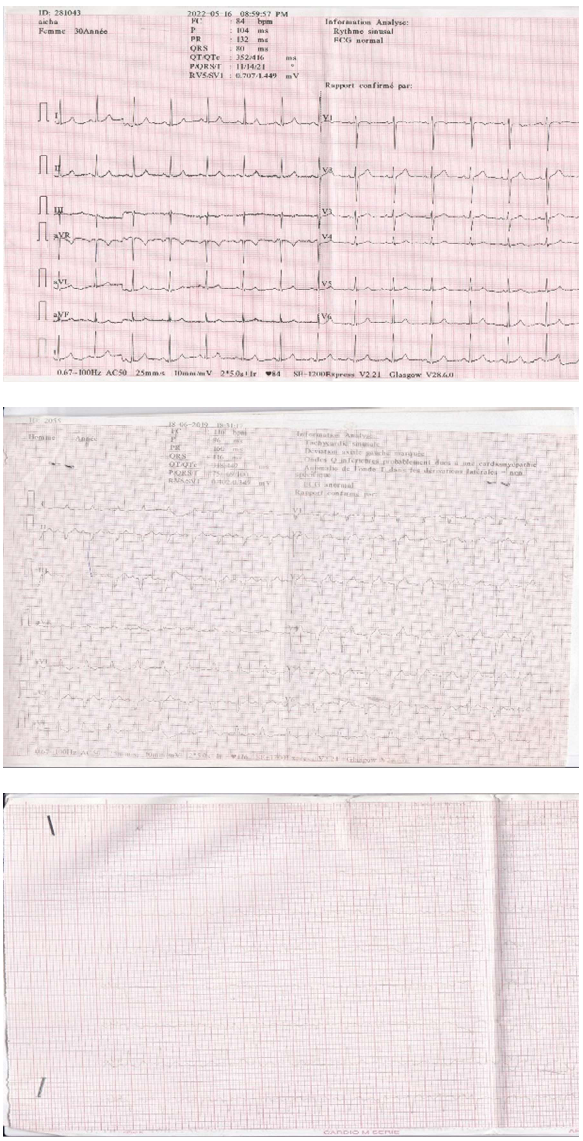

Figure.2. An electrocardiograph Trace from: (a) recorded on 2022-06-01, (b) recorded on 2019-06-18, and (c) recorded on 2015-04-01.

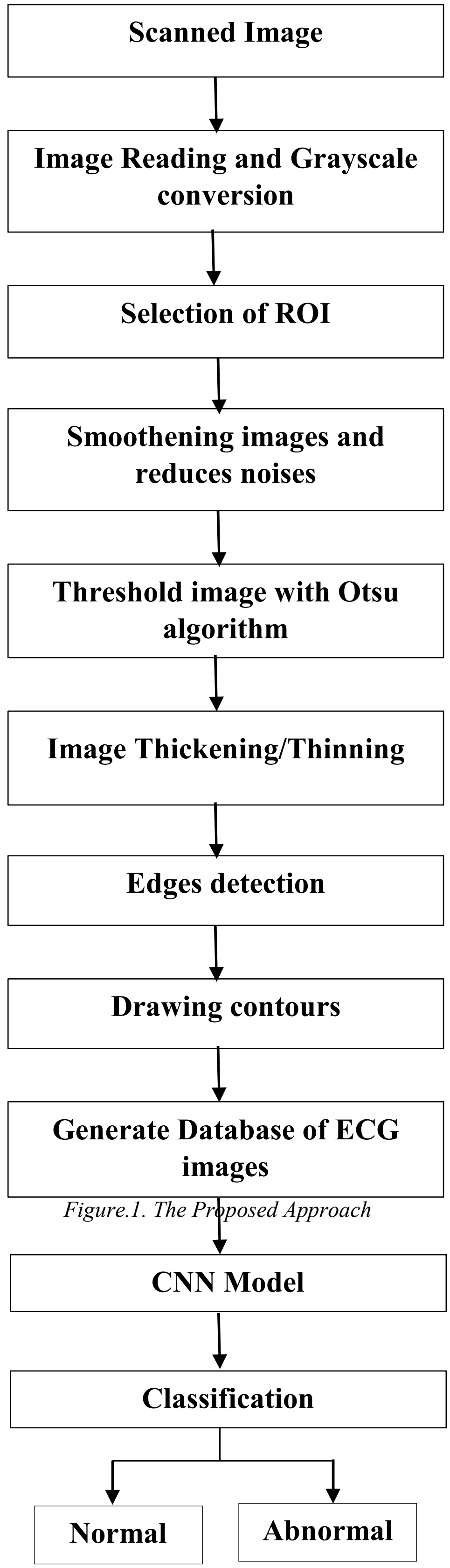

Figure.1. The Proposed Approach

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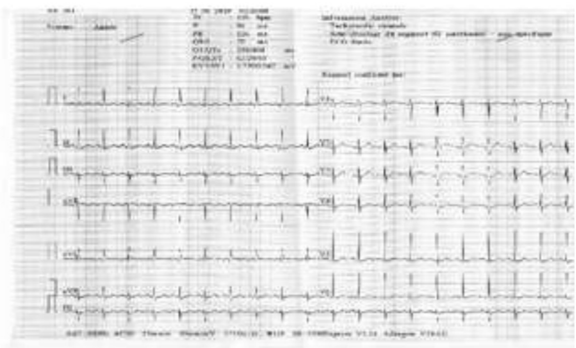

Figure.3. An Electrocardiograph Converted to Grayscale

2.3 Crop ROI

Each ECG paper contains the patient's personal information on top and the 12 leads on the bottom, as shown in Figures 2 and 3. Therefore, to extract the information, it is necessary to slice the region of interest. After reading the image using the above method, it is stored as an n-dimensional NumPy array. To crop an image to remove all unwanted objects or areas or even to highlight a particular feature of an image, NumPy array clipping is sufficient to do the job. All you have to do is specify the start and end indices of the image. This method is a crucial step in image processing to extract a region of interest and patches.

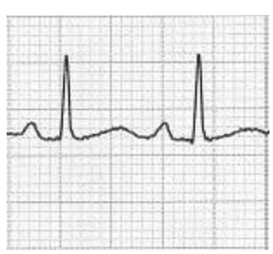

Figure.4. Selection of ROI

2.4 Smoothening images and reducing noises

In the literature, we have several techniques for image smoothing i.e. 2D Convolution, Averaging Blur, Gaussian Blur, Median Blur [29]. However, these convolutions often result in significant information loss as they blur everything including noise and edges. Therefore, Tomasi et al. introduced the bilateral filter in [30] to solve this problem. By computing a weighted average of the pixel values in the neighboring area, it extends the concept of Gaussian low pass filters. Two Gaussian filters are applied to the neighborhood of a target pixel: the domain filter and the range filter [31]. The bilateral filter can be expressed as follows:

$$BF[I]_P = \frac{1}{W_p} \sum_{q \in S} G_{\sigma_s}(\|p - q\|)\, G_{\sigma_r}(I_p - I_q) I_q \quad (2)$$

Where W_p is a normalization factor

$$W_p = \sum_{q \in S} G_{\sigma_s}(\|p - q\|)\, G_{\sigma_r}(I_p - I_q) \quad (3)$$

Range weight

$$G_{\sigma_r}(I_p - I_q) I_q \quad (4)$$

Gaussian Blur

$$GB[I]_P = \sum_{q \in S} G_{\sigma_s}(\|p - q\|)\, I_q \quad (5)$$

σ_s denotes the spatial extent of the kernel and σ_I denotes the minimum amplitude of an edge. In this case, to obtain a better result in the binarization step, we used a bilateral filter to smooth the images and reduce the noise, while preserving the edges. As seen in Figure 5, shows different filters on the ECG image Averaging, Median, Gaussian Filter and in Figure 5.d we applying bilateral filter to smooth the images, most of the noise has been removed and the edge is conserved, the ECG signal is more visible compared to the background.

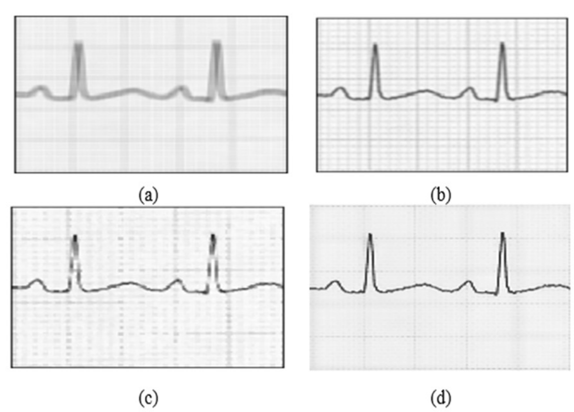

Figure.5. Comparison of Different Filtering Methods on an ECG ROI: Averaging(a); Median filter (b); Gaussian filter (c) with a kernel size (3, 3) and Bilateral filter with parameters space (10,50, 50) (d)

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15th January 2024. Vol.102. No 1
© 2023 Little Lion Scientific
ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

2.5 Threshold image with Otsu algorithm

The grey shades of the object's pixels are very different from those of its background pixels in many images processing applications Thresholding is a useful but simple tool for distinguishing the background from the objects. This step consists of separating the signal from its background in the image [32]. The first step is to find the grey threshold. In the literature we have many thresholding algorithms (a) ow us to find the grey threshold, such as the m median, the adaptive method and the Otsu algorithm [25] [33] [34]. The Otsu approach is used in computer vision and image processing to automatically execute image thresholding based on the histogram's shape [35]. The OTSU thresholding approach solely considers the image's foreground and background information. In order to reduce th (c) iance between the foreground and background, a thorough search is performed before deciding on the threshold [35].

The whole computation equation can be described as:

$$\sigma_\omega^2(t) = \omega_1(t)\sigma_1^2(t) + \omega_2(t)\sigma_2^2(t)$$
(6)

where $\omega_1(t)$ and $\omega_2(t)$ are the two class probabilities divided by a threshold t, whose value is between 0 and 255.

The first step is to minimize the intra-class variance defined above $\sigma_\omega^2(t)$ using the expression below:

$$\sigma_b^2(t) = \omega_1(t)\omega_2(t)[u_1(t) = u_2(t)]^2,$$
(7)

Where u_i represents the class. Using the cluster probability functions denoted as follows, the probability P is determined for each pixel value in the two distinct clusters $C1$ and $C2$:

$$\omega_1(t) = \sum_{i=1}^{t} P(i) \quad \text{and} \quad \omega_2(t) = \sum_{i=t+1}^{I} P(i)$$
(8)

The total number of pixels in the image is n.

The probability of a grey level being present is thus

$$P(i) = \frac{n_i}{n}. \qquad (9)$$

The pixel intensities for $C1$ are within [1; t] and for $C2$ within [t + 1; I], where I is the value of the maximum pixel (255). The next step is to obtain the averages for $C1$ and $C2$, which are appropriately denoted by $u_1(t)$ and $u_2(t)$:

$$u_1(t) = \sum_{i=1}^{t} \frac{iP(i)}{w_1(t)} \quad \text{and} \quad u_2(t) = \sum_{i=t+1}^{I} \frac{iP(i)}{w_2(t)}$$
(10)

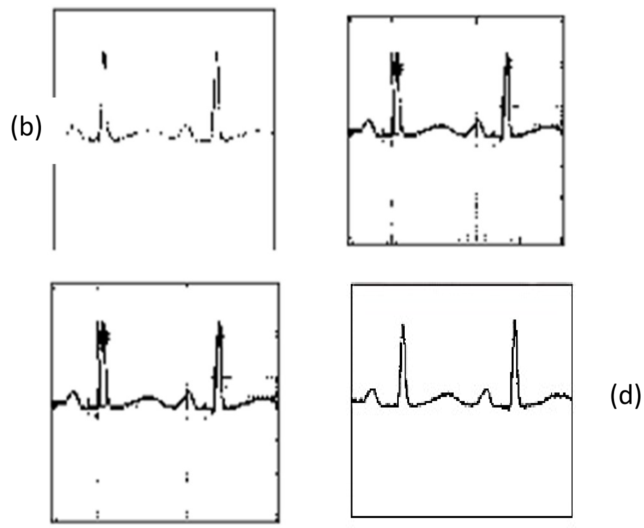

Figure. 6. Comparison of Different Segmentation Methods after the Smoothening and Denoising step: Global Thresholding with value of threshold v=127 (a); Adaptive Gaussian Thresholding (b); Adaptive Mean Thresholding (c) and Otsu Thresholding(d)

2.6 Morphological Operations

Structuring Elements (SEs), first introduced by Serra in [36], were utilized to gather data on the geometry, boundaries, and skeleton of an image. Getting a morphological feature map involves three steps. In this paper, we'll focus on the morphological functions, which constitute the third step in this process. Erosion and dilation are two fundamental morphological processes that are frequently applied to binary pictures.

Erosion:

Dilation:

$$(BI \ominus g)(i,j) = min[BI(i+m),(j+n) - g(m,n)] \quad (11)$$

$$(BI \oplus g)(i,j) = min[BI(i-m),(j-n) - g(m,n)] \quad (12)$$

Where $BI(i,j)$ is the binary image, $g(m,n)$ is the SE, and ⊕ and ⊕ are the corresponding dilation and erosion operators. Erosion deletes pixels from the object boundary, which can help to separate closely related objects. Dilation causes the object boundary to increase by one pixel [37].

In this approach, the opening operation, which is a procedure of erosion followed by dilation, is used to remove the remaining noise from the binary image.

2.7 Edges Detection

Edge detection in image processing is the process that allows the detection of discontinuities and sharp changes in image brightness, this process consists of extraction of large gradient magnitude of brightness from images [38]. We have many methods of edge detection in literature like Robert's detector, Prewitt, Sobel, Laplace, canny and other operators [39]. The Canny edge detection technique is considered one of the most effective methods compared with other techniques used in this field [38] [40]. Canny's edge detection algorithm was developed by John F. Canny in 1986. It is an edge detection operator used to extract a large set of edges from images. This algorithm is one of the first-order edge detection methods, where the edge represents discontinuous changes in brightness on digital images. In this study, we used Canny's edge detection method after a comparison between this one and Sobel technique. The comparison shows that the Canny method gives results better than the Sobel method.

2.8 Drawing contours

Contours are lines connecting all points that have the same value. Contours are a useful tool for analyzing shapes and detecting and recognizing objects [41] [42]. herein we used the Opencv Contours image processing cv.findContours and cv.drawContours. The Find Contours function is used to search for contours and place them in list with their hierarchy. All the identified contours by the function above are drawing by using the cv.DrawContours function.

2.9 CNN Architecture

This section presents two CNN model applied to the resulting images from the above-proposed approach for classification into two classes of normal and abnormal arrhythmia. In this paper, we tested two CNN models, one with a 32-filter convolution and a second model with two convolutions one of 32 filters and the other of 64 filters to extract the image features followed by Relu activation function. After each convolution a Max_pooling of (2,2) is applied to reduce the dimensions and parameters of the image, then the two-dimensional image is flattened into a vector by applying the Flatten() class, then the Dense layer which is a fully connected layer with the Relu activation function and at the end another Dense layer with the sigmoid activation function which is commonly used in binary classification.

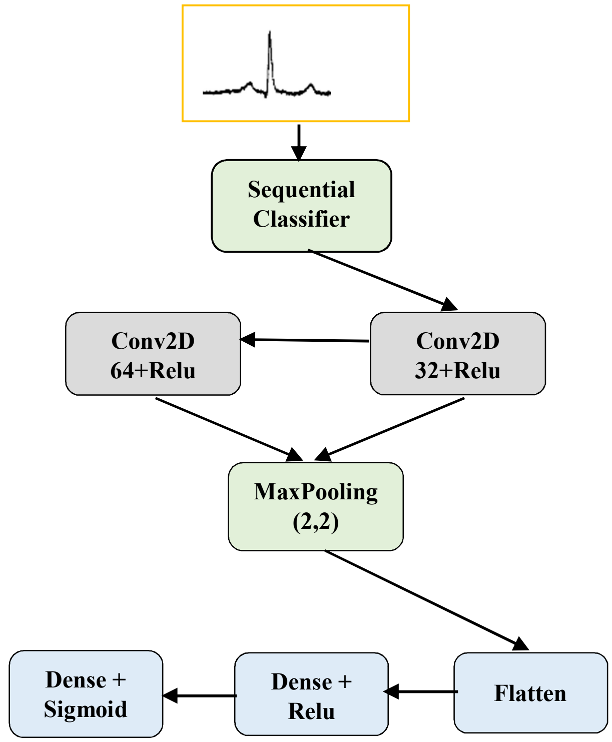

Figure.7. Diagram of Proposed CNN Model

3. EXPERIMENTS AND DISCUSSION

3.1 Data Set

The feasibility of the introduced method is demonstrated on images of electrocardiograph collected from the archive room and the emergency room of the National Cardiology Center of Nouakchott Mauritania where I spent an internship to understand the structure of the institution and how the records of patients are filed. The images were digitized by the approach proposed in this manuscript and then stored in two different files

N°	Data set	Training Accuracy	Training loss
1	Train 90 Test 10	0.9	0.34
2	Train 80 Test 20	0.94	0.27

normal and abnormal electrocardiogram. For the test base 100 samples were used for classification.

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© 2023 Little Lion Scientific
ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

3.2 Experimental Procedure

The algorithm implementation programs in python language [43] by using the OpenCv library [21] who played an important role in this project. The proposed CNN classifier is implemented Python, with an open-source library Tensor Flow developed by Google for deep learning.

The aim of this binary classification is to obtain a prediction and an accuracy of the arrhythmia from the database generated to measure its performance, by calculating the accuracy and the loss function of the CNN model.

Accuracy is defined as the proportion of correct forecasts to the total number of forecasts. Its equation is defined by:

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} \quad (13)$$

Where: TP = true positive; FP = false positive; TN = true negative; FN = false negative.

In this work the loss function used is the Binary cross-entropy defined by:

$$H_p(q) = -\frac{1}{N}\sum_{i=1}^{N} yi.\log(p(y_i)) + (1 - y_i).\log(1 - p(y_i)) \quad (14)$$

Where y is the label, and p(y) is the predicted probability of the point for N points.

The following tables show the validation test with different rates of data sets.

TABLE I: VALIDATION TEST OF THE FIRST MODEL (CONV2D 32 FILTERS)

N°	Data set	Training Accuracy	Training loss
1	Train 90 Test 10	0.9	0.2
2	Train 80 Test 20	0.97	0.12

TABLE II: VALIDATION TEST OF THE SECOND MODEL (CONV2D 64 FILTERS)

Tables I, and II show different training models of the generated database. Table 1 shows the results of the 32-filter convolution model with two training and testing batches. The first batch with 90% training and 10% testing gave an accuracy of 0.9 and a loss of 0.2, for the second batch with 80% training and 20% testing, the model showed an accuracy of 0.97 and a loss of 0.12. Table II shows the results of the model for two convolutions of 32 and 64 filters with two training and test batches. In the first trial with 90% training and 10% testing the rate gave an accuracy of 0.9 and a loss of 0.34, for the second batch 80% and 20%, the model shows an accuracy of 0.94 and a loss of 0.27.

It is concluded that the first model (Conv2D 32filters) with the training base (80% and 20%) gives the best results with an accuracy of 0. 97 and a loss of 0.12.

Discussion

this paper, we compared and evaluated different threshold methods in order to extract the ECG signal. First in section2, in Figure 5 we compared bilateral filter [30] and other filter method [29] to show the efficiency of this method. we apply the Otsu binarization method [35] on the resulting image, Figure 6.d gives a better result compared to other ·esholding techniques. Same in Figure 6 where we mpared two techniques of edges of detection [38]. As shown the canny edges detection give best result compered to sobel edges detection that explain the use of this technique. Furthermore, we compared our global proposed method with traditional method of threshold [31] in this section as shown in Figure 8. This is composed of three different scanned ECG images that are shown in the first column the original image, the second column present the result of global freeholding [44] [45] that gives good result but we noticed in 1.a, we have a loss of a part of the signal, in 2.a, 3.a and 4.a we have a presence of salt of noise and grid and have the inconvenient that we chose a value of threshold for each image to have a good result. the third column present the result of Otsu method that shown a bad result of ECG binarization in 1.b, 2.b, 3.b and 4.b in this case we have the advantage that give an automatic value of threshold, that explains our choice in the last column which represents the approach proposed by the use of the Bilateral filter method and after the Otsu method, the morphological operations and the Canny edges detection method. We can see that in the four line 1.c, 2.c, 3.c and 4.c dated 21-12-2020, The result is better and the signal is more clearly with

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the high differentiation between the foreground and the background. After the digitization process, we trained the generated images in a classical convolution network which is composed of 4 convolution layers, pooling layers, and a fully connected layer. We obtained a very high accuracy level for the binary classification, which shows the performance of the proposed approach. Tables I and II show that the generated database gives an effective result with an accuracy of 97% for the CNN model.

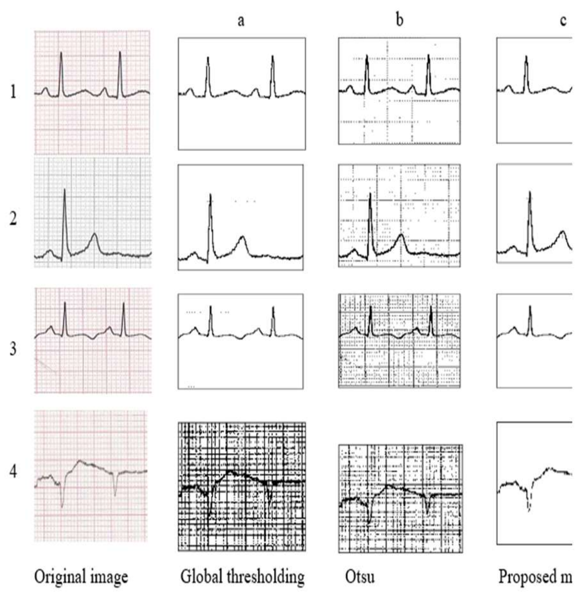

Figure. 8. Comparison of Thresholding Results on ECG Paper ROI. From the first column to the fourth one, they show in order: the original image, Global thresholding, Otsu, proposed method.

4. CONCLUSION

In this article a new approach to classifying scanned ECG documents has been developed. The scanned images of the electrocardiograph trace were digitized to extract and generate a new database to help doctors preserve these images for monitoring and diagnosing cardiac arrhythmias. In the signal extraction method, we used the Bilateral filter for denoising and smoothing the image, Otus algorithm for the binarization of the images, morphological operations (eroding, dilating), canny edges detection and finally drawing the contours in order to preserve all the chains of points of signal. The experiments result of different techniques conclude that the proposed method shows that applying bilateral filter before thresholding process gives best result and allows processing scan ECG images gains best results compared to others techniques viewed in this paper and can be applied on every types of ECG paper records. The CNN model used diagnoses two cases, normal and abnormal ECG graph. The classification result on a set of 100 images gives us a satisfactory result with an accuracy of 97%. Both proposed methods can be improved by augmenting the images by developing an image digitization application with the proposed method to form a large ECG database, improving the CNN method for classification and differentiation of several types of cardiac arrhythmia classes and measuring its performance against other databases in the literature. The proposed method will allow us to create a dataset of digital ECG signals, to classify different cardiac arrhythmias and use other deep learning methods as part of this project's perspectives.

ACKNOWLEDGMENT

We thank the National Cardiology Center of Nouakchott (CNC) for their hospitality and availability and the interest they have shown in the research project.

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ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

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