Android-based ECG Monitoring System for Atrial Fibrillation Detection using a BITalino® ECG Sensor

Gabriel Saatkamp Lazaretti[1,2][a], João Paulo Teixeira[1][b], Eduardo Vinicius Kuhn[2][c], and Pedro Henrique Borghi[3][d]

[1]Research Centre in Digitalization and Intelligent Robotics (CEDRI), Instituto Politécnico de Bragança (IPB), Portugal
[2]Federal University of Technology - Paraná (UTFPR), Toledo, Brazil
[3]Faculty of Engineering of University of Porto (FEUP), Porto, Portugal

Keywords: Android, Atrial Fibrillation, BITalino, ECG, Smartphone.

Abstract: Cardiac arrhythmias are disorders that affect the rate and/or rhythm of the heartbeats. The diagnosis of most arrhythmias is made through the analysis of the electrocardiogram (ECG), which consists of a graphical representation of the electrical activity of the heart. Atrial fibrillation (AF) is the most present type of arrhythmia in the world population. In this context, this work deals with the implementation of a system for automatic analysis of ECG signals aiming to identify AF episodes. The system consists of a signal acquisition step performed by an ECG sensor connected to an acquisition platform. The acquired signal is transmitted via bluetooth to a smartphone with Android™ operating system. The signal processing is carried out through an application developed using the IDE Android™ Studio. When assessed over signals from the MIT-BIH Atrial Fibrillation database, the R-wave peak detection algorithm showed mean values of sensitivity and positive predictivity of 98.99% and 95.95%, respectively. The classification model used is based on a long short-term memory (LSTM) neural network and had an average accuracy of 94.94% for identifying AF episodes.

1 INTRODUCTION

Cardiovascular diseases (CVDs - cardiovascular diseases) are one of the main causes of death around the world. According to data from the world health organization, it is estimated that about 17.9 million people died from some type of CVD in 2019, which represents 32% of the deaths in the world with 85% of them being from stroke and myocardial infarction (commonly called heart attack) (World Health Organization, 2021). In this context, arrhythmias are disorders that affect the frequency and/or rhythm of heartbeats (Antzelevitch & Burashnikov, 2011). Among the various types of arrhythmias, atrial fibrillation (AF) is the most common. In the European Union, it is estimated that the number of AF cases in the adult population over 55 years of age reached 8.8 million in 2010 (Krijthe et al., 2013). Worldwide, this number reached the 33.5 million mark in the same year (Chugh et al., 2014). This predominant arrhythmia, if not treated, increases the chances of developing an eventual cardiac arrest (Wang et al., 2003), dementia (Ott et al., 1997), as well as strokes (Dulli et al., 2003; Jørgensen et al., 1996; H.-J. Lin et al., 1996; Marini et al., 2005; Wolf et al., 1991, 1998). So, since AF is associated with an increased risk of mortality, it deserves medical attention (Miyasaka et al., 2007; Stewart et al., 2002).

Developed by Willem Einthoven in 1902 (AlGhatrif & Lindsay, 2012), the electrocardiogram (ECG), which is a graphical representation of the heart's electrical activity, made it possible to observe variations in the frequency and rhythm of the heartbeats; thus, the ECG provides a way to visualize how the electrical system of the heart behaves. In this context, the 12-lead system is the most widely used for diagnosing cardiac arrhythmias (Mittal et al., 2011). Figure 1 shows a typical waveform of a

[a] https://orcid.org/0000-0003-2993-5398
[b] https://orcid.org/0000-0002-6679-5702
[c] https://orcid.org/0000-0003-0881-4888
[d] https://orcid.org/0000-0003-2918-6630

Lazaretti, G., Teixeira, J., Kuhn, E. and Borghi, P.
Android-based ECG Monitoring System for Atrial Fibrillation Detection using a BITalino® ECG Sensor.
DOI: 10.5220/0010905400003123
In *Proceedings of the 15th International Joint Conference on Biomedical Engineering Systems and Technologies (BIOSTEC 2022) - Volume 1: BIODEVICES*, pages 177-184
ISBN: 978-989-758-552-4; ISSN: 2184-4305

complete cardiac cycle (one beat) in an ECG signal, consisting of a sequence of waves and complexes called P wave, QRS complex, T wave and U wave.

The AF occurs due to the generation of multiple electrical impulses in different regions of the atria (ectopic foci) which cause irregular muscle cell stimulation, resulting in ineffective or even non-existent atrial contraction (fibrillatory behavior). The main symptoms that may indicate the presence of AF in the patient are the feeling of weakness, chest pain, shortness of breath, and palpitations. However, in some cases, AF can occur without any evident symptoms (asymptomatically). The main features observed in an ECG signal for diagnosing AF are:

- Irregular heart rate, i.e., unexpected changes in the R-R interval (termed RRi) over time; and
- Absence of a clearly distinguishable P wave which is then replaced by fibrillatory waves (F waves).

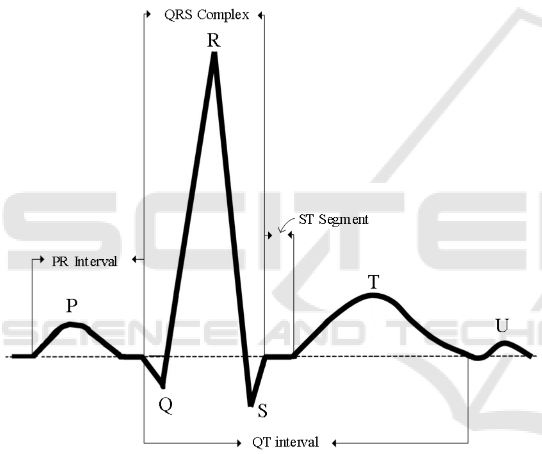

Figure 1: Points and intervals of interest in the electrical representation of a heartbeat.

2 PROBLEM FORMULATION

The diagnosis of CVDs, as AF, is in general performed through the analysis of the ECG signal by a qualified health professional. Nevertheless, due to the advances of medical technology, computer systems for automatic ECG analysis have been able to assist professionals in the diagnoses of pathologies. The use of computer-aided diagnosis systems (CADx) becomes especially interesting in the analysis of ECG recordings with long hours of duration (Hagiwara et al., 2018). [Such systems consist in general of four main sequential steps, namely: 1) Pre-processing; 2) Segmentation; 3) Feature extraction; and 4) Classification.] Note that, with the development of the Holter monitor in the 1940s, methods for ambulatory and external monitoring of the ECG (AECG -Ambulatory External Electrocardiogram), as described in (Mittal et al., 2011), have emerged as an important tool to perform AF diagnosis for the 12-lead ECG.

Considering the processing capacity, portability, and affordable price of smartphones, researchers are proposing their use as processing devices in automatic ECG signal analysis systems for the diagnosis of cardiac arrhythmias. Specifically for the detection of AF events, the “ECG Check” device, developed by Cardiac Designs®, and the “Kardia Mobile”, developed by AliveCor®, are examples of professional devices which use smartphones to detect the presence of AF events based on a single lead of the ECG signal. The effectiveness of these devices is discussed in (Aljuaid et al., 2020; Chan & Choy, 2017; Evans et al., 2017; Garabelli et al., 2017; T. Hickey et al., 2017).

In this context, the present research work has the following objectives:

- To acquire a single lead ECG signal using 3-electrode configuration;
- To transmit the signal from the acquisition device to the processing device using bluetooth technology;
- To assess the received signal and implement, if necessary, a pre-processing step to remove artifacts from the acquired signal;
- To implement a segmentation algorithm for detecting QRS complex and R-peaks in ECG signals;
- To extract features from the ECG signal which will serve as input to the machine learning model used in the classification step; and
- To implement a classification step, based on a Long Short-Term Memory (LSTM) neural network capable of classifying segments of ECG signal according to their rhythm (normal rhythm, AF, or another rhythm).

3 ECG SIGNAL ACQUISITION AND TRANSMISSION

The ECG acquisition step is concerned with the proper placement of electrodes and the design of a signal conditioning system used to amplify, filter, and digitalize the signal. Particularly, the acquisition of the ECG signal was performed here by a BITalino® ECG sensor (using a 3-electrode configuration) connected to the A1 analog port of the BITalino®

(r)evolution Core platform, which works with a rechargeable battery and has bluetooth technology for transmitting the acquired signals [for details, see (BITalino, 2021a)].

Considering the nomenclature presented in (Drew et al., 2004), the electrodes were positioned as follows: Positive electrode in RA; Negative electrode on LL; Reference electrode in LA. The acquired ECG signal is transmitted to the smartphone via bluetooth, since both the BITalino® (r)evolution Core platform and the smartphone support it. Furthermore, bluetooth is a consolidated communication protocol for transmitting information wirelessly over a short distance requiring low-power consumption. Moreover, the use of bluetooth protocol in an Android™ environment is made easy through some APIs (Android, 2021). Still, the manufacturer of the BITalino platform, PLUX - Wireless Biosignals S.A, provides an API that makes it possible to establish and manage the bluetooth communication [for details, see (BITalino, 2021)]. Finally, the smartphone receives a digital ECG signal with resolution of 10 bits (see specifications of the A1 analog port), sampled at 100 Hz, and with a limited frequency range between 0.5 Hz and 40 Hz (which is, to some extent, enough to deliver a high-quality ECG signal). In turn, the processing of the ECG signal on the smartphone is done through 20-second windows, i.e., a new window containing the last 20-seconds samples of the ECG signal is ready to be processed every 20 seconds. It is important to mention that the acquisition of the signal is done asynchronously in relation to the processing; so, while a 20-second window is being processed, another one is being acquired. The first processing step, carried out over the 20-seconds window of the acquired signal, involves the use of the ECG sensor transfer function (BITalino, 2021). After applying the sensor transfer function, the signal samples are transformed to values whose amplitude is within the range of -1.5 mV to 1.5 mV. The signal is then resampled to 250 Hz (using the “resample” function of the MATLAB® software) to meet the input conditions of the segmentation step used.

It is worth mentioning that the BITalino device can acquire the ECG signal with good quality and low noise level when the measure is done with the user at rest. On the other hand, the signal obtained while the user was walking contains several artifacts that end up mischaracterizing the ECG. For this reason, the acquisition of the signals considered in this study was conducted with the user at rest and it was ensured that there was good contact between the electrodes and the skin surface at each measurement. Thereby, it was not necessary to implement any other signal pre-processing step in the system.

4 R-PEAK DETECTION ALGORITHM

Figure 2 depicts a block diagram of the implemented R-wave peak detection algorithm, which is based on (D. Benitez et al., 2001; Kaur et al., 2019; Manikandan & Soman, 2012). Although the same algorithm was used and validated in the work of (Borghi et al., 2021), some modifications were made in the original algorithm aiming to process 20-second windows and to port the code to the C language through the MATAB Coder™ application. Basically, in this algorithm, the ECG signal is first filtered by a 480-order FIR-type bandpass filter, with a passband between 5Hz and 15Hz, designed using the self-convolution method of a 60th-order Hamming window (Kaur et al., 2019). Then, the first-order derivative of the filtered signal $f(n)$ is calculated through

$$d'(n) = f(n+1) - f(n). \tag{1}$$

According to (Manikandan & Soman, 2012), signal differentiation acts as a high-pass filter to reduce interference from P and T waves. Next, $d'(n)$ is normalized as

$$d(n) = \frac{d'(n)}{\max_{n=1}^{N}[|d'(n)|]} \tag{2}$$

where N denotes the number of samples corresponding to a 20-second window of the ECG signal. The nonlinear Shannon energy (SE) transformation is applied to $d(n)$, i.e.,

$$E_s(n) = -d^2(n)\log_2[d^2(n)]. \tag{3}$$

This transformation aims to rectify and to highlight the region of the QRS complex, facilitating the detection of R peaks. The resulting Shannon energy signal is smoothed by a 38-sample window moving average filter (approximately, 152.7 ms for a sampling frequency of 250 Hz). The Hilbert transform is applied to the smoothed signal $s(n)$, resulting in $h(n)$. In turn, $h(n)$ is applied to a rectangular moving average filter with a duration of 625 samples, yielding $h'(n)$. Then, we compute

$$z(n) = h(n) - h'(n) \tag{4}$$

aiming to smooth out the signal and identify the lower amplitude R-peaks. At the end of this process, a smoothed odd symmetry signal $z(n)$ is obtained, where its zero-crossing point corresponds to the peak of $s(n)$, which is a strong candidate for the R-peak position. Finally, using these candidate points as a reference, an R-peak position detection is done by searching for the local maximum near each candidate point. The algorithm was validated considering the MIT-BIH Atrial Fibrillation database (Moody & Mark, 1992), which contains 23 recordings of ECG signals of 10 hours each taken in patients diagnosed with AF. Each of these recordings has two ECG signal leads, sampled at 250 Hz, with 12-bit resolution and with a bandwidth between 0.1 Hz and 40 Hz. Only the first lead of each recording was used in the validation of the implemented segmentation algorithm. The same database was used in the work of (Borghi et al., 2020, Borghi et al., 2021) for validating the R-peak detection algorithm, as well as for validating the classification model.

The performance of the algorithm is shown in Table 1 in terms of the sensitivity metric, defined as

$$Se = \frac{TP}{(TP + FN)} \tag{5}$$

and positive predictivity metric, given by

$$P+ = \frac{TP}{(TP + FP)} \tag{6}$$

where TP (True Positive), FP (False Positive), and FN (False Negative) indicate, respectively, the number of labels that represent a heartbeat, the number of labels that does not represent a heartbeat, and the number of beats that were not marked (Luz et al., 2016). As in (Borghi et al., 2020), it was considered that the labeling made by the algorithm regarding the position of the R-peak is correct if within a context region of 150 ms centered on this mark (75 ms before and 75 ms after) there is an original annotation in the database. The algorithm presents good detection results, with mean values of Se and P+ equal to 98.99% and 95.95%, respectively.

In (Borghi et al., 2020), the segmentation algorithm was validated using the measure of accuracy, calculated for each subject as

$$ACC = \frac{TP}{N_b} 100\% \tag{7}$$

where N_b represents the total number of beats marked in the database annotations. The average accuracy found in (Borghi et al., 2020) is 98.95%, while the average accuracy found here is 98.99%. These results are consistent and confirm the effectiveness of the approach used to port the code made in MATLAB to C language.

When the algorithm is applied to an ECG signal acquired by the BITalino platform, the results were validated through visual inspection. Figure 3 shows the detection results for a 5-second signal acquired with the user at rest. Notice that the algorithm can properly detect the position of R-peaks in ECG signals.

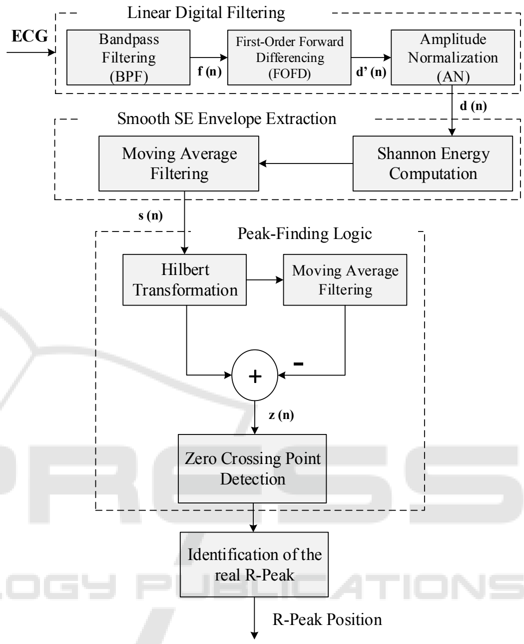

Figure 2: Block diagram of the R-peak detection algorithm adapted from (Manikandan & Soman, 2012).

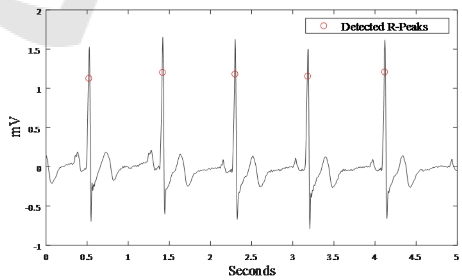

Figure 3: R-peaks detected by the segmentation algorithm with the subject at rest.

5 FEATURE EXTRACTION AND CLASSIFICATION MODEL

Considering the position of the R-peaks properly detected, we proceed now to the extraction of features

Table 1: Performance of the segmentation algorithm over the signals from the MIT-BIH Atrial Fibrillation database.

SUBJECT	Se(%)	P+(%)	SUBJECT	Se(%)	P+(%)	SUBJECT	Se(%)	P+(%)
1	98,62	95,24	**9**	97.79	96,25	**18**	99,54	96,75
2	99,69	97,1	**10**	99,58	95,98	**19**	98,49	96,11
3	99,71	92,03	**11**	98,49	96,12	**20**	99,99	97,49
4	98,42	95,02	**12**	99.93	98,09	**21**	99,67	96,64
5	99,78	96,55	**13**	99,83	96,88	**22**	99,81	96,49
6	99,87	97,35	**15**	92,64	90,24	**23**	99,43	97,21
7	99,75	96,37	**16**	99,6	96,48			
8	98,97	94,49	**17**	99,95	95,84			
Mean Se (%)		98,99		**Mean P+ (%)**		95,95		

that will serve as input to the classification model. Among these features, the interval between two consecutive R peaks is calculated from

$$\text{RRi}=\frac{\mathbf{R}_{\mathbf{detec}}(n)-\mathbf{R}_{\mathbf{detec}}(n-1)}{250} \tag{8}$$

with vector $\mathbf{R}_{\mathbf{detec}}(n)$ containing the ECG signal samples referring to the moment of occurrence of the R-peaks. In a vector $\mathbf{seg}'(n)$, 60 consecutive RRi values are stored, thus forming a segment. Each segment $\mathbf{seg}'(n)$ is then normalized with respect to its maximum absolute value, i.e.,

$$\mathbf{seg}(n)=\frac{\mathbf{seg'}(n)}{\max_{n=1}^{60}[|\mathbf{seg'}(n)|]}. \tag{9}$$

So, $\mathbf{seg}(n)$ serves as input for the classification model whose output can be one of the following categories, namely: normal rhythm, AF rhythm or other rhythm (see Figure 4). The machine learning model selected to be used in this work was trained by (Borghi et al., 2020) to perform heart rhythm classification and AF event detection, based on a bidirectional LSTM neural network. Such a model, which contains 50 nodes in the hidden layer and needs only the knowledge of RRi, showed an accuracy of 94.94% when validated over the MIT-BIH-Atrial Fibrillation database in (Borghi et al., 2020). As discussed in (Borghi et al., 2020), the RRi is the most significant characteristic to differentiate segments that present a normal behavior from those that exhibit AF events. Note that, since the chosen model uses only 60 RRi values as input features, its implementation is not computationally expensive, ratifying its use on a smartphone.

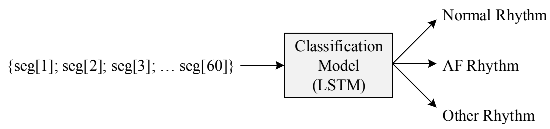

Figure 4: Illustration of the input and possible outputs of the classification model.

6 ANDROID APPLICATION

When launching the app, the user is asked to activate the smartphone's bluetooth function. Once the bluetooth is activated, it is needed to turn on the BITalino platform and press the "Connect" button on the smartphone screen. If the BITalino platform is within the range of bluetooth communication, the platform name and Media Access Control (MAC) address will be displayed on the application screen and, when selecting it, the connection will be established (see Figure 5). Once the smartphone is connected to the BITalino platform, a graphical interface is presented to the user, in which it is possible to visualize the ECG signal, the connection status between the smartphone and the BITalino platform, the name, and MAC address of the platform. Still, three buttons are visible, one named "Disconnect" that allows user to disconnect the platform and smartphone, another named "Find R Peaks", and a third one named "Screen for AF". When the connection status between the platform and the smartphone is indicated on the screen as "CONNECTED", the user can click on either of the two processing buttons. Note that the electrodes need to be properly placed on the body of the user.

6.1 Segmentation Functionality

By clicking the "Find R-peaks" button, the application starts the ECG signal segmentation function. This function analyzes 60 seconds (3 windows of 20 seconds) of the ECG signal and detects R-peaks. Meanwhile, it is possible to visualize in real-time the signal being acquired. The visualization of the ECG signal on the smartphone screen is not restricted to the segmentation functionality. At the end of the measurement, the application notifies the user about how many beats were detected and stores the signal and the annotations regarding the position of the founded R-peaks in a text file saved in the memory of the smartphone. This functionality only performs the segmentation of the ECG signal and does not apply any classification regarding the rhythm of the acquired signal.

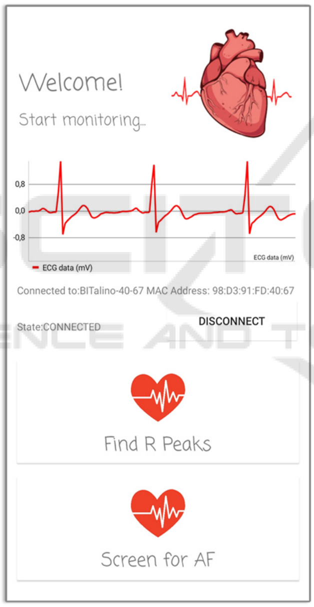

Figure 5: Graphical interface of the application during the ECG signal acquisition.

6.2 Quick Check Functionality

By clicking on the "Screen for AF" button, two options to search for AF episodes are presented to the user. In the first one, called "Quick check", the application will collect one segment with 60 values of RRi and classify it according to its rhythm. Every 20 seconds, the R-wave peak detection algorithm is executed and the detected peaks are counted. The acquisition is interrupted when the system detects the presence of 61 R-peaks. (The number of 20-second windows needed depends on the heart rate of the user.) From these 61 R-peaks, 60 RRi are calculated to yield a segment which serves as input for the classification model. The system then classifies the segment into one of the possible categories (see Figure 4). At the end of the analysis, the user is notified with a message that depends on the classification results. As in the segmentation functionality, the analyzed ECG signal, the position of the R-peaks, and the classification results are saved in a text file in the memory of the smartphone.

6.3 Continuous Monitoring Functionality

The continuous monitoring function, named "Monitor", starts the acquisition of the ECG signal and segments each new 20-second window available. Upon detecting the presence of 61 R-peaks, the application generates a 60 RRi segment, and classifies it into the 3 possible rhythms (as described in Figure 4). In this functionality, the acquisition is not interrupted after the classification of the first segment, i.e., the system continues acquiring signal until the user clicks on the "Stop Monitoring" button. Therefore, this type of monitoring allows collecting the ECG signal for an indefinite period and classifying multiple segments, as long as the bluetooth communication between the platform and the smartphone is maintained. The construction of segments is made considering an overlap of about 50 RRi such that each RRi is analyzed more than once in different segments, reducing the probability of misclassification. At the end of continuous monitoring, i.e., when the user clicks on "Stop Monitoring", a notification will be presented to the user regarding the duration of the signal and the classification results. The acquired signal, the position of the detected R-peaks, and the results of the rhythm classification are saved in a text file stored in the memory of the smartphone. Lastly, it is important to remark that a MATLAB function (called "app2mat") used to read the text file stored in the memory of the smartphone and a video demonstrating the use of the developed application are available in (Lazaretti, G.S. et al., 2021).

7 CONCLUSIONS

A system capable of performing the automatic analysis of an ECG signal and detecting the presence of AF episodes was implemented. The application was developed using the Android™ Studio IDE and the processing steps were developed and validated using MATLAB®. The processing functions and routines were ported to C language through the MATLAB Coder™ and integrated into the application written in Java programming language through the JNI interface. Note that the implementation methodology adopted here makes it possible to implement changes to existing functions and/or to include new processing functions, which can be done first using MATLAB®. So, this methodology saves implementation time and allows testing new processing techniques.

Regarding the acquisition of the signals, it was verified that the ECG sensor and BITalino platform, when used with the subject at rest, can deliver to the smartphone, through the BITalino API, an ECG signal with good quality. On the other hand, when the subject is in motion, artifacts were observed in the acquired signal. Therefore, a pre-processing step should be implemented aiming the use of this application in the ambulatory monitoring of patients.

As presented in (Borghi et al., 2020), one of the most important characteristics for identifying AF events is the RRi. Despite this aspect, Borghi noted that the inclusion of information about the P and T waves of the ECG signal as input characteristics for the classification model increases the classifier accuracy (going from 94.94% to 98.17 %). So, the accuracy of the proposed system could be improved by replacing the classification model used by another one that operates also with input characteristics extracted from P, T and U waves.

In future research works, the application could be redesigned such that it can operate even when minimized. Furthermore, adaptations could be made to include the application in a telemedicine system. In this sense, the application could then send data and results to a server, becoming thus available to a health professional. Still, greater processing capacity can be exploited and new analysis of the signal could be carried out using sophisticated algorithms.

New processing functions can be implemented in the application, since an interesting workflow was developed that allows adding any function written using MATLAB. So, the developed application allows quick implementation and validation of other ECG signal processing algorithms. Furthermore, it is possible to evaluate the performance of these algorithms dealing with real ECG signals acquired by the BITalino sensor and platform. These characteristics, along with the integration between the MATLAB® and the Android™ Studio platform through the MATLAB Coder™ and the JNI interface, are, therefore, the main contributions of this work.

ACKNOWLEDGEMENTS

This work has supported by Fundação para a Ciência e Tecnologia within the Project Scope: UIDB/05757/2020, and by the European Regional Development Fund (ERDF) through the Operational Programme for Competitiveness and Internationalization (COMPETE 2020), under Portugal 2020 in the framework of the NanoID (NORTE-01-0247-FEDER-046985) Project.

REFERENCES

AlGhatrif, M., & Lindsay, J. (2012). A brief review: history to understand fundamentals of electrocardiography. Journal of Community Hospital Internal Medicine Perspectives, 2(1). https://doi.org/10.3402/jchimp.v2i1.14383

Aljuaid, M., Marashly, Q., AlDanaf, J., Tawhari, I., Barakat, M., Barakat, R., Zobell, B., Cho, W., Chelu, M. G., & Marrouche, N. F. (2020). Smartphone ECG monitoring system helps 54 lower emergency room and clinic visits in post–atrial fibrillation ablation patients. Clinical Medicine Insights: Cardiology, 14. https://doi.org/10.1177/1179546820901508

Android. (2021, May 19). Bluetooth overview. https://developer.android.com/guide/topics/connectivity/bluetooth

Antzelevitch, C., & Burashnikov, A. (2011). Overview of basic mechanisms of cardiac arrhythmia. Cardiac Electrophysiology Clinics, 3(1), 23–45. https://doi.org/10.1016/J.CCEP.2010.10.012

Benitez, D., Gaydecki, P. A., Zaidi, A., & Fitzpatrick, A. P. (2001). The use of the Hilbert transform in ECG signal analysis. Computers in Biology and Medicine, 31(5). https://doi.org/10.1016/S0010-4825(01)00009-9

BITalino. (2021a). Documentation. Available at: https://bitalino.com/documentation

BITalino. (2021b). Custom software. Available at: https://bitalino.com/downloads/apis

Borghi, P. H., Teixeira, J. P., & Borges, R. C. (2020). Classificação de episódios de fibrilação atrial por análise do ECG com redes neuronais artificiais MLP e LSTM. Master Thesis in Instituto Politécnico de Bragança.

Borghi, P. H., Teixeira, J. P., & Borges, R. C. (2021). Atrial fibrillation classification based on MLP networks by extracting Jitter and Shimmer parameters. Procedia Computer Science – Elsevier, 181, pp. 931-939. https://doi.org/10.1016/j.procs.2021.01.249.

Chan, N., & Choy, C. (2017). Screening for atrial fibrillation in 13 122 Hong Kong citizens with smartphone electrocardiogram. Heart, 103(1). https://doi.org/10.1136/heartjnl-2016- 309993

Chugh, S. S., Havmoeller, R., Narayanan, K., Singh, D., Rienstra, M., Benjamin, E. J., Gillum, R. F., Kim, Y.-H., McAnulty, J. H., Zheng, Z.-J., Forouzanfar, M. H., Naghavi, M., Mensah, G. A., Ezzati, M., & Murray, C. J. L. (2014). Worldwide epidemiology of atrial fibrillation. Circulation, 129(8). https://doi.org/10.1161/CIRCULATIONAHA.113.005119

Drew, B. J., Califf, R. M., Funk, M., Kaufman, E. S., Krucoff, M. W., Laks, M. M., Macfarlane, P. W., Sommargren, C., Swiryn, S., & van Hare, G. F. (2004). Practice Standards for Electrocardiographic Monitoring in Hospital Settings. Circulation, 110(17). https://doi.org/10.1161/01.CIR.0000145144.56673.59

Dulli, D. A., Stanko, H., & Levine, R. L. (2003). Atrial fibrillation is associated with severe acute ischemic stroke. Neuroepidemiology, 22(2). https://doi.org/10.1159/000068743

Evans, G. F., Shirk, A., Muturi, P., & Soliman, E. Z. (2017). Feasibility of using mobile ECG recording technology to detect atrial fibrillation in low-resource settings. Global Heart, 12(4). https://doi.org/10.1016/j.gheart.2016.12.003

Garabelli, P., Stavrakis, S., & Po, S. (2017). Smartphone-based arrhythmia monitoring. Current Opinion in Cardiology, 32(1). https://doi.org/10.1097/HCO.0000000000000350

Hagiwara, Y., Fujita, H., Oh, S. L., Tan, J. H., Tan, R. S., Ciaccio, E. J., & Acharya, U. R. (2018). Computer-aided diagnosis of atrial fibrillation based on ECG Signals: A review. Information Sciences, 467. https://doi.org/10.1016/j.ins.2018.07.063

Jørgensen, H. S., Nakayama, H., Reith, J., Raaschou, H. O., & Olsen, T. S. (1996). Acute stroke with atrial fibrillation: The Copenhagen Stroke Study. Stroke, 27(10). https://doi.org/10.1161/01.STR.27.10.1765

Kaur, A., Agarwal, A., Agarwal, R., & Kumar, S. (2019). A novel approach to ECG R-Peak detection. Arabian Journal for Science and Engineering, 44(8). https://doi.org/10.1007/s13369-018-3557-8

Krijthe, B. P., Kunst, A., Benjamin, E. J., Lip, G. Y. H., Franco, O. H., Hofman, A., Witteman, J. C. M., Stricker, B. H., & Heeringa, J. (2013). Projections on the number of individuals with atrial fibrillation in the European Union, from 2000 to 2060. European Heart Journal, 34(35). https://doi.org/10.1093/eurheartj/eht280

Lazaretti, G. S., Kuhn, E. V e Teixeira, J. P. R. (29 October 2021). Illustrative video of the use of the application and function to read the stored variables [Online]. Available at: http://lapse.td.utfpr.edu.br/downloads/TCC_Lazaretti_2021.zip

Lin, H.-J., Wolf, P. A., Kelly-Hayes, M., Beiser, A. S., Kase, C. S., Benjamin, E. J., & D'A ostino, R. (1996). Stroke severity in atrial fibrillation. Stroke, 27(10). https://doi.org/10.1161/01.STR.27.10.1760

Luz, E. J. da S., Schwartz, W. R., Cámara-Chávez, G., & Menotti, D. (2016). ECG-based heartbeat classification for arrhythmia detection: A survey. Computer Methods and Programs in Biomedicine, 127. https://doi.org/10.1016/j.cmpb.2015.12.008

Manikandan, M. S., & Soman, K. P. (2012). A novel method for detecting R-peaks in electrocardiogram (ECG) signal. Biomedical Signal Processing and Control, 7(2). https://doi.org/10.1016/j.bspc.2011.03.004

Marini, C., De Santis, F., Sacco, S., Russo, T., Olivieri, L., Totaro, R., & Carolei, A. (2005). Contribution of atrial fibrillation to incidence and outcome of ischemic stroke. Stroke, 36(6). https://doi.org/10.1161/01.STR.0000166053.83476.4a

Mittal, S., Movsowitz, C., & Steinberg, J. S. (2011). Ambulatory external electrocardiographic monitoring. Journal of the American College of Cardiology, 58(17). https://doi.org/10.1016/j.jacc.2011.07.026

Miyasaka, Y., Barnes, M. E., Bailey, K. R., Cha, S. S., Gersh, B. J., Seward, J. B., & Tsang, T. S. M. (2007). Mortality trends in patients diagnosed with first atrial fibrillation. Journal of the American College of Cardiology, 49(9). https://doi.org/10.1016/j.jacc.2006.10.062

Moody GB, Mark RG. MIT-BIH Atrial fibrillation Database 1992. https://doi.org/10.13026/C2MW2D.

Ott, A., Breteler, M. M. B., de Bruyne, M. C., van Harskamp, F., Grobbee, D. E., & Hofman, A. (1997). Atrial fibrillation and dementia in a population-based study. The Rotterdam Study. Stroke, 28(2). https://doi.org/10.1161/01.STR.28.2.316

Stewart, S., Hart, C. L., Hole, D. J., & McMurray, J. J. V. (2002). A population-based study of the long-term risks associated with atrial fibrillation: 20-year follow-up of the Renfrew/Paisley study. The American Journal of Medicine, 113(5). https://doi.org/10.1016/S0002-9343(02)01236-6

T. Hickey, K., B. Biviano, A., Garan, H., Sciacca, R. R., Riga, T., Warren, K., Frulla, A. P., Hauser, N. R., Wang, D. Y., & Whang, W. (2017). Evaluating the utility of mHealth ECG heart monitoring for the detection and management of atrial fibrillation in clinical practice. Journal of Atrial Fibrillation, 9(5). https://doi.org/10.4022/jafib.1546

Wang, T. J., Larson, G., Levy, D., Vasan, R. S., Leip, E. P., Wolf, P. A., D'Agostino, R. B., Murabito, J. M., Kannel, W. B., & Benjamin, E. J. (2003). Temporal relations of atrial fibrillation and congestive heart failure and their joint influence on mortality. Circulation, 107(23). https://doi.org/10.1161/01.CIR.0000072767.89944.6E

Wolf, P. A., Abbott, R. D., & Kannel, W. B. (1991). Atrial fibrillation as an independent risk factor for stroke: the Framingham Study. Stroke, 22(8). https://doi.org/10.1161/01.STR.22.8.983

Wolf, P. A., Mitchell, J., Baker, C. S., Kannel, W., & D'Agostino, R. B. (1998). Impact of atrial fibrillation on mortality, stroke, and medical costs. Archives of Internal Medicine, 158(3). https://doi.org/10.1001/archinte.158.3.229

World Health Organization. (2021, June 11). Cardiovascular diseases (CVDs). https://www.who.int/news-room/fact-sheets/detail/cardiovascular-diseases-(cvds)