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Telemedical Transport Layer Security based Platform for Cardiac Arrhythmia Classification using Quadratic Time–Frequency Analysis of HRV Signal

Ismail HADJ AHMED¹ · Abdelghani DJEBBARI¹ · Amar KACHENOURA² · Lotfi SENHADJI²

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Abstract The heart rate variability signal is a valuable tool for cardiovascular system diagnostics. Processing this signal detects arrhythmia during long-term cardiac monitoring. It is also analyzed to recognize abnormalities within the autonomic nervous system. Processing this signal helps in detecting various pathologies, such as atrial fibrillation (AF), supraventricular tachycardia (SVT), and congestive heart failure (CHF). As a beneficial alternative to the commonly used HRV spectrum analysis, quadratic time–frequency analysis of HRV signals could be helpful in heart pathology detection. Indeed, in this study, we have created a client–server paradigm deployed as a telemedical platform for real–time remote monitoring of the cardiovascular function in patients suffering from arrhythmia. This platform detects arrhythmia in real-time by deploying time–frequency analysis, feature extraction, feature selection, and classification of Heart Rate Variability (HRV) signals. We gathered all these functionalities in a Graphical User Interface (GUI) in addition to data acquisition. As a client, a Raspberry Pi Zero ensures data acquisition and connects to a server over TCP/IP that involves a 4G/3G connection encrypted through the transport layer security (TLS). This telemedical tool continuously monitors the heart rate variability. In the case of an alarm, medical professionals may immediately interact with their patients in the hospital or at home.

Keywords Heart rate variability, Smoothed pseudo Wigner–Ville Distribution, Support Vector Machine, Mutual Information, Feature Selection, Adaptive Structure Learning, Transport Layer Security.

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1 Introduction

Cardiovascular diseases cause several chronic illnesses and disabilities around the world. Every year, millions of people die due to cardiac arrhythmias. Cardiac arrhythmias are due to alterations in the heart's electrical system that yield abnormal heart beating. It causes the heart to beat too fast (tachycardia), too slowly (bradycardia), or any other irregular pattern. Some types of arrhythmia are harmless, but they can induce annoying symptoms like dizziness and fainting. Numerous types of arrhythmia can lead to complications, such as cardiac death, stroke, and heart failure. The Autonomic Nervous System (ANS), through its sympathetic and parasympathetic activities, modulate the beat-to-beat duration and induce a variability of the heart rate (Atalar et al., 2019; Dorey et al., 2020). Detecting the R-peak within electrocardiogram signals generates the heart rate variability (HRV) signal, which contains two frequency bands associated with the sympathetic and parasympathetic parts of the autonomic nervous system (ANS). The low-frequency (LF: from 0.04 up to 0.2 Hz) band is related to sympathetic activity, and the high-frequency (HF: from 0.2 up to 0.6 Hz) band is a marker of parasympathetic activity in the heart. Spectral analysis of a signal calculates its magnitude over the frequency domain. Seong *et al.* (Seong et al., 2004) studied the LF/HF ratio in 17 healthy subjects to improve the prognostic value of heart rate variability and the changes of the ANS between mental stress and sympathetic activation by analyzing their time-varying spectrum over the time-frequency plane.

Numerous studies have shown that HRV signals help in identifying and characterizing arrhythmias. More precisely, several studies examined the time, frequency, time-scale, and time-frequency domains in order to extract some specific features (Anderson et al., 2019),(Joshi et al., 2019; Ardissino et al., 2019; Geng et al., 2020; Singh et al., 2019). HRV signals were analyzed for diagnosis using classification approaches such as Support Vector Machine (SVM), Artificial Neural Networks (ANN), and decision trees (Poddar et al., 2019; Kobayashi et al., 2019; Chen et al., 2019; He and Jiang, 2019). These classifiers classify HRV signals according to features of interest. By plotting the power of HRV signals in the frequency domain, the spectral analysis may reveal their informative content. The frequency-domain representation, on the other hand, cannot provide any temporal information on the occurrence of frequency changes within the analyzed signals.

As a solution, time-frequency analysis can generate a three-dimensional representation of the analyzed signal's power in the time and frequency domains. Combining the obtained TF representation with an efficient classification of HRV signals may provide a viable method for identifying cardiac arrhythmias.

Additionally, an appropriate classification approach with reliably selected features effectively detects abnormal patterns within HRV signals. The Wigner-

Wigner–Ville distribution (WVD), which is the popular and basic time–frequency analysis method, can be enhanced to analyze and characterize the HRV signals in the time–frequency plane. Indeed, the Smoothed Pseudo Wigner–Ville Distribution (SPWVD) method was used to analyze HRV signals to quantify low and high–frequency bands in regard to sympathetic and parasympathetic systems, respectively.

To identify cardiac arrhythmia by analyzing heart rate variability (HRV), several researchers (Chang et al., 2018; Valliappan et al., 2017; Clark et al., 2019) developed a Raspberry Pi–based portable ECG to offer a diagnostic aid for arrhythmia detection. The Raspberry Pi acquires the ECG signal from AD8232 through the analog–digital circuit (MCP3008) and transmits the ECG data to the station (server or mobile application). A network access security secures the communication between the Raspberry Pi and the application.

In this paper, we developed a client–server model implemented as a telemedical platform for real–time remote monitoring of the cardiovascular function in arrhythmia patients. This system allows continuous recording when the ECG sensor is attached to the patient’s body. The ECG is first acquired using a data acquisition system designed around the Raspberry Pi Zero, which communicates with a server through TCP/IP secured by Transport Layer Security to secure the exchange of ECG data transmitted over the internet network. An HRV time series is then extracted from the acquired ECG signals and analyzed by quadratic time–frequency distributions, to calculate new TF–features to differentiate between various cardiac pathologies such as Atrial Fibrillation, Supraventricular Tachycardia, and Congestive Heart Failure by analyzing their respective HRV signals.

The TF–features of interest are selected using Mutual Information and Feature Selection with Adaptive Structure Learning. An SVM classifier processes these features to classify the analyzed case among the various classes within the training database. According to the classification result, the system notifies the healthcare professional of any cardiac arrhythmia case. The system sends a medical report to the cloud server, which issues a warning to the patient.

2 Related work

Within the context of the Internet of Things, some research groups developed applications for the health monitoring system of the cardiovascular function (see Table 1). Francesca Stradolini *et al.* (Stradolini et al., 2017) developed an architecture for continuous monitoring of anesthesia with no cloud integration. Stradolini *et al.* (Stradolini et al., 2018), on the other hand, describes the development of an IoT cloud–based solution for anesthesia monitoring during surgeries. Several studies presented IoT platforms for the prediction of cardiovascular disease using an IoT–enabled ECG telemetry system (Hossain and Muhammad, 2016; Thilakanathan et al., 2014; Abualsaud et al., 2020; Devi and Kalaivani, 2020). Thilakanathan *et al.* (Thilakanathan et al., 2014) have built a remote care system for patients at home using ECG sensors, cloud

storage providers, and mobile technology. This work consists of finding solutions that allow patients to share their health information with the medical professional team in a reliable, secure, and confidential manner. M. Shamim Hossain *et al.* (Hossain and Muhammad, 2016) have used IoT technologies for ECG health monitoring, where ECG signals have been recorded via ECG sensors at home and sent the data to smartphones or computers via the Internet. They describe a cloud-integrated IoT monitoring framework, where ECG-data is watermarked before being sent to the cloud for security. Smartphones were used as a client-side that allows the processing of the ECG signal (removing unwanted noise from the recorded signal) and detecting the R-peaks. The acquired ECG signal was then transmitted to a server for analysis and characterization; the temporal and spectral characteristics were extracted and classified using an SVM classifier. Their classification results can be sent to the medical professional team for analysis and diagnosis, where they will later transfer the medical report to the cloud server for the patient. R. Lakshmi Devi *et al.* (Devi and Kalaivani, 2020) have developed a classification system for cardiac arrhythmia using IoT that enables the ECG monitoring system to analyze the signal acquired from the data acquisition system (AD8232 & Arduino). The statistical features were extracted from the HRV signals in the temporal domain and used as inputs for an SVM classifier to identify the cardiac arrhythmia disease. The developed system acquires the ECG signal, processes, classifies the cases and sends the result to a smartphone. Khalid Abusalim *et al.* (Abualsaud et al., 2020) have used an IoT ECG monitoring system that allows sending the ECG data to a cloud server through wireless networks with a security system using Multi-Arts with lightweight security. The developed system includes storing, processing, and classifying cardiac arrhythmia from different healthy subjects available in the MIT-BIH database. This study deploys features extracted from ECG signals from the time, frequency, and time-frequency domains. K-nearest neighbor is used as a classification approach to identify and classify cardiac arrhythmias. However, (Devi and Kalaivani, 2020), (Stradolini et al., 2017), and (Stradolini et al., 2018) developed a novel m-Health system for wireless monitoring of patients. however, these studies do not include any security protocol.

Figure 1 represents a system for the continuous monitoring of the cardiovascular system that detects in real-time cardiac arrhythmia. Indeed, our client-server architecture allows the cardiologist to monitor multiple patients at home or in hospital simultaneously.

3 Research questions

The study presented in this section seeks to answer the following research questions:

RQ1: "How the proposed study is different or contributes to revamping the cardiac arrhythmia classification by using the TFD method? "

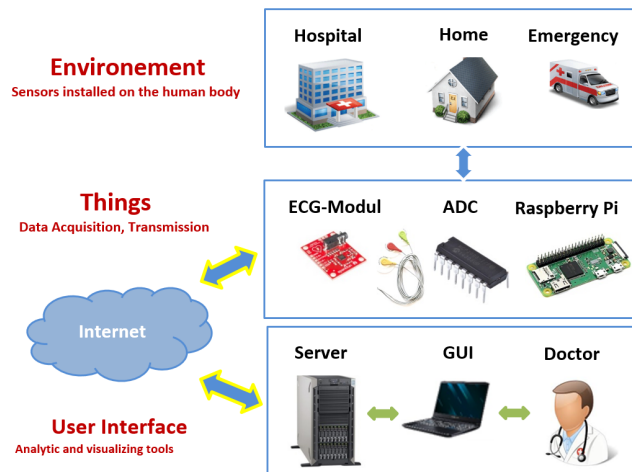


Fig. 1: Architecture for the continuous monitoring of the cardiovascular system.

Studies	Medical applications	Architecture	Cloud	Security protocol	Hospital (HS) or Home (HM) monitoring
(Thilakanathan et al., 2014)	Elderly patients health monitoring	Cloud storage provider, ECG sensor, mobile device app	Yes	Yes	HM
(Hossain and Muhammad, 2016)	ECG health monitoring	Cloud system, ECG sensor, mobile device app, desktop software	Yes	Yes	HM
(Devi and Kalaivani, 2020)	IoT-based cardiac arrhythmia diagnosis	ECG sensor, Cloud system, Statistical features, HRV SVM, mobile device app	Yes	No	HM
(Abualsaud et al., 2020)	IoT-based monitoring, collecting ECG data	ECG cloud server, for storage and further processing	Yes	Yes	HM
(Stradolini et al., 2017)	Anesthesia monitoring	Therapeutic and drug monitoring system, mobile device app, smartwatch	No	No	HS
(Stradolini et al., 2018)	Anesthesia monitoring	Priv middleware cloud, cloud, mobile device app, smartwatch, webApp	Yes	No	HS
Our study	Telemedical platform, cardiac arrhythmia, classification	ECG sensor, cloud server, TLS, HRV, TF-analysis, TF-features, feature selection, SVM, client-server app	Yes	Yes	HM & HS

Table 1: Comparison between some IoT solutions in health monitoring

In this paper, we studied the activity of sympathetic and parasympathetic subsystems of the autonomic nervous system (ANS) through time–frequency analysis of the heart rate variability (HRV) signal of normal and abnormal subjects. Indeed, we proposed new classification features of HRV signals to assess the activity of the autonomic nervous system (ANS). We defined time–frequency features calculated by the Smoothed Pseudo Wigner–Ville Distribution (SPWVD). This analysis included 44 healthy subjects with a normal sinus rhythm (NSR), 77 patients with supraventricular tachycardia (SVT), 63 subjects with atrial fibrillation (AF), and 44 CHF. In this study, the extracted features are the mean, the variance, the coefficient of variation, the skewness, the kurtosis, the flatness, the Shannon entropy, and the flux. Two algorithms,

namely the MI-based method and the FSASL based algorithm, are used to select the more valuable features before an SVM classification step. The SP-WVD combined with the SVM discriminate the VT, AF, and NSR classes with $Se=95.65\%$, $Sp=98.55\%$, and $Acc=97.82\%$.

RQ2: "How effective is the proposed approach in protecting the transmitted data from the client to the server?"

The profile proposed in this work represents how the client-server architecture establishes communication between the different stations under the TCP/IP protocol secured by the TLS protocol. The acquired ECG signals can be transmitted to a server for further advanced digital signal processing through TCP/IP protocol secured by the transport layer security (TLS). The TLS secures the client-server application by transmitting ECG data from Raspberry Pi Zero (client) to another remote station by establishing an encrypted connection for private communication over the public Internet.

4 Materials and Methods

Our system is composed of two main blocks (see figure 2): a hardware block, named the client block, devoted to the acquisition and transmission of the ECG; and a software block, called the server block, dedicated to HRV extraction, analysis, and classification (features extraction, features selection, and patient classification) (see figure 16). Three essential parts form the client block : (1) the analog shaping circuit ECG AD8232, (2) the analog-to-digital converter MCP3008, and (3) the data acquisition card (Raspberry Pi zero) for acquiring ECG signals. Through a clock signal, the internal analog-to-digital (ADC) converter of the MCP3008 sets up the sampling frequency to 100 Hz, following the Nyquist rate theorem.

4.1 Dataset

To select the best features for the SVM classifier, we collected data of normal and abnormal subjects from several databases, namely, the PhysioNet research repository (Goldberger et al., 2000): the congestive heart failure RR interval database (chf2db), the BIDMC congestive heart failure database (chfdb), the MIT-BIH Arrhythmia database (MITdB), the LongTerm AF database (LTAFdB), the Supraventricular tachycardia (SVDB), the St. Petersburg Institute of Cardiological Technics 12-lead Arrhythmia (INCARTdB), and the MIT-BIH normal sinus rhythm database (NSRDB). We considered 44 NSR, 77 SVT, 63 AF, and 44 CHF ECGs. Collected data, shown in Table 2, is formed by 228 signals, which we reorganized into four classes, namely: SVT, NSR, AF, and CHF. The length of ECG recordings varies from one database to another (see 2). In this study, we concerned the whole data processing (long-term HRV) to analyze all the durations of the HRV signal to capture various cardiovascular pathological cases and achieve more accuracy than by portraying the

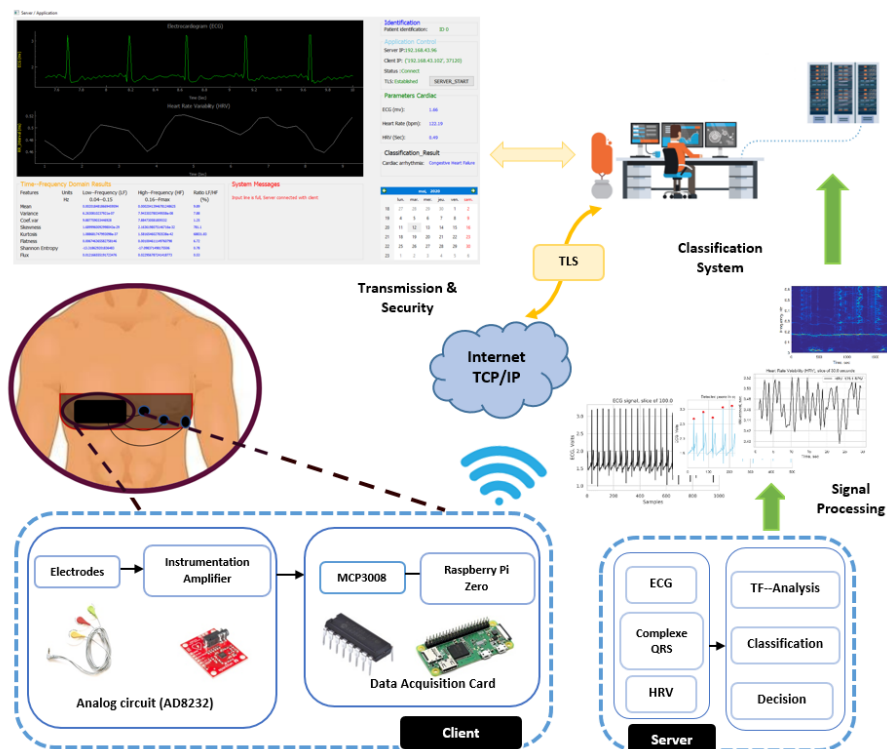


Fig. 2: Block diagram of a Telemedical platform for real-time monitoring and classifying cardiac arrhythmias

condition of the subjects using lower samples. Long-term HRV analysis is a stable tool for assessing autonomic function and can reliably predict prognosis in patients with cardiovascular diseases. Indeed, long-term spectral analysis can effectively capture high-frequency and low-frequency components, while short-recordings are unstable owing to the constant fluctuation of HRV parameters and cannot estimate lower-frequency components.

4.2 Detection of Heart Rate Variability (HRV)

We generated HRV signals by detecting QRS-complexes within Electrocardiogram (ECG) signals using the Pan-Tompkins algorithm (Pan and Tompkins, 1985). The Pan-Tompkins' algorithm is summarized in figure 3.

Notch filtering of the 50 Hz interference, baseline removal, and T-wave interference filtering improves the signal-to-noise ratio of ECG signals. The bandpass digital filter from 5 Hz to 15 Hz boosts the ECG signal's QRS strength while reducing muscle noise. Then the filtered ECG signal is derived to highlight the slope of the R wave. Then, the signal is squared and

Table 2: ECG Database collected from Physionet.

Classes	Data base details			
	Data base	Number of ECG	Sampling Frequency (Hz)	Duration (h/min)
Atrial Fibrillation (AF)	INCARTdB	4	257	30 min
	MITdB	6	360	30 min
	LTAFdB	53	128	24 h
Normal sinus rhythm (NSR)	INCARTdB	3	257	30 min
	MITdB	23	360	30 min
	NSRDB	18	128	24 h
Supraventricular tachycardia (SVT)	SVDB	77	128	30 min
Congestive Heart Failure (CHF)	chf2db	29	128	24 h
	chfdb	15	250	20 h

filtered through a moving average filter to favor the slope of the R wave. Two thresholds are automatically adjusted to float over the noise.

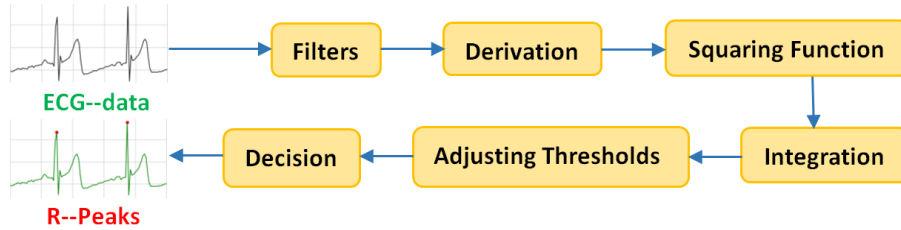


Fig. 3: QRS detector based on the Pan–Tompkins algorithm.

4.3 Quadratic Time–Frequency Analysis

Time-frequency (TF) representations of non-stationary signals such as HRV signals help overcome the limitations of temporal and spectral analysis methods. More specifically, QTFDs represent the energy of a signal in time and frequency domains at a high joint time–frequency resolution (Boashash, 2015). QTFDs mainly satisfy time–shift and frequency–shift invariance properties. Therefore, QTFDs provide appropriate representations of multicomponent non-stationary signals. Formally, QTFDs can be expressed as given in (1) (Boashash, 2015; Boashash and Ouelha, 2017);

$$\rho_z(t, f) = \iint_{-\infty}^{+\infty} AF(\nu, \tau) g(\nu, \tau) e^{j2\pi(t\nu - f\tau)} d\nu d\tau \quad (1)$$

where $g(\nu, \tau)$ is the smoothing kernel defined in the Doppler-lag domain as given in (2);

$$g(\nu, \tau) = G_1(\nu) g_2(\tau) \quad (2)$$

where $G_1(\nu)$ is the Doppler window, and $g_2(\tau)$ is the lag window. The Ambiguity Function (AF) is defined as given in (3);

$$AF(\mu, \tau) = \int_{-\infty}^{+\infty} R(t, \tau) e^{-j2\pi\nu t} dt \quad (3)$$

where,

$R(t, \tau)$ represents the time-dependent instantaneous auto-correlation of $z(t)$, as given in (4).

$z(t)$ is the analytic version of the analyzed signal $s(t)$.

$s(t)$ represents the HRV signal, therefore, the HRV signals were created by identifying QRS complexes in the time-domain of an Electrocardiogram (ECG).

$$R(t, \tau) = z\left(t + \frac{\tau}{2}\right) z^*\left(t - \frac{\tau}{2}\right) \quad (4)$$

Because of their quadratic structure, the conventional QTFDs approaches may suffer from the cross-terms that can blur the TF plane. Time and frequency filtering reduce these interferences.

4.3.1 Smoothed Pseudo Wigner-Ville Distribution (SPWVD)

According to (refeq:R), the quadratic character of smoothed Wigner-Ville distributions results in cross-terms within the TF plane. Smoothing the TF plane in time and frequency domains improves auto-term representation. A separable time and frequency smoothing kernel can provide high time and frequency resolution. The SPWVD (Smoothed Pseudo Wigner-Ville Distribution) is given in (5);

$$SPWVD(t, f) = \int_{-\infty}^{+\infty} g_2(\tau) \int_{-\infty}^{+\infty} g_1(s-t) z\left(s + \frac{\tau}{2}\right) z^*\left(s - \frac{\tau}{2}\right) se^{-2\pi\nu\tau} d\tau \quad (5)$$

Smoothing carried out by the SPWVD is achieved at the price of spread auto-terms bursts within the TF plane. Therefore, smoothing windows have to be set to keep a representative TF distribution of the analyzed signal.

Spectrogram

Arranging spectra of a Welch PSD estimator by considering the central instant of each weighting window as a time position within the time–frequency plane leads to the spectrogram (SP). Indeed, the STFT–spectrogram is the squared magnitude of the Short–time Fourier transform (STFT) as defined in (6);

$$SPEC(t, \omega) = |STFT(t, \omega)|^2 \quad (6)$$

where the STFT can be expressed as in (7);

$$STFT(t, \omega) = \int_{-\infty}^{+\infty} z(\tau) h(\tau - t) e^{-j\omega\tau} d\tau \quad (7)$$

where $h(t)$ represents the analysis window smooths cross–terms through the frequency–domain. The STFT uses a weighting window $h(t)$ to subdivide the signal into overlapping segments. The spectrogram is the squared magnitude of the obtained STFT (Barkat and Boashash, 2001).

4.4 Feature extraction

We are particularly interested in two frequency bands of HRV signals: the LF and HF bands. We examined these bands by computing their cumulative properties, including flux, flatness, Shannon entropy, mean, variance, skewness, kurtosis, and coefficient of variation. To quantify each frequency band, we calculate energy–based features of the HRV signal across the LF and HF bands in the TF plane (contrary to most existing studies, which exploit the frequency domain). To be more specific, we extract eight features from the TF plane of the analyzed HRV signals for both the LF and HF bands: (i) three TF energy–based features and (ii) five TF statistical–based features.

4.4.1 TF energy–based features

Flux Squaring the magnitudes of Fourier transforms of two neighboring frames within the power spectrum to estimate the signal’s spectral change defines the spectral flux. This parameter gives an estimate of the energy within time–frequency distributions, as given in (8);

$$FL_{(t,f)} = \sum_{n=1}^{N-l} \sum_{k=1}^{M-m} | \rho_z[n+l, k+m] - \rho_z[n, k] | \quad (8)$$

where $\rho_z[n, k]$ represents the TF representation of the analyzed HRV signal (size $N \times M$) of the analytic version $z[n]$ of the analyzed signal $s[n]$, and l represents the time duration between the two slices. The spectral flux measures changes in the power spectrum of a signal.

Flatness Spectral flatness is the ratio between the geometric mean and the arithmetic mean of the power spectrum of a signal within the time domain. The spectral flatness of TF representations of size $N \times M$ is calculated by measuring the ratio between the geometric mean and the arithmetic mean of the energy distribution over the TF plane, as given in (9) (Boashash et al., 2015; Löffhede et al., 2010);

$$SF_{(t,f)} = MN \frac{\prod_{n=1}^N \prod_{k=1}^M |\rho_z[n, k]| \frac{1}{NM}}{\sum_{n=1}^N \sum_{k=1}^M \rho_z[n, k]} \quad (9)$$

Normalized Shannon Entropy The normalized Shannon entropy is a concentration measure which can be extended to a TF representation as given in (10);

$$SE_{(t,f)} = - \sum_{n=1}^N \sum_{k=1}^M \frac{\rho_z[n, k]}{\sum_n \sum_k \rho_z[n, k]} \log_2 \frac{\rho_z[n, k]}{\sum_n \sum_k \rho_z[n, k]} \quad (10)$$

The Shannon entropy is an extension of spectral entropy by replacing the Fourier Transform (FT) of a non-stationary signal with the TFD (Boashash, 2016).

Statistical-based features

Mean The mean value calculated for the TF distribution (Boashash, 2015) is given by (11);

$$m_{(t,f)} = \frac{1}{NM} \sum_n \sum_k \rho_z(n, k) \quad (11)$$

Variance The TF variance, which represents the spread of the TF distribution (Boashash, 2015), is given by (12);

$$\sigma_{(t,f)}^2 = \frac{1}{NM} \sum_n \sum_k \left(\rho_z(n, k) - m_{(t,f)} \right)^2 \quad (12)$$

Skewness The skewness represents the asymmetry of the probability distribution of the energy from its mean. This parameter can be defined in the TF plane (Boashash, 2015) by (13);

$$\gamma_{(t,f)} = \frac{1}{NM\sigma_{(t,f)}^3} \sum_n \sum_k \left(\rho_z[n, k] - m_{(t,f)} \right)^3 \quad (13)$$

Kurtosis The kurtosis measures whether the data points are heavy-tailed or light-tailed relative to a normal distribution. In the TF plane (Boashash, 2015), it is given by the following equation (14);

$$k_{(t,f)} = \frac{1}{NM\sigma_{(t,f)}^4} \sum_n \sum_k \left(\rho_z[n, k] - m_{(t,f)} \right)^4 \quad (14)$$

Coefficient of variation The coefficient of variation is defined as the ratio between the variance and the mean in the TF plane (Boashash, 2015), and is given by (15);

$$c_{(t,f)} = \frac{\sigma_{(t,f)}}{m_{(t,f)}} \quad (15)$$

4.5 Feature selection

Filter methods, wrapper methods, and embedded methods are feature selection techniques that improve the classification (Kohavi and John, 1997). Filter methods are based on ranking features to select highly ranked features considered as inputs for classifiers. Wrapper methods search for the best feature subsets to get high-performance metrics from the predictor. Embedded methods focus on the training process without segmentation of data into training and test data to select relevant features (Guyon and Elisseeff, 2003). In this study, we used two efficient methods: the MI algorithm and the FSASL method (Peng et al., 2005; Du and Shen, 2015).

Mutual information (MI)

We used the MI as a feature selection criterion. The aim of this approach is to distinguish between relevant features within a particular class in order to create a subset formed by highly ranked features. The mutual information between two random variables X and Y is a measure of their mutual dependence (Peng et al., 2005), and is defined as given in (16);

$$I(X, Y) = \sum_{x,y} p_{X,Y}(x, y) \log \frac{p_{X,Y}(x, y)}{p_X(x)p_Y(y)} \quad (16)$$

where p_X and p_Y represent probability density functions (pdf) of X and Y , respectively, and $p_{X,Y}$ is the joint pdf of X and Y . The mutual information between features $V = (v_1, v_2, \dots, v_d)$ and class variables $C = (c_1, c_2, \dots, c_k)$ is expressed as given in (17);

$$I(V, C) = \sum_c p(v) \sum_c p(v/c) \log \frac{p(v/c)}{p(v)} \quad (17)$$

The MI is based on the measure of dependency between the variables to reduce the number of features. This type of feature selection method is symmetric and non-negative. The MI can be equal to zero when the variables are independent.

Feature Selection with Adaptive Structure Learning (FSASL)

Unsupervised feature selection methods identify features that can reveal and sustain the underlying structure of data (Du and Shen, 2015). The feature selection with adaptive structure learning (FSASL), based on linear regression, has a high computational complexity, which is costly for high dimensional data. The FSASL is formulated as given in 18;

$$\begin{aligned} \min_{W,S,P} (\| W^T X - W^T X S \|^2 + \alpha \| S \|_1) \\ + \beta \sum_{i,j}^n (\| W^T x_i - W^T x_j \|^2 P_{ij} + \mu P_{ij}^2) + \gamma \| W \|_{21} \end{aligned} \quad (18)$$

Subject to, $S_{ii} = 0, P1_n = 1_n, P \geq 0, W^T X X^T W = I$.

Where β, α, γ , and μ are regularization parameters used to balance the adjustment error of global and local structure learning.

X : considered as input Feature

set $X \in \mathbb{R}^{d \times n}$,

x_i = is the data sample.

For each data sample x_i , the entire set of data points $x_j^n, j = 1$ is treated as the neighborhood of x_i = with probability $P(i, j)$.

S : Weight matrix of the data matrix.

W : Feature selection and transformation matrix.

4.6 Classification: Support vector machine(SVM)

The SVM is used for binary classification. The set of examples and their corresponding labels is called the learning set. An effective learning machine learns features of the training set to minimize classification errors.

$D = \{(x_1, y_1), \dots, (x_n, y_n)\}$ represents the training set, with $x_i \in \mathbb{R}^m$ and $y_i = \pm 1$. The objective of SVM is to maximize the margin between two classes by distinguishing them by a hyperplane. The optimal hyperplane requires the determination of the Euclidean distance between the hyperplane and the closest training of the two classes (Abe, 2005; Hong and Cho, 2008). The optimal hyperplane can also be solved by calculating the following classification function (19);

$$H(x) = \text{sign}\left(\sum_{i=1}^m \alpha_i y_i K(x, x_i) + b\right) \quad (19)$$

And $\forall (x_i, y_i) \in S, 0 \leq \alpha_i \leq C$.

Where;

y_i is the class label of support vector x_i

x is a test tuple

α_i is a Lagrangian multiplier
 b is a numeric parameter
 m is the number of support vectors
 C is the coefficient of regularization
 S is of dimension m
 K is the kernel function

The radial basis function (RBF) kernel (σ is a positive parameter for controlling the radius) is the default kernel used within the SVM classification algorithm and is expressed as follows:

$$K(x_i, x_j) = \exp - \frac{\|x_i - x_j\|^2}{2\sigma^2} \quad (20)$$

4.7 Multi-class extensions

The support vector machine (SVM) is binary in its origin. However, in most cases, real world problems are multi-layered. The SVM algorithm is one of the lazy learning techniques used for multi-class as well as a relatively recent design learning model (Mamouni El Mamoun, 2019). Therefore, multi-class SVM reduces the problem to a composition of many two-class hyperplanes to draw the decision boundaries between the different classes.

The main function is to decompose the examples into several subsets; each of them represents a binary classification problem.

In recent literature, the SVM multi-class case can be done in four different ways, which depend on the size of the dataset: Directed Acyclic Graph (DAG), Binary Tree (BT), One-Against-One (OAO), and One-Against-All (OAA) classifiers. In this study, one-against-one (OAO) of SVM multiclass using the radial basis function kernel (RBF) has been chosen to discriminate between pathological cases. This method of multiclass is much faster to train and seems preferable for problems with a very large number of classes (Chamasemani and Singh, 2011).

4.7.1 One-against-one SVM (OAOSVM)

One-against-one SVM, also called pair-wise combinations of the N classes, consists of using a classifier for each pair of classes (Chamasemani and Singh, 2011). The One-against-One support vector machine (OAOSVM) method discriminates against each of the other classes, resulting in the construction of an $N(N - 1)/2$ binary classifier with $N(N - 1)/2$ decision functions. The OAOSVM defines a binary classifier as $h_{N_s}(x): \mathcal{R} \rightarrow \{+1, -1\}$ based on the Radial Basis Function (RBF) kernel for every two classes (N, s) (Mamouni El Mamoun, 2019). The assignment of a new example used for training is based on a voting list. An example is tested by applying the decision function (Equation 19) to each hyperplane. For each test, there is a vote for the class to which the example belongs.

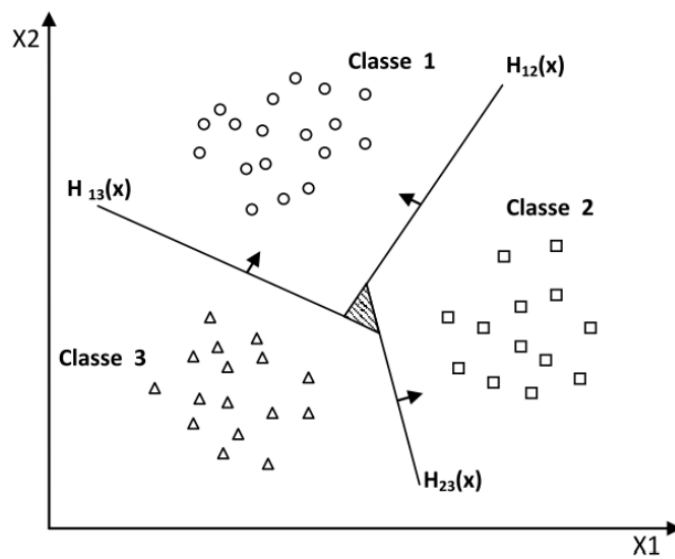


Fig. 4: Approach One-against-one (Mamouni El Mamoun, 2019).

4.8 Performances evaluation

The performance of the classifier is estimated by calculating the Sensitivity (S_e), the Specificity (S_p), and the Accuracy (Acc). The sensitivity defines the true positive rate (21);

$$S_e = \frac{TP}{TP + FN} \quad (21)$$

The specificity defines the true negative rate as given in (22);

$$S_p = \frac{TN}{FP + TN} \quad (22)$$

The accuracy is defined as the ratio of correct predictions over the total number of predictions (23);

$$Acc = \frac{TP + TN}{TP + TN + FP + FN} \quad (23)$$

TP True positive: correctly classified as positive.

FP False positive: falsely classified as positive.

TN True negative: correctly classified as negative.

FN False negative: falsely classified as negative.

4.9 Client–server architecture

The communication mechanism in the client–server application allows exchanging data between them via the Internet using the secured TCP/IP protocol (Transport Layer Security). So, the client–server architecture is developed around the use of sockets and threading. All communication between client and server is processed via sockets, which can be reliable. These sockets can be used in connected mode (TCP: Transmission Control Protocol) or non–connected mode (UDP: User Datagram Protocol). The standard protocols used by the Transport Layer to enhance its functionalities are TCP, UDP. TCP is a secure, connection–oriented protocol that uses a handshake protocol to establish a strong connection between different stations, ensuring that messages are delivered reliably. On the other hand, UDP is a stateless and unreliable protocol that ensures best–effort delivery. UDP is suitable for applications that have little concern with flow or error control and require transmission of the bulk of data. The communication process using sockets in connected mode (TCP) that is used in the current study is presented in figure 5.

As a first step, the creation of a socket is done using `socket ()` function. Once the socket has been created, it has to be linked to a communication point defined by an address and a port, this is the role of the `bind()` function. In connected mode, the `listen()` function is used to put the socket in passive mode (listening to messages). In case of an incoming message, the connection can be accepted with the `accept()` function. When the connection has been accepted, the server receives the data using the `recv()` function. The end of the connection is done with the `close()` function.

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In this study, we used socket programming to illustrate the client-server model using Multi–threading in Python. According to the multi–threading function, the server side accepts or handles multiple clients (an unlimited number of clients) connected simultaneously (Kim et al., 2019). The server can keep track of the threads or the clients that connect to it. The server uses the instances of a client object and individual threads to listen to the data that is being sent by each client while establishing new connections with the server. The main thread of the server creates a thread and forwards the client’s request to this thread with its ID. The thread will start processing the client request, generate the report, and send it back to the client. The figure 6 represents the process of the Threading function.

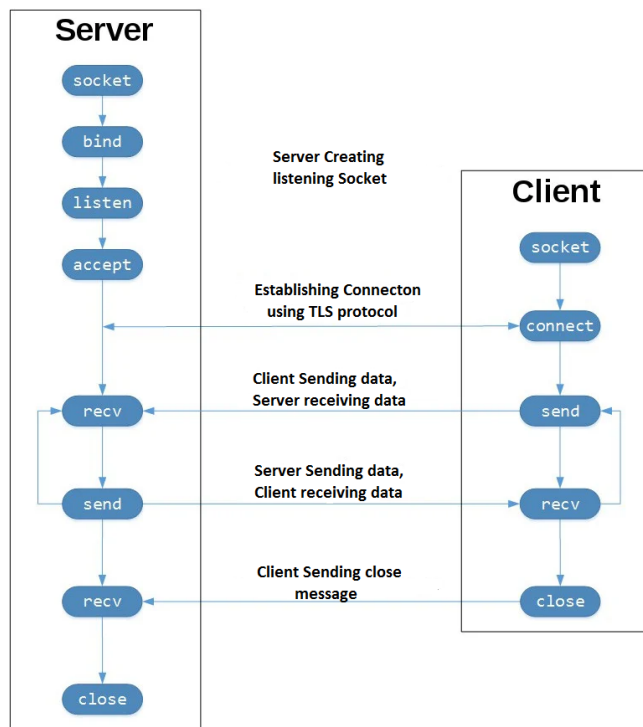


Fig. 5: Client-server architecture.

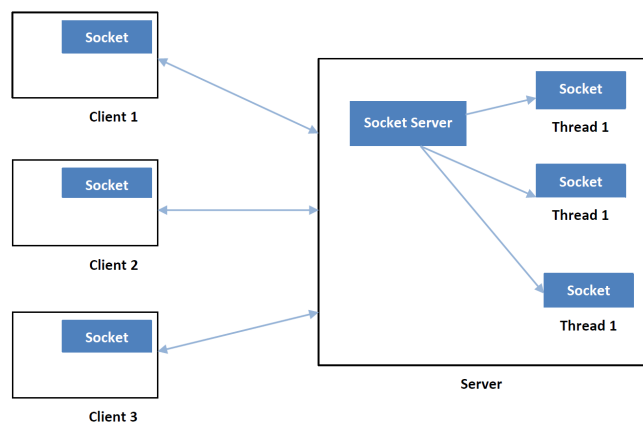


Fig. 6: Socket Server with Multiple Clients: implementing a Multi-threaded Python Server.

5 Results and discussion

In this study, we built a client-server application as a telemedical platform for real-time remote monitoring of cardiac arrhythmia illness diagnosis.

As depicted in Figure 2, the client block hardware consists of an analog shaping circuit and a Raspberry Pi Zero acting as a data collection card. The Raspberry Pi Zero is small and inexpensive, making it ideal for low-budget applications. Its compact dimensions, low energy usage, and inexpensive price set it apart.

The element parameters of the ECG sensor, the analog circuit, the communication system, and the server are listed in Table 3. ECG-data will be transmitted over an Internet network (TCP/IP) between the client and the server station using a Transport Layer Security protocol (TLS) that ensures the security of the transmitted data (see figure 4).

Concerning the server block (software part) (see figure 2), we developed a Graphical User Interface (GUI) to record the data acquisition task. The recorder ECG signal is then analyzed: we first estimate the HRV times series, then an SPWVD is applied on this HRV signal to extract features of interest. Finally, the learned SVM is applied to classify and label the analyzed ECG as AF and SVT, NSR and CHF.

5.1 Real-time QRS complex-based detection of the HRV signal

In this study, we used the online implementation of the Pan-Tomkins algorithm to detect the HRV from real-time acquired ECG signal (see figure 7(a)). The HRV signal illustrated in figure 7(c) is detected by localizing R-peaks in relation to cardiac cycles within real-time ECG signal as represented in figure 7(b). The amplitude within HRV signals refers to the consecutive duration between R-peaks within ECG signals. Therefore, HRV signals will be amplitude-centered around the cardiac cycle mean value. We performed detection of the R-peaks within the ECG through regular real-time localization of the consecutive maxima which we used as cardiac cycles.

5.2 Identification of features of interest and SVM parameters learning

The Physionet database is used to help us to choose the best features and to learn the SVM parameters. More precisely, 228 ECG signals divided into four classes, namely SVT, NSR, AF, and CHF. (See Data set section) are exploited. Time-frequency representations of HRV in Figures 8(a) & 8(b) calculated by the STFT-spectrogram and the SPWVD, respectively. The Short-time Fourier Transform-based Spectrogram (SP) was calculated to show the high time and frequency joint resolution of the SPWVD. Spectrogram of the HRV signal of Figure 8(a) was calculated with a Hamming window at duration of 171 samples. Specify 169 samples of overlap between adjoining sections.

Table 3: Element Parameters of the cardiac arrhythmia monitoring system.

	Parameters	Vlaues
ECG sensor	Type	AD8232
	Supply Voltage	2.0V–3.5V
Analog circuit	Type	Amplification, Filtering
ADC	Type	MCP3008
	Interface	SPI, Serial
	Supply Voltage	2.7V–5.5V
	Output Voltage	4.1V
	Number of Bits	10
Raspberry Pi	Type	Raspberry pi zero
	Power voltage	1.24A–5V
	Core	32 bit ARM1176JZF–S single–core
	GPU	Broadcom Video–Core IV
	CPU clock	1 GHz
	Memory	512 MB
Communication system	Wireless transmission protocols	3G/4G
	communications security	TLS Protocol
Server	CPU	Intel(R) Core(TM) i53230M
	Operation system	Windows 10, 64 bit

We found out that the TF calculated from Spectrogram (SP) ensures both time and frequency resolutions trade-off. Figure 8(b) demonstrate that the SPWVD outperformed the SP in localizing the non stationary multicomponent content of HRV signals at a high joint time–frequency resolution with a reduced amount of cross–terms within the time–frequency plane. Figure 9 shows an example the SPWVD calculated for the four different classes. Clearly, the shape and the TF distribution of the amplitude of the spectra are different between the four classes, which confirm that the analysis of HRV signals in TF domain is a good choice instead of the frequency domain. In addition, we can also remark that SPWVD provides a good resolution in both time and frequency domains, with less cross–terms.

Figure 10 depicts the mean and standard deviation values of eight features (see Feature extraction section), calculated from the TF distributions of HRV signals, for NSR, CHF, AF, and SVT. We can observe that mean and standard deviation values of each feature are clearly different between the different classes. However, the manual selection of the best set of features is not straightforward and the testing all combinations will be very times consuming. The automatic selection of the best features using FSASL and MI methods is reported in Table 4. It is interesting to see that the MI method is

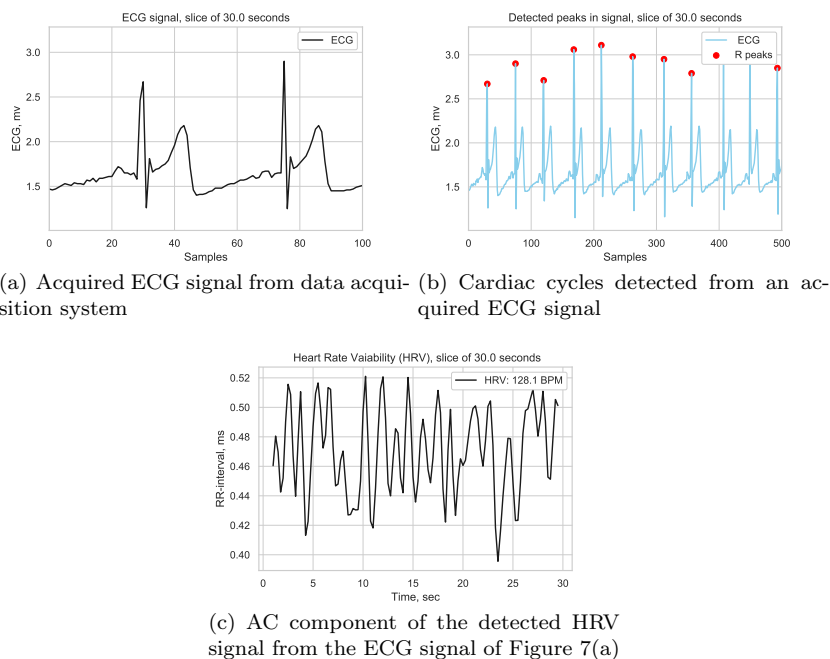


Fig. 7: ECG and HRV signals.

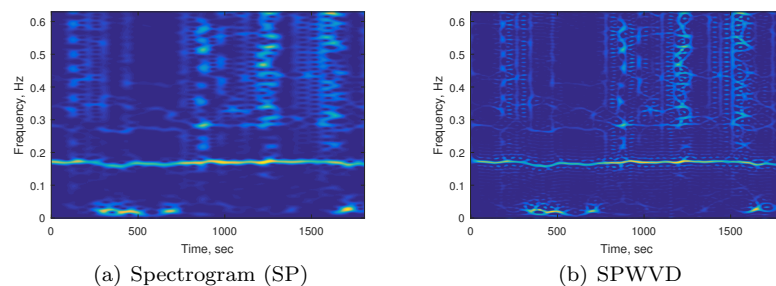
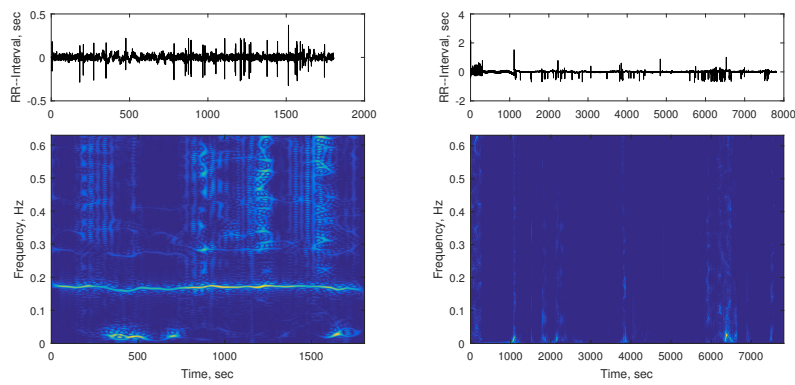
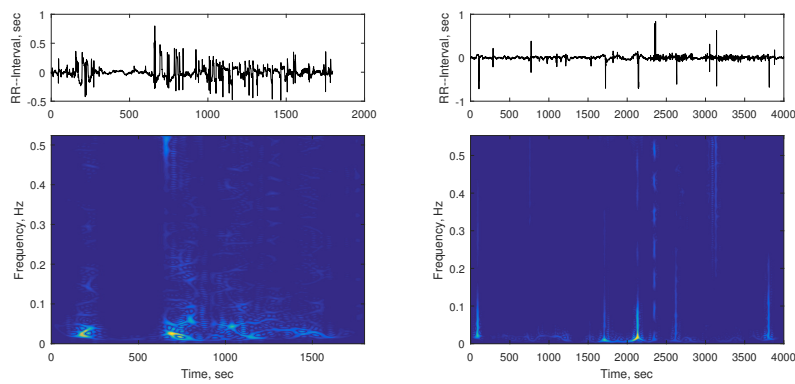


Fig. 8: MIT-BIH database ECG datafile, the ECG Record 100: Time-frequency representation of HRV signals using SPWVD and SP.

not able to select a set of features between the eight ones, whereas the FSASL algorithm select just three valuable feature, namely Coef.variation, Skewness and Shannon Entropy. Regarding the classification rate, we can observe that our approach combining SPWVD and SVM, seems to be very effective in discriminating between SVT, AF, CHF, and NSR classes (see the results of Table 4). In addition, the best classification rate is yield using the FSASL features selection algorithm: i) Se= 95.65 %, Sp=98.55 % and Acc=97.82 %, and ii)

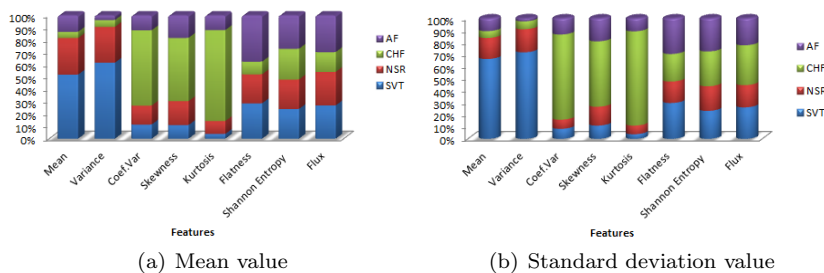


(a) HRV times series and SPWVD of normal sinus rhythm (NSR) (b) HRV times series and SPWVD of atrial fibrillation (AF)



(c) HRV times series and SPWVD of conspicuous tachycardia (SVT) (d) HRV times series and SPWVD of congestive heart failure (CHF)

Fig. 9: Time–frequency analysis of the detected HRV signal for different classes.



(a) Mean value

(b) Standard deviation value

Fig. 10: Statistical result of various Features extraction from TF–representation of HRV signal for different classes.

Se=91.30 %, Sp=95.65 % and Acc=94.20 % (using MI). Table 5 presents, in detail, the classification rate of AF and SVT among CHF and NSR, using the features selected by the FSASL. The global proposed procedure seems to be very efficient whatever the classified pathology. Note that, all the previous results are obtained by randomly dividing the database into a training set (90 % of ECG) and a testing set (10 % ECG) using a bootstrap strategy. Confusion matrix (MCTFD) for the 4 classes (AF, SVT, CHF, NSR) classification, is defined in figure 11;

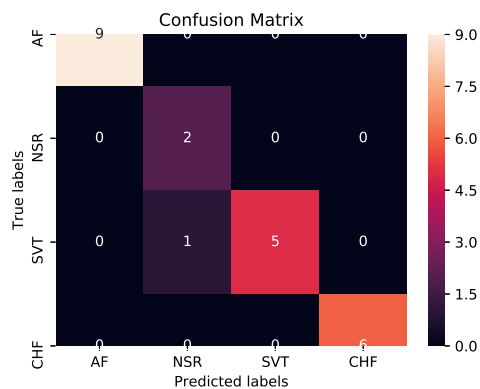


Fig. 11: Confusion matrix (MCTFD) for the 4 classes (AF, SVT, CHF, NSR).

Table 4: Result of classification using MI and FSASL as feature selection methods.

FSM	Metrics performance				
	NF	FS	Sensitivity (%)	Specificity (%)	Accuracy (%)
MI	08	Mean, Variance, Coef.variation, Kurtosis Shannon Entropy, Skewness, Flux, Flatness	91.30	95.65	94.20
FSASL	03	Coef.variation, Skewness, Shannon Entropy	95.65	98.55	97.82

5.3 Secure transmission of ECG data via the internet

In this study, the server and the client could initiate a communication via the Graphical user interface (GUI) by using one IP address, the following procedure explains how the client connects to the server in different cases:

Table 5: Classification metrics of cardiac arrhythmia (AF and SVT) among NSR and CHF using FSASL.

Classes	Metrics performance		
	Sensitivity (%)	Specificity (%)	Accuracy (%)
Atrial Fibrillation (AF)	100	100	100
Supraventricular Tachycardia (SVT)	83.33	100	95.65
Normal Sinus Rhythm (NSR)	100	95.23	95.65
Congestive Heart Failure (CHF)	100	100	100
Overall Accuracy	95.65	98.55	97.82

- Run the client on the same computer as the server, it uses the IP address as the host name.
- Run the client in the same network as the server’s (local network), it uses the local server IP address in the client interface.
- The port can be any 16-bit number, but must be forwarded to the router where the client is located, if the server and client are located in a different network, the client uses the IP address (internet IP) of the network under which the server is running (contrary to the local network). The internet IP is extracted from the web: **google what is my ip** .

The Tele-vigilance station can communicate with the various remote stations through a secure communication system to exchange the data and the processing results of the data collected. Transport Layer Security has been widely recognized as one of the most widely used cryptography protocols to protect and secure data transmitted between client and server. TLS protocol uses a certificate and key to establish encryption between server and client. For this, the hacker retrieves only the encrypted data. The following steps describe the the TLS handshake step by step, as shown in figure 12 (Pukkawanna et al., 2014).

- The client sends (1) a Client "Hello message" to the server for a secure session.
- The server replies with (2) a Server Hello message.
- The server responds by sending its X.509 digital certificate to the client, with (3) a Certificate message to the client.
- The server (4) sends a "Server Hello Done" message to notify the client that the server is waiting response.
- The client uses the server certificate to authenticate the server, then sends (5) a "Client Key Exchange" message containing a generated premaster secret key to the server.

- The client transfers (6) "Change Cipher Spec" and (7) "Client Finished" messages to inform the server that future messages will be encrypted using the session key.
- Finally, the server sends (8) "Change Cipher Spec" and (9) "Server Finished" messages to end the process of handshake. Now, data can be exchanged between client and server.

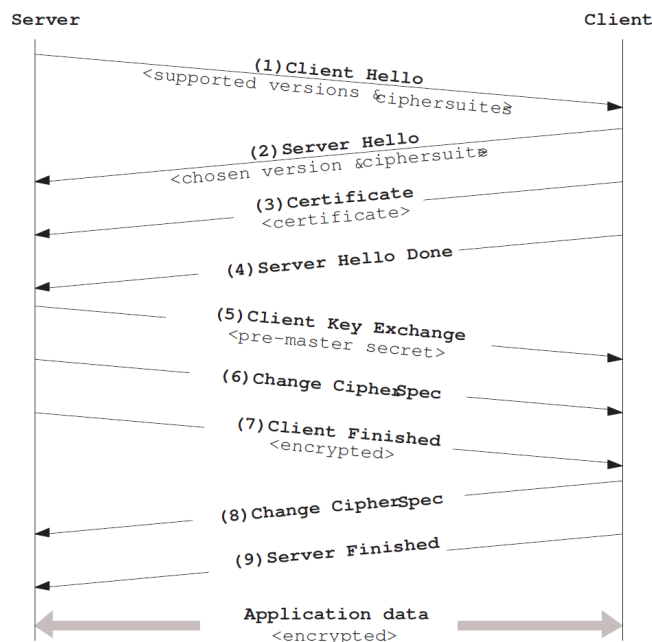


Fig. 12: Steps of the TLS Negotiation between Client and Server (Pukkawanna et al., 2014)

To secure the exchange of data transmitted over the internet network, we used the TLS 1.2 version. This security protocol has more than 300 cipher suites registered on the Internet Assigned Numbers Authority (IANA). Each cipher suite is a combination of the following cryptographic mechanisms:

- A key exchange mechanism, which specifies an exchange algorithm and possibly the signature algorithm used to authenticate the exchanges. RSA, ECDHE-RSA and PSK are some examples.
- Mechanisms ensuring the confidentiality and integrity of the data exchanged after the handshake, defined:
 - As the composition of an encryption algorithm and a hash function used in HMAC mode, such as AES-256-CBC-SHA38.
 - Either as an integrated encryption mode, also called combined mode, simultaneously offering encryption and integrity, such as AES-256-GCM.

- Optionally, for suites defined in version TLS 1.2, a hash function used for the derivation of secrets from the premaster secret. This option is used in particular by suites using integrated AES–GCM encryption.

Cryptographic suite of the TLS 1.2 is given by ECDHE–RSA–AES–256–GCM–SHA384 which was referenced by the IANA under code 0xC030. It indicates the combination of the ECDH handshake, the RSA digital signature, the AES–256 encryption which has a key length of 256 bits, the SHA256–based PRF, and the SHA384 (Secure Hash Algorithm 384). The figure 13 present the combinations of cryptographic suit of TLS protocol used in our application to secure the transmission of ECG–data from the acquisition system (client) to remote station (server).

```
('192.168.43.102', 37520)
('ECDHE-RSA-AES256-GCM-SHA384', 'TLSv1.2', 256)
TLS established. Peer: {'subject': (((('countryName', 'fr')), (('stateOrProvinceName',
'rennes')), (('localityName', 'beaulieu')), (('organizationName', 'laboratoire')),
(('organizationalUnitName', 'ltsi'))), 'issuer': (((('countryName', 'fr')),
(('stateOrProvinceName', 'rennes')), (('localityName', 'beaulieu')),
(('organizationName', 'laboratoire')), (('organizationalUnitName', 'ltsi'))),
'version': 3, 'serialNumber': '59551EFAD80C156E960C211ACCA105FB017E106D', 'notBefore':
'Feb 20 18:21:54 2020 GMT', 'notAfter': 'Feb 19 18:21:54 2021 GMT'}
```

Fig. 13: The output of the server: indicates the establishment of the TLS protocol and the cipher suites used.

Figure 14 describes the transmission of ECG–data using TLS protocol and without TLS protocol.

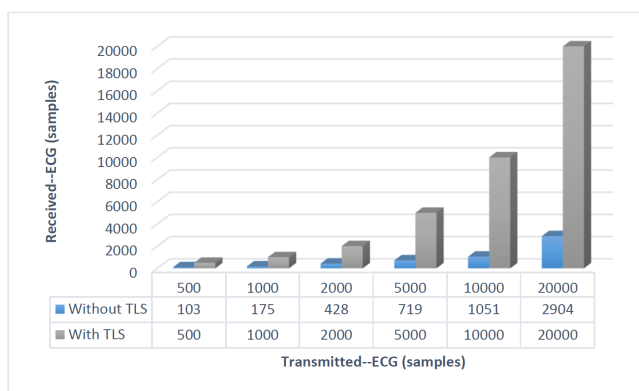


Fig. 14: Transmission process with and without using the security protocol (TLS).

As a result, we found that there is a loss of information between the transmitter and receiver during transmission of ECG–data without using TLS pro-

ocol. Further interpretation, the recordings data is obtained from the client where the acquisition card is located. The analogue signal delivered from the ECG AD8232 is converted from analog to digital form before transmission to the attached computer (computers need digital data). Timed sampling for the ECG recording was digitized at 100 Hz. During transmission of ECG-data , the server without security protocol, may miss data from the client because it does not have the capacity to record and store data every 0.01 sec, and the data acquisition at the Raspberry Pi is done quickly ($T_e=0.01$ sec). Further, it takes a certain time which is greater than 0.01 sec to receive another data Which leads to the loss of one or more points. The causes of packet loss include inadequate signal strength at the destination and overburdened network nodes (packet processing problem receive). Without using TLS, the server block received less than 25 percent of the overall ECG-data acquired in the client block.

Table 6: The loss information compared to the original ECG at source to With TLS at Destination.

Acquired ECG-data (Samples)	500	1000	2000	5000	10000	20000
Received ECG-data without TLS (%)	21	18	21	14	11	15
Received ECG-data with TLS (%)	100	100	100	100	100	100

On the other hand, we received the same length of data (100 % of the overall ECG-data) in the server as in the client when we used the TLS protocol (see table 6). Because, the acquired ECG-data will be encrypted one by one by using Cryptographic suite of TLS 1.2 and sent it to the server to ensure the confidentiality and integrity of all data exchanged. Finally, the server, in return, decrypts the received ECG-data. This result confirms the importance of using the data security protocol during transmission of ECG-data over wireless interface.

5.4 Client-server application

The graphical user interface (client-server) is dedicated to remote monitoring of cardiac arrhythmia, display, archiving, digital signal processing, classification, and transmission of ECG-data to a remote station under a secured TCP/IP protocol.

Client application is a graphical interface implemented with python environment connected with a data acquisition system to acquire the ECG signal for

transmitting over internet network to the remote station (server). The client application is represented in figure 15 and involves:

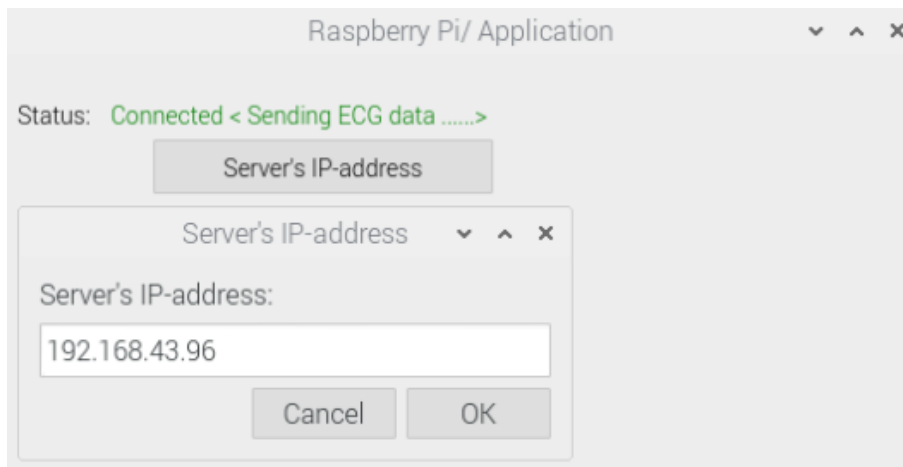


Fig. 15: Client Application: send ECG-signal from the Raspberry PI to the Server.

- Connection establishment window: relating to the communication phase between the server and the client (establish and open the connection through an internet network using the server's IP address).

Server application is implemented using the python environment, consists of visualization, archiving, processing of HRV signal, and classification of received ECG signal. The server application is illustrated in figure 16 and involves:

- Control window for viewing and recording the signal: allows to view and record the ECG signal and its corresponding HRV in real-time.
- Consultation window: allows measuring some parameters related to the heart rate such as heart rate (bpm), average HRV value (sec), and ECG signal values (mv).
- Connection establishment window: this phase establishes the communication between the server and the client under the secured TCP/IP protocol.
- Digital processing window: is devoted to analyze the HRV times series, by calculating there TF distribution and extraction of the three best features.
- Classification window: the learned SVM is used to classify the new HRV signal.
- Message window: used to display and indicate messages corresponding to the application.

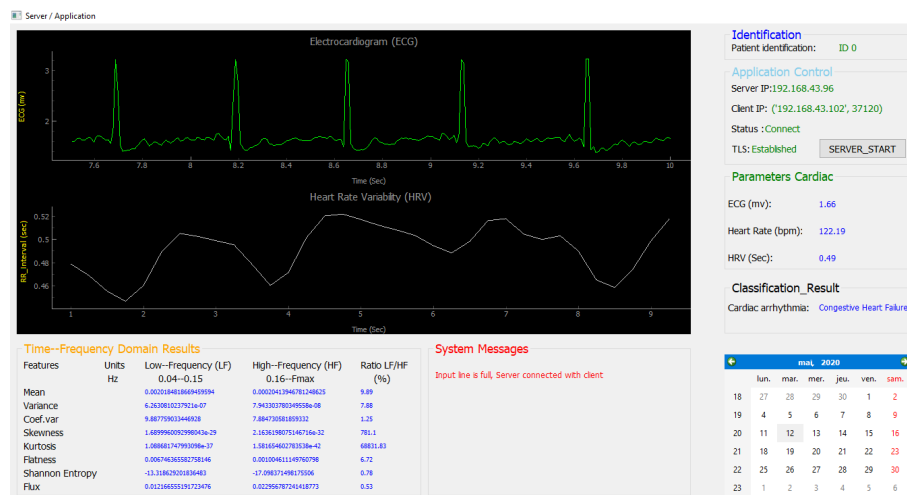


Fig. 16: Tele-monitoring and classification of cardiac arrhythmia.

6 Conclusion

In our study, we designed a new low-energy consumption, and a very affordable price system capable of performing continuous recording of HRV times series for easy monitoring of the heart rhythm for the detection of arrhythmia. We used an electronic circuit formed by an analog shaping part and a data acquisition system. As a software part, we developed a Graphical User Interface (GUI) within a python environment to establish the connection between the client and the server through the TCP/IP secured by the Transport Layer Security, to acquire, transmit, monitor, process and classify the hearth rhythm. We developed a new approach that combines SPWVD and SVM, for analyzing and classifying HRV signals. More precisely, three features of interest were extracted from the TF-representation of HRV signal: the coefficient of variation, the skewness, and the Shannon entropy. The obtained results show clearly that the proposed system is very efficient to differentiate between cardiac arrhythmia as AF and SVT among CHF and NSR cases. The result of classification can be sent to the medical professional for analysis and diagnosis.

7 Acknowledgments

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8 Data Availability

The data used in the current study are available in the PhysioNet repository, managed by the MIT Laboratory for Computational Physiology. For more information about the data used in this study, visit <https://physionet.org>.

9 Conflicts of Interest

The authors declare that there is no conflict of interest.

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