A Review on the State of the Art in Atrial Fibrillation Detection Enabled by Machine Learning

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***Abstract*—Atrial Fibrillation (AF) the most commonly occurring type of cardiac arrhythmia is one of the main causes of morbidity and mortality worldwide. The timely diagnosis of AF is an equally important and challenging task because of its asymptomatic and episodic nature. n this paper, state-of-the-art ECG data-based machine learning models and signal processing techniques applied for auto diagnosis of AF are reviewed. Moreover, key biomarkers of AF on ECG and the common methods and equipment used for the collection of ECG data are discussed. Besides that, the modern wearable and implantable ECG sensing technologies used for gathering AF data are presented briefly. In the end, key challenges associated with the development of auto diagnosis solutions of AF are also highlighted. It is the first review paper of its kind that comprehensively presents a discussion on all these aspects related to AF auto-diagnosis at one place. It is observed that there is dire need of low energy, low cost but accurate auto diagnosis solutions for the proactive management of AF.**

***Index Terms*—Atrial Fibrillation, ECG, Machine Learning, Arrhythmia, AF Diagnosis.**

I. Introduction

Cardiac diseases have been the main cause of deaths worldwide, according to the stats shared by the World Health Organization (WHO) from 2000 to 2016. Throughout this time, cardiac disease like Ischemic heart disease (IHD) has been reported as the first and stroke as the second most common reason for the mortality globally. Just in 2016, IHD alone took lives of more than 9.4 million people and stroke caused deaths of around 5.7 million people. These number of deaths caused by IHD and stroke have increased by 34% and 12%, respectively, since 2000. Contemporary studies show a strong correlation of AF with IHD and stroke, for an instance 20–30% of patients of Ischaemic stroke are diagnosed with Atrial Fibrillation (AF) at some stage [1]. AF is also a very common cardiac disease today, based on a multisource study in 2010, it was estimated that around 33.5 million individuals had AF worldwide [2]. The widespread prevalence of AF is alarming and it is expected that around 17.9 million people, from Europe only, can be at risk of AF by 2060 [3].

Based on this trend, some of the researchers expect an epidemic in the next 10 to 20 years. The mortality rate due to AF has increased two times from 1990 to 2010, for male and female both, with almost the same prevalence rate [3]. In particular, the population above the age of 35 are at higher risk of developing AF, amongst which the men are reported to have a higher incidence of AF in comparison to females [2]. WHO stats for 2016, show cardiac diseases as the main cause of death in lower-middle income groups to higher income groups contrary to low income group. Developed countries seem to be larger affectees of AF as compared to developing countries. This could be due to the lack of sufficient healthcare facilities and resources that impinge the timely detection and diagnosis of diseases such as AF.

Factors that can contribute towards the incidence and prevalence of AF can broadly be categorized as cardiac and non-cardiac causes. Some of them are merely related to lifestyle like smoking and drinking habits, whereas others are defined by genetics and may not be changed like ethnicity, gender, inherited disease etc., [1], [4]. Presence of AF can also increase the risk of other cardiac disease like Ischemic heart disease, valvular heart disease, congenital heart disease, congestive heart failure (CHF) etc., and non-cardiac disease like depression, cognitive dysfunction, chronic kidney disease etc., [4], [5]. Some potential medical and non-medical factors that can contribute towards the occurrence of AF are presented in Figure2 along with some serious medical conditions that can be caused by AF [1], [2], [4]–[10].

The comprehensive knowledge about the causes and effects of AF can help in proper diagnosis and management of AF. The information about these contributing factors can also be used in machine learning algorithms for auto-detection of AF as it is used by [8]. Authors used the statistical information bout clinical, biomarker and genetic attributes like blood pressure, Glomerular filtration rate (GFR), Genotype, Age and Gender in multivariate multinomial logistic regression based model for AF detection. It is found that different factors have different level of association with different types of AF. Similarly, authors in [7] found that for their multivariable competing risk model different factors like increasing age, body mass index, and weight are comparatively strongly associated with the development of non-paroxysmal AF. Whereas they

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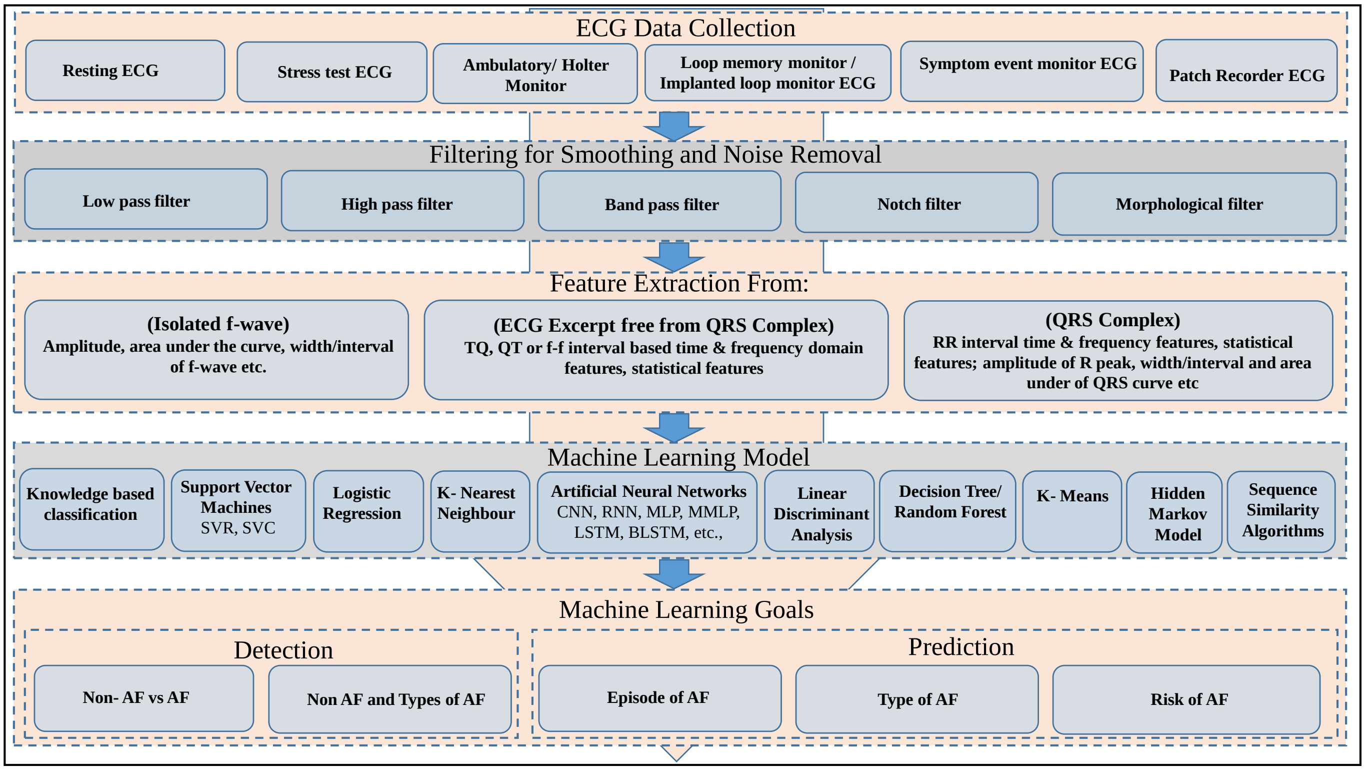


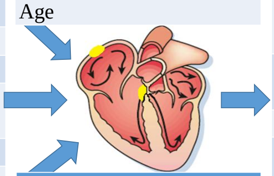
Figure 1. ECG data based AF detection process with important steps and characteristics

are weakly associated with paroxysmal AF.

The timely AF diagnosis is very crucial to avoid a life threatening situation, however, it is quite challenging specially diagnosis at the early stage also referred to as Paroxysmal AF (PAF). PAF is asymptotic and episodic in nature and often goes undetected during diagnosis with conventional ECG monitoring devices. This is due to the fact that such devices are event-based which measure heart activity for a certain time interval. Besides that, commonly a clinical set up is required for the recording of an electrocardiogram (ECG). On top of that a medical expert is needed to interpret the ECG data. These inefficient diagnosis tools and dependency on domain experts decreases the chances of timely detection of AF many folds. The under-reporting of AF in developing countries is coherent with this deduction. Hence, there is need for such smart devices that collect ECG data efficiently for longer intervals. In addition, they are required to be equipped with artificial intelligence for the auto-diagnosis of AF without external aid from a medical expert.

Medical
- Hypertension
- Diabetes
- Coronary Artery Disease
- Valvular Heart Disease
- Heart Failure
- Chronic Kidney Disease
- Ion Channel Disorder
- Cardiac Surgery
- High Blood Cholesterol
- Ischemic Heart Disease
- Electrolyte Depletion
- Pulmonary Embolism
- Myocardial Infarction

Genetics
- Family History
- Ethnicity
- Gender
- Age



Lifestyle
- Smoking
- Obesity
- Sleep Deprivation
- Vigorous Intensity Exercise
- Physical Inactivity
- Excessive Alcohol Intake

Risks Associated
- Stroke
- Heart Failur
- Depression
- Left Ventricular Dysfunction
- Cognitive Impairment and Dementia
- Physical Disability
- Thromboembolic Events
- Extracranial Systemic Embolic Events
- Chronic Kidney Disease
- Myocardial Infarction
- Sudden Cardiac Death

Figure 2. Causes and Risks associated with Atrial Fibrillation

The emerging landscape of wearable and implantable sensing technologies [11] provides a plethora of opportunities for developing low cost, low energy and efficient solutions for the data collection and monitoring of various human biomarkers including ECG. On the other hand, the state of the art machine learning algorithms can harness intelligence required for the auto-decisions of AF exploiting the ECG data collected from smart sensing devices. Though opportunities are endless and continuous progress can be seen in both fields independently, but for the time being, single smart sensing device equipped with artificial intelligence for auto-detection or prediction of AF is a futuristic concept. Such device is desired to have low energy and low computational cost to meet the demands of 'always on' scenario and real-time diagnosis. Besides the computational efficiency, high detection accuracy is also very important to avoid false alarms which can lead to unnecessary in-clinic visits and stress.

In this paper, literature is reviewed and presented in a systematic way covering pertinent concepts and key steps involved in developing a machine learning based solution for AF detection as highlighted in Figure 1.

The key contributions of this paper are as follows:

- *It presents a summarized overview of common causes of AF and risks associated*
- *It provides a brief introduction of AF and its important types for an audience foreign to the concept*
- *It lists popular methods and equipment used for AF data collection*
- *It identifies, reviews and discusses key biomarkers relevant for the design of machine learning driven AF detection models.*
- *It elaborates with use cases, each key step involved in data pre-processing and machine learning model development for the detection and prediction of AF*
- *It briefly discusses the modern methods and smart devices for monitoring and data collection for AF*

This review paper is unique in the sense that it comprehensively presents discussion on all these aspects related to AF auto-diagnosis at one place which is not done before. This review paper can provide a comprehensive guideline for researchers, from engineering and medical background, interested in developing machine learning based solutions for the auto-detection and prediction of AF.

II. Atrial Fibrillation and its Types

AF is the presence of an abnormal heart rhythm caused by irregular contraction pattern of atria, may be symptomatic or asymptomatic. Common noticeable symptoms of symptomatic AF include heart palpitations, fainting, dizziness, shortness of breath, or chest pain. However, AF is often asymptomatic without any prominent symptoms. This concealing characteristic of AF may result in its late diagnosis and may lead to morbidity or even mortality.

AF can be classified based on symptoms, aetiology, electrophysiology etc. [12]. A joint committee of American Heart Association (AHA), American College of Cardiology (ACC) and European Society of Cardiology (ESC) has proposed a scheme of classification based on temporal rhythm [13]. They recommend this classification scheme for simplicity and clinical relevance. It is the most popular and commonly accepted classification approach for AF. Four main classes identified in this scheme are presented in Figure 3 and discussed below. Pattern or electrical signature of single episode of each type of AF is same in its essence. Classes are defined based on the frequency of occurrence of those episodes and how long they last.

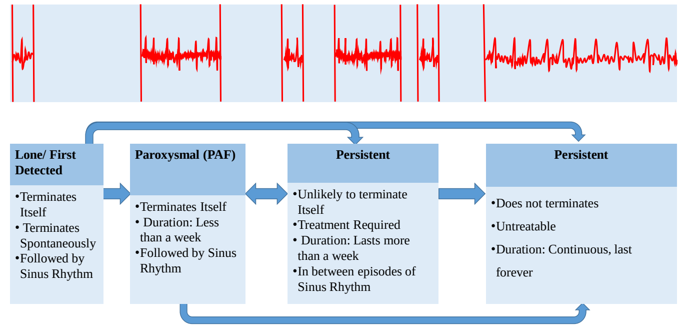


Figure 3. Types of AF and possible patterns of their occurrence

A. First detected

It is the occurrence of the first episode of AF when AF is diagnosed. Irrespective of the duration or intensity of AF episode, AF initially falls in this category. Early detection of such episodes is almost impossible particularly using the conventional event based ECG monitoring solutions. Event based ECG is taken for a certain interval of time and mostly when some serious symptoms are already observed. But AF can be silent and may not have any symptoms at all particularly for the first episode, so it may go completely unnoticed. On the contrary if complete medical history of the patient is available then big data analytic may help to identify the preceding patterns that lead to AF. Similarly, data collected from multiple sensors for various biomarkers can be collected and fused to generate high quality data rich in information about the medical condition of the person under monitoring [14]. Data analytic performed on public healthcare databases can help to identify potential biomarkers from similar cases. Once patterns or biomarkers leading to AF are identified then ML solution can be devised to predict forthcoming possible first episode of AF. But for this beforehand continuous monitoring is needed. Data collection may be done by continuous sensing devices like wearable smart watches or after a flag raised by any prior disease associated with AF. Aged persons or patients with some disease at high risk of AF can be kept under observation.

B. Paroxysmal (PAF)

When the first detected episode of AF does not last for more than a week and it stops on its own, it is labelled as Paroxysmal. Most of the time it terminates in less than 24 hours. Because of its interim episodic nature, its detection is also very difficult. However, its identification is very important as the chances of cure with treatment are very high at this stage. Auto-detection of PAF is a hot research topic with two main approaches for PAF diagnosis. First focuses classification of PAF episodes from the sinus rhythm it is helpful to diagnose the patients with AF episodes already happening. In second approach, various machine learning algorithms [15] have been studied to predict the onset of PAF. This approach can help in preempting an upcoming episode. But both approaches have the limitations that they are applicable for the patients who already have AF. They do not address the cases where the subjects can be at the risk of AF but they do not have it yet. For such cases again the approach highlighted in preceding section can be adopted. Machine learning algorithm based on biomarkers for potential AF cases can be helpful for the diagnosis of patients at risk of AF.

C. Persistent (PeAF):

If AF prolongs more than a week, it is unlikely that it will stop on its own. An intervention like the application of direct current cardioversion or use of medicine may be needed to stop the episode. It is still curable and effective monitoring and detection system can help in its management from diagnosis to treatment. In such cases patients are mostly already diagnosed with AF and are under treatment. Machine learning can play an important role for patients under treatment.It can help to predict the upcoming episode so it may be managed with timely action. With the exploitation of the preceding pattern to an AF episodes ML can predict the onset episodes in PeAF patients [16].

D. Permanent

At this stage, AF is continuous and does not go away for a very long period of time like for one year or more. If medication, cardioversion or medical procedure is unsuccessful or not attempted at all the persistent AF can turn into permanent AF [17]. Advance medical procedures may help some patients in improving their quality of life at this stage. Identification of AF beats can help in the provision of necessary treatment at an appropriate time. Since, at this stage, it is continuous instead of being episodic, so it can be easily detected with the conventional ECG methods. It is also easy to gather data of such patients as compared to data from patients with other types of AF because they are more likely to be registered with healthcare facilities for more frequent examinations. This data can be helpful in the identification of key characteristics of AF patterns. These key features then can be used in the development of machine learning models for AF-diagnosis.

The progression of AF from one stage to other is highlighted by the direction of arrows in Figure 3. Patient with PAF can go to the persistent stage and vice versa based on the intensity and frequency of AF episodes or progress made due to treatment. Once AF changes into permanent AF, it is highly unlikely to reverse it. The inability to detect AF in a timely fashion can not only increase the risk of progression of AF into an advance stage but it can also lead to other prevalent diseases like presented in Figure 2. So, early the AF is detected higher are the chances to take preventive or corrective measures to avoid severe conditions like stroke or heart failure. Machine learning is commonly applied to detect AF [18], [19], predict episodes of AF [20], [21] or differentiate between the AF types [22].

Some other important categories defined by the same joint committee of ACC, AHA, ESC are as follows:

Lone atrial fibrillation (LAF): The term Lone atrial fibrillation (LAF) is used when the patient experience no symptoms such as ones listed in Figure 2. The detection of LAF is challenging because of the absence of apparent symptoms. However smart machine learning solutions that exploit the preceding patterns for AF can help in the diagnosis of LAF, as discussed earlier for 'First Detected' or 'PAF'.

Valvular and Non-valvular atrial fibrillation: When AF is caused by any valvular disorder it is called as valvular AF. This disorder can be due to some valvular disease or replacement of any valve of heart with an artificial valve. On the contrary, AF is called non-valvular AF when it is present in the absences of a prosthetic heart valve, mitral valve or any disease associated to these valves.

Secondary AF: When AF is present along with other diseases it is called secondary AF. It is follows reversible aetiology (i.e AF can be caused or lead to other diseases like heart failure, cardiac surgery, stroke, etc.). Even in patients who undergo non-cardiac or non-thoracic surgery, there are high chances of AF incidence ranging from 0.4% to 26%. AF following a surgery is also called postoperative atrial fibrillation (POAF) and it is a very common type of pre-operative arrhythmia. The incidence of POAF depends on multiple factors like age, lifestyle, type of surgery performed, and the presence of other heart diseases [23], [24]. In the case of cardio-thoracic surgery, chances of POAF are higher than those after non-cardiac surgery. For example, patients undergone coronary heart surgery have approximately 33% chances to suffer POAF. Prospects of the incidence of POAF after valvular heart surgery are even higher. [25]. Data analysis and machine learning may help to identify some patterns in the medical history of POAF patients.These patterns then can be exploited further to detect potential POAF cases among post surgery cases.

III. Data Collection for AF Diagnosis

Different medical tests including ECG, ultrasound scan, echocardiogram are conducted to assess the health status of the heart. The information obtained from such examination is then used to identify the nature and type of AF. A chest X-ray or blood test can also be conducted to evaluate any possible predisposed or associated disease. All these tests can help to have detailed look on cardiac functioning but ECG is considered the main most reliable test for the diagnosis of AF and other arrhythmia [27]. [28] provides a comprehensive review of screening test for AF. The subsequent section details the most common equipment used in practice for ECG data collection, discusses the key ECG features, and the available data repositories that have been used to advance the ECG data driven research.

ECG Equipment	**Duration of Recording**	**Functionality/ Characteristics**
Resting ECG device	5-10 minutes	The subject is supposed to lie down quietly without any movement to avoid any interference from any other muscular activity.
Stress test ECG devices	15-30 minutes	ECG is carried out while subjects performs some physical activity like walking on a treadmill.
Ambulatory ECG devices [26]	Few hours to few years	Used to record ECG over days, weeks or years. They are primarily used for the outpatients.
		They can record ECG continuously or intermittently.
		Recording can be started by the patient like in case of loop memory monitor or symptom monitor or automatically based on the auto-sensing of arrhythmic signals.
		They can be fitted externally e.g Patch recorder or can be implanted below the skin like implanted loop recorders.

Table I
Some Popular ECG Devices

Components of the ECG	Association in the heart	Duration (T) / Amplitude (V) / Length (L)
Standard		
P Wave	Represents firing of the SA node and normal depolarization of atrium	T <=0.11 sec
RR Interval	It is duration between two consecutive R peaks in R wave. R wave represents early depolarization of ventricular.	T: 0.6 - 1.20 sec
QRS Complex	One single heart beat corresponding to the depolarization of the right and left ventricles (lower heart chambers)	T <= 0.12 sec
	Q-wave = first negative deflection	T <= 0.04 ssec
	R-wave = first positive deflection	
	S-wave = second negative deflecton	
ST Segment	The beginning of ventricular repolarization. It should be isoelectric (flat at baseline).	T <= 2.0 mm in some precordial leads, L <0.5 mm in any lead
T Wave	Repolarization of the ventricles	A=>0.2 mV in leads V3 and V4 and A=>0.1 mV in leads V5 and V6
Secondary		
U-Wave	Last, inconsistent, smallest, rounded and upward deflection controversial in origin, sometimes seen following the T wave making TU junction along the baseline or fused with it. Can be present in a healthy heartbeat as well.	L <= 1 mm, A <1/3 of T-wave amplitude in same lead

Table II
KEY ARTEFACTS OF ECG OF SINUS RHYTHM

A. ECG Equipment

ECG presents variation in the electrical signal, related to contractile activity of the heart, over time. It can be easily recorded using noninvasive electrodes on the chest or limbs. Continuous or real-time ECG monitoring can help detect the AF. Some popular devices for ECG data collection are listed in Table I along with the detail about their functionality. Quality of the ECG data collected has significant dependence on the data collection method and the equipment used. ECG devices vary based on the use of the number of leads used and length of time interval of data collection besides their portable nature. Commonly used ECG equipment in clinic are very sophisticated and use more leads which help to collect detailed information about the electrical activity of the heart like it is in the case in resting or stress test ECG. Such equipment is not portable and they can collect data for shorter intervals where patients are required to be in clinic and maintain certain body postures. But they are not very helpful for continuous or real-time monitoring of subjects on the go.

Implantable or wearable ECG equipment like loop monitor, patch recorders or ambulatory devices can be used for continuous data collection for longer intervals in mobile users. They are portable, user can wear them and collect ECG data anytime anywhere. Some devices can collect data continuously for longer intervals like upto few days. To support a portable or wearable design these devices are smaller in size, lower in computation power and have fewer leads which limits the information to be collected. Besides that, as the data can be collected for longer intervals and the physical activity of the participants may not be restricted, ECG data can be polluted by the signals produced by the activity of the muscles. Hence there is a trade-off between the quality of the data collected and mobility of the participants. Use of more leads in an controlled environment can help to obtain better quality data but it restricts the movement of the participants and duration of data collection. On the other hand mobile devices give freedom of choice for the time and location but quality of data is compromised because of the low sensing capacity of wearable devices and inevitable muscle activity.

B. ECG Characteristics

1) ECG Characteristics of Sinus Rhythm: A labelled ECG excerpt for sinus rhythm, recorded by 12 leads equipment, is shown in Figure 4 and its key features are described in Table II [29].

A sinus rhythm has a set pattern which repeats itself. Amplitude and duration of artefacts are constant. If they change then it is not sinus rhythm. Sinus rhythm always has a same round shape P-wave which does not change. The P-wave is followed by QRS Complex and duration between any two consecutive R peaks remains same and constant.

2) Key ECG Markers of AF Detection: Some salient characteristics of ECG of an AF episodes are present in Table III with a description of how they can help in identification of AF. Absence of P-wave is a key indicator of the presence of AF. As shown in Figure 5, the ECG excerpt at the right bottom shows the sinus rhythm where P-wave is present, but from the

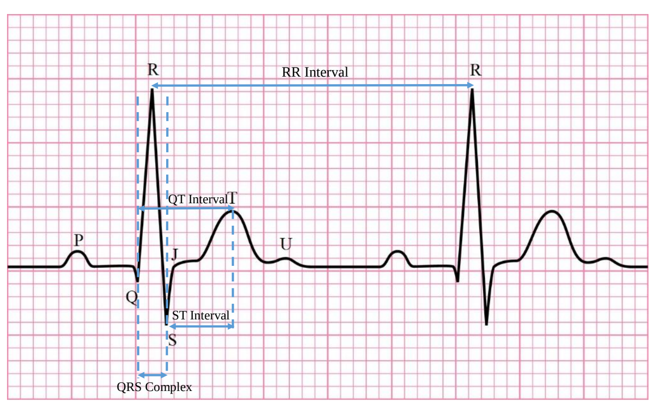


Figure 4. ECG of Sinus Rhythm with its Key Artefacts

Features	Effect	Challenges	Morphology Parameters
P Wave	Missing P-wave	Common among other Arrhythmia	Amplitude, width,area under the P-wave; Time duration between its onset and peak; Time duration between P and R peaks.
RR Interval	Inconsistent Intervals	Common among other Arrhythmia	Duration between consecutive R peaks
QRS complexes	Widens/ shrinks in some cases	Mostly remains unchanged	Area under the QRS curve, Width of the QRS complex,Amplitude of the R peak;

Table III
KEY ARTEFACTS OF ECG OF AF ARRHYTHMIA

left ECG excerpt of AF patient, it can be seen that there is no clear and explicit P-wave, instead, many random fluctuations can be seen. An expert, with visual inspection, observing the absence of P-wave can diagnose a potential AF case. Similarly, the irregular RR interval can also indicate AF but some other arrhythmia also have the similar irregularity.

However, this whole process, involving paper ECG and personal inspection by an expert, is slow, reactive and time consuming. This demands an automated system that can analyze the patterns in the ECG data and accordingly classify possible AF episodes without the need of a medical expert. Current state-of-the-art solutions that strive to automate the detection of AF episodes extract various features from the ECG data such as detection of absence of P-wave, duration between consecutive RR intervals, height and spread of various sections of ECG wave. There has been ongoing research on engineering suitable features to increase the accuracy of aforementioned automated models.

C. AF ECG Registries

The collection of ECG data often requires access to expensive hardware, medical expert and consent of target patients. Therefore, to advance the ECG centric research for various application, AF being the one, researchers have made public databases like Physionet. In the context of developing machine-learning driven solutions, the availability of such information opens up a lot of possibilities to experiment with various feature extraction techniques and algorithmic models, in order to design accurate predictive models for AF diagnosis. Thanks to publicly available databases like Physionet [31]–[36] which provides such opportunities They are not limited to just the provision of databases but some theme specific competitions have foster research for different aspects of AF detection and prediction. For example Computers in Cardiology Challenge 2001 had the theme of prediction of PAF. Participants and other researchers have contributed by developing a number of different machine learning solution for PAF prediction [20], [38]–[42]. Publicly available Physionet registries and related challenges are mentioned in Table III along with some other important data bases which may be acquired on request.

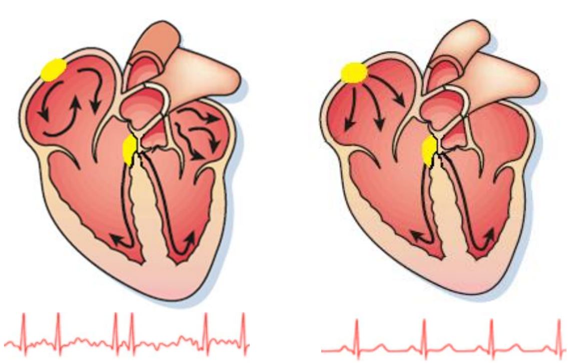


Figure 5. Atrial Fibrillation VS Normal Heartbeat

IV. ECG SIGNAL DATA PROCESSING

Machine Learning involves some preliminary steps crucial for the development of an efficient and accurate model. These steps, including data cleaning, filtering, feature extraction, feature selection, etc., are commonly grouped into the category of data preparation for ML algorithms [43], [44], or labelled as datamining steps for ML [45]. These steps are very important as the performance of the models highly depends on the quality of data and the right combination of features used in the ML algorithm, besides the choice of algorithm itself [44]. Authors in [46] have proposed generalized algorithms listing key steps involved in ECG signal processing and ML implementation for AF detection. ECG data collected using different equipment may vary in signal quality depending on

Registry/ Database	Specification
Gulf Survey of AF Events [30]	Scope: Patients from 23 hospitals in 6 Middle Eastern Gulf countries: Bahrain, Kuwait, Qatar, Oman, United Arab Emirates, and Yemen. Leads: 12, Sample size 30(sec). Features: Demographics, Medical history, History of AF, Type of AF, Prior AF interventions
MIT-BIH AF 2000 [31]	25 long-term ECG recordings of human subjects with atrial fibrillation (mostly paroxysmal). Of these, 23 records include the two ECG signals
PAF Prediction Challenge Database 2001 [32]	ECG: Two Channels,Subjects:48, Samples:50 records 4 values (Onset of PAF,No PAF within 45,just after PAF, just after no PAF)& 50 pairs SNR, Sample Size: 5,30 (minutes). Features: PAF, SNR, Target: Predict PAF
Intracardiac Atrial Fibrillation Database 2003 [33]	Subjects: 8 PAF Patients, ECG: 3 leads, Data:8 sets of 4 records
AF Termination Challenge Database 2004 [34]	Subjects:20 (10 Noramal,10 S/T AF), ECG: Two channels, Sample Size:60 (Sec), Samples:Training 30 (10 N,10 SAF,10TAF)& Test 20(10 SAF,10TAF),
Long Term AF Database 2008 [35]	Samples:84, Sample Size: 24-25 hour , ECG: Two channels
Physionet 2017 [36]	Device:AliveCor, Leads:Single, Training samples:8,528,Test data:3,658, Sample length:9-60(Sec)
RECORD AF 2008 [37]	Subjects:5,604, Area covered: worldwide 532 sites in 21 countries, Target: PAF, PeAF in recently diagnosed patients

Table IV
ECG REGISTRIES

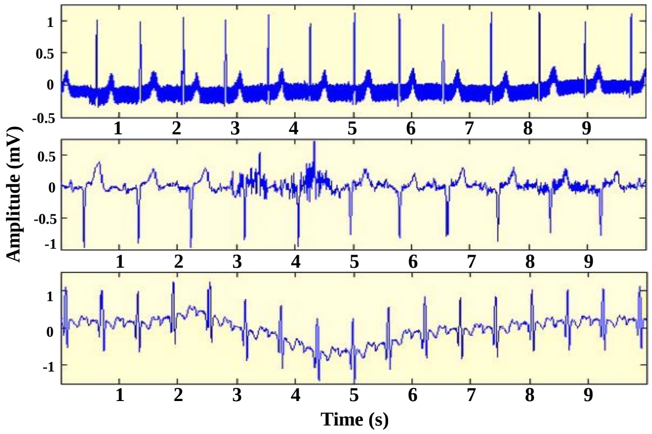


Figure 6. Common types of noise in ECG (a) 50 Hz power line interference, (b) Electromyographic noise , and (c) Baseline wander. Adapted from [47]

the quality of equipment used and method of data collection (e.g., number of leads used, location of their placement on the body, interval of data collection etc). ECG data collected, particularly from the wearable devices, contains noise and can be low in quality. The contributing factors towards noise include interference, non-alignment of artefacts, baseline drift, sensor displacement, errors in defibrillators or malfunctioning of the pacemakers. Besides that, ECG signal data needs to be pre-processed and features need to be extracted to use as input for machine learning model. Hence, selecting and extracting right set of features is a crucial step that directly impacts the AF detection model performance. Discussion on important data preparation steps like noise filtering, feature extraction and feature selection in the context of machine learning based AF diagnosis is presented here, but first, we briefly discuss some popular filters used in ECG processing for different purposes:

A. *Filtering*

Filters can remove undesired elements from the ECG signal data and can help to sync artefacts. Researchers have used different types of filterers on ECG signals for different goals. Most commonly used filters are linear filters which mainly control a set of frequencies to pass. In e.g [48] authors have used 'low pass filter' that allows frequencies less than certain level to repress the artefacts, [19] has used bandpass filter to allow a certain bandwidth (5- 26 Hz), remove baseline wandering (BLW), power-line interference, and maximize the QRS energy. Whereas [21] has used Fast Fourier transform based brick-wall filter with the bandpass frequency (1 Hz, 45 Hz) to allow a band-limited frequency to pass. Then they applied a sliding window (500 ms) with root mean square filter and the median value of the filtered signal for the removal of the motion artefacts. Opposite to bandpass filter, there also exists band stop filter that suppresses a particular band and allows other frequencies to pass, e.g. [49] uses such filter called notch filter (for a narrow band to stop) to eliminate 50-60 HZ power line interference (PLI). On the other hand, a non-linear morphological filter can be used to remove BLW and detect specific artefacts or fiducial points e.g. QRS complex, P-wave etc. In the context of down sampling, filtering methods are helpful for increasing computational efficiency in the step of feature extraction and model training. Another very popular filter used for smoothing, noise removal and feature extraction is wavelet transform [50] Different types of filter used for ECG data processing are discussed in detail in the following sections with respect to their pre-processing applications.

B. *Noise Removal*

Since the signal to noise ratio of ECG is low, therefore, there are high chances that ECG data collected can be contaminated with noise [51]. Significant and commonly found types of noises as presented in Figure 6 and summarised in Table V are discussed below along with the possible denoising and filtering techniques used to remove them:

1) Electromyogram (EMG) Noise: ECG is an electrical signal generated by the movement of heart muscles whereas EMG is the electrical activity generated by the skeletal muscles. Surface EMG comprises almost the same procedure as it is for the surface ECG. Both involve placing electrodes on the skin and measure the voltage difference between any two electrodes. As ECG and EMG frequency spectrum overlaps, i.e both are sensitive to a similar range of frequencies, therefore, it is very difficult to avoid contamination of signals generated from muscles other than heart muscles in the process of ECG recording. An EMG contaminated ECG signal is shown in Figure 6 (c). It is more likely to find this type of noise in exercise ECG or long-term ECG particularly with wearable devices because it is not possible to avoid muscle activity in such cases.

As compared to other types of noises present in ECG, removal of EMG artefacts is more difficult because of spectral overlapping and its random nature [53], [55]. Different type of filters like discrete wavelet transformation, band filter(low pass), adaptive filter or their variants like least-mean-square (LMS) and recursive least-squares (RLS) are used to suppress or remove EMG artefacts from the ECG signal. However, the challenge faced is that techniques such as low-pass filtering

Type of Noise	Common Causes	Popular Filters/Solutions
Electromyogram (EMG) noise	Contraction of muscles, sudden movement of body	Discrete wavelet transform [52]–[54]; low pass filters;signal slope dependent approximation filter [55]
Power line interference	Electromagnetic fields by power-lines or nearby electric devices	Proper insulation and grounding of wires and equipment, Band pass filter; Discrete wavelet transform [54], [56]; Adaptive Filter [51], [56], Subtraction procedure [57]
Baseline wandering	Respiration, body movements, poor electrode contact,perspiration	Linear high pass filters, polynomial filters [47]

Table V
ECG NOISE TYPES, POSSIBLE SOURCES AND POTENTIAL SOLUTION FOR REMOVAL

methods that are used to suppress EMG artefacts lead to reduction in the sharpness of Q, R and S wave important component of the ECG signal. Subsequently, the artefacts may lose their commercial shapes and subsequently some important information. In [55] authors have proposed a solution to address this challenge by applying a dynamic approximation filter which uses a varying number of weight coefficients and tries changing the number of samples, according to the slope of ECG signal [55]. To address the same problem a threshold-based wavelet transformation scheme has also been experimented with [52]. It id used to removes EMG artefacts while retaining the original geometrical properties of the ECG signal.

2) Power line interference (PLI): It is produced by the electromagnetic field produced by the regular AC current of 50-60 Hz passing through the wires around ECG equipment. It can be caused by the electronic devices not grounded properly or other electronic devices in operation near the ECG device as shown in Figure 6 (b).PLI can be minimized by properly grounding the electric equipment or keeping other electronic devices away from the ECG recording device. Fixed notch filters like infinite impulse response (IIR) and finite impulse response (FIR) [58] and their variant like High-Q Comb FIR [59] are commonly used to removed PLI from ECG signal [56], [60]–[62]. Disadvantages of the fixed notch filter are that it modifies the ECG signal, produces ripples and also requires some fixed parameters.

There also exist some alternative solutions which, unlike Notch filter, does not have fixed parameters, they are called adaptive filters [63] and they have different implementation schemes like LMS [51], RLS [64], Hilbert Huang Transform adaptive filter [65], [66]. But their drawback is that they also require a reference signal and QRS complex may have interference with the parameter estimation [61]. [67] provides a comparative study of adaptive and non-adaptive filters for the reduction of PLI in ECG. Subtraction method [68], [69] is another common approach used for PLI removal from ECG. [57] provides a comprehensive study on different subtraction methods.

For futuristic low energy ECG devices for the monitoring of longer hours, PLI is a serious point of concern. Authors in [70] discuss the PLI removal in the context of low power wearable ECG devices. They evaluate the performance of different PLI removal methods like Notch Filter, Sinusoidal Modeling, Regression Subtraction, and Adaptive Filter. They present results showing that except adaptive filter other methods are not robust enough to perform well for the wearable smart devices, particularly adoptive filter recursive least squares (RLS) outperforms the other filters.

3) Baseline wandering (BLW): Baseline wandering is low-frequency noise mainly caused by respiratory movements, body movements, scars on the skin, depletion of gel on electrodes or poor contact between electrodes and skin due to sweating. It is another very common cause of noise in ECG data and therefore, its removal is also well-sought research problem. Different methods like high-pass filter, bandpass filter, digital filters (IIR, FIR), adaptive filter, blind source separation (BSS) [62], wavelet transformation [71]–[73] etc., are often applied for BLW removal from ECG. The common challenges associated with the aforementioned methods are the need of the reference signal and the delineation of ECG. To overcome these challenges [74] propose a hybrid method comprising adaptive notch filter and BSS that has shown to outperform the conventional BLW removal techniques.

A comparative study of nine most cited and widely used methods of BLW removal is presented in [75]. Authors compare the performance of filter like FIR, wavelet transformation, interpolation using cubic splines, IIR , LMS adaptive filter, moving-average filter, and independent component analysis. In addition they also asses some hybrid approaches of wavelet transformation filter like wavelet adaptive filter [76], an adaptive filter based on discrete wavelet transform and artificial neural network [77], mean-median and discrete wavelet transformation (DWT) [78]. After the empirical evaluation against the parameters like low computational cost, implementation simplicity and low distortion criteria, authors in [75] recommend FIR filter for the removal of BLW. They find it equally efficient for the both, embedded device and computer-based ECG analysis.

In addition to the aforementioned noise sources, researchers have highlighted other artefacts which needs to be removed to get the relevant information from the ECG signals. For the current requirements of continuous monitoring for longer intervals of time, on low-energy devices, an increased amount of noise is expected. Smart wearable devices often have prolonged usage and demand effective yet less computational hungry algorithms for noise removal, since they have energy constrained. Therefore, such filters are needed which should be computationally low cost, efficient in eliminating multiple noise elements without removing valuable artefacts. Single or fewer low-cost filters for the removal of multiple noise types are ideal for low-energy devices, particularly those with capacity for ECG delineation.

In [54] authors have proposed a hybrid approach, an adaptive dual threshold filter (ADTF) with discrete wavelet transform (DWT) for the removal of the three main types of noise (EMG, PLI, White Gaussian Noise). They empirically show their approach outperforms other methods namely Riemann–Liouville (RL) integrator, fractional zero-phase filtering (FZP) and the zero-phase average window filter (AZP) for all the three types of noise. There are two main limitations of their research, particularly important in the context of smart ECG monitoring and analysis devices. First, their approach involves three different filters, applied in three separate steps. Second, they have applied it for the removal of each noise type separately. Authors in [77] present a more efficient hybrid approach for the removal of multiple noise types at the same time. They propose an adaptive filter based on wavelet transform and artificial neural networks to remove all the noise types at the same time. They improve the signal to noise ratio for individual noise types e.g., power-line interference (22.36 db), baseline wander (11.56 db), white noise (11.80), electrode motion artefact (9.64 db), and muscle contraction noise (5.19 db) and 15.72 dB when all noises types are removed at the same time.

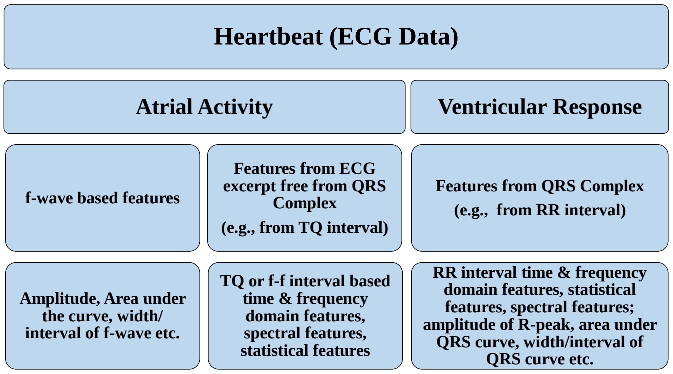


Figure 7. Features extracted from different segments of ECG of atrial activity and ventricular response

C. Features Extraction

Features are the input information for a ML algorithm that can help to detect or predict AF. It can be any piece of information like age, gender, or medical history presented in Figure 2 or biomarkers which individually or combined can help to develop a model for the identification or prediction of AF. Biomarkers that can distinctly identify existing or potential patients [79] of AF are very valuable features. In this section, important artefacts or characteristics of ECG and popular features derived using those artefacts, valuable for the detection and prediction of AF, are presented. Besides that, some commonly used methods of feature extraction are also discussed.

The raw ECG signal data may be used directly as input in machine learning algorithms as the authors in [18] have used it in their deep learning based model. Using raw ECG signal data as input has its own pitfalls like high computational cost and high sensitivity to noise, making it inefficient for the smart AF diagnosis devices. On the other hand, features based approach is more pragmatic for developing energy efficient and accurate solution supportive for continuous or prolonged monitoring. For AF auto-diagnosis features can be extracted from the key patterns observed on ECG of AF patients. Features extracted from ECG like statistical attributes of f-wave [80], RR interval [81], and QRS complexes [82] act as input to the ML algorithms for AF detection. Characteristics or key element of normal sinus rhythm are already presented in Table II which basically present the regular electrical activity generated form the normal contraction and retraction of heart muscles. Deviation in heartbeat patterns from the sinus rhythm is referred arrhythmia. Patterns of some types of arrhythmia are presented in [83] with some examples of ECG excerpts.

Features are commonly grouped and studied in two domains Time and Frequency. New features are extracted from their temporal or frequency attributes. Additionally, commonly known classes include statistical or distribution function features. For the features extraction study with conventional domains please consult [84]. But here in this study, classification of feature extraction is driven by the source activities that generate the data or features. In the presence of AF, atrial activity is disturbed and, as a result of it, ventricular response also does not remain normal. Therefore, the representative ECG characteristics of these two activities are used for AF detection. The main AF characteristics based on irregularity in atrial activity or ventricular response are as follow:

- The signature wave of atrial activity known as P-wave is absent or replaced with f-wave [85]. f-wave reflects irregular atrial beat rate that varies between 240 and 540 with an average of 350 beats/min. It is a low amplitude fibrillatory wave [86].
- QRS complex, representing the ventricular response on the ECG, is disturbed. It is mainly reflected by irregular RR intervals also known as ”irregularly irregular”. For their measurement the first task is to detect QRS complex, then detect R-peaks in QRS complex, and then measure the duration between consecutive R peaks.

In research, therefore, machine learning algorithm for AF detection commonly use features extracted from the ECG data of atrial activity, ventricular response or combination of both [81], [87].

1) Atrial activity based Features:
P-wave and f-wave represent atrial activity in normal and atrial fibrillation respectively and QRS complex represents a ventricular response. Therefore, to extract features from atrial activity either an isolated f-wave or ECG excerpt excluding QRS complex (e.g TQ interval) are used. To get an isolated f-wave or ECG free from QRS complex, QRS cancellation is a common preliminary step [88]. Popular methods of QRS cancellation include direct suppression of QRS, average beat subtraction (ABS) [89], [90], use of filters (e.g, bandpass filter, adaptive filter) [91], spatiotemporal QRS cancellation, blind source separation, independent component analysis, and principal component analysis.

Important step for the cancellation of QRS, in most of the cancellation methods, is the detection of QRS complex. Different algorithms are used for the detection of QRS Complex, the popular ones include wavelet transformation [92], [93], neural networks [89], [94], and Pan and Tompkins algorithm [95], [96]. Pan Tompkins algorithm is the most popular algorithm used for the detection of QRS complex and it is found to outperform other methods in terms of detection accuracy and computational cost [97]. Authors in [98] has proposed Neural Network based approach for QRS cancellation which they consider to be more robust to noise and QRS variations. Once the QRS complex is detected it is subtracted from the ECG. Features are extracted from isolated f-wave or residual ECG. Those features can be based on the amplitude, interval between consecutive f-waves or area under the curve of f-wave. They can also be derived from the spectral or time-frequency analysis of atrial activity [99].

Use of atrial activity based features are not as popular as the ventricular response. It is so because the signal to noise ratio of atrial activity is very low, detection of isolated f-wave or t-wave for TQ/QT interval is less efficient and performance of AF detection algorithms based on the atrial activity is also not very well [87], [98]. Besides that, atrial behaviour for AF varies from patient to patient and it overlaps with other arrhythmia e.g., atrial flutter [86].

2) Ventricular response based Features:
QRS complex presents the ventricular response which is dependent on the atrial activity anyways. Fiducial points of QRS complex (e.g onset, offset points and peaks of waves in QRS complex) can help to find useful features important for AF detection and prediction. However, prior to extraction of the fiducial points an estimation of QRS complex in the ECG signal is performed using methods mentioned in the previous section. R-peak is considered the most significant biomarker in ventricular response with the highest amplitude.

The time distance between two consecutive R-peaks is called R-R interval [50]. RR Interval is the most popular feature for the detection of AF and many other types of arrhythmia. Some commonly used RR interval based time, frequency, spectral and distribution domain features are listed in Table VI [19], [84], [100]–[102].

Authors in [100] have used a pool of 122 features, grouped into three main categories, time domain, frequency domain and distribution domain. They developed a ML model with low complexity and computational cost. It is found that though the statistical features like mean, variance etc., are very simple, yet they provide vital information for ECG rhythm classification. Besides time, frequency and statistical features, authors in [102] have also used some other features like Zero Crossing Rate, Energy Entropy, Spectral Centroid and Spread, Spectral Flux and Roll-off, Harmonic-to-Noise ratio, Spectral Peaks, Spectral Power Features, Median Amplitude Spectrum, Covariance Features, Fast Approximate Entropy, Spectral Entropy, Shannon Entropy, Higuchi Fractal Dimensions, Hjorth Parameters, and RMS Level.

Time Domain Features from RR Interval
AVRR: Average of RR intervals
SDRR: Standard deviation of the RR intervals
SDARR: Standard deviation of the average of RR intervals
RMSSD: Root Mean Square Standard Deviation
RR50: Number of pairs of successive RRs that differ by more than 50ms
PRR50: Proportion of RR50 divided by total number of RRs.
TIRR: Triangular interpolation of RR interval histogram
Bradycardia flag
Tachycardia flag
MRR: Median RR interval
5% ranked RR interval
95% ranked RR interval
AF evidence from Lorenz plots
Max deviation
Poincaré mean stepping increment
Poincaré dispersion of points around diagonal line
CV of RR intervals
CV of Δ RR intervals
p value of KS test of RR intervals
p value of KS test of RR intervals
KS test statistic of RR intervals
KS test statistic of RR intervals
Frequency Domain Features for RR Interval
ULF: (0.003Hz)
VLF: (0.0033–0.04Hz)
LF (low-frequency power: 0.04 and 0.15 Hz
HF (high-frequency power): 0.15 and 0.40 Hz
LF/HF: ratio Ratio of low- to high-frequency power
RR intervals PSD
Δ RR intervals PSD
Statstical Features
mean, median, kurtosis, standard deviation, range and skewness
Distribution domain
RR intervals histogram
ΔRR intervals histogram

Table VI
TIME AND FREQUENCY DOMAIN RR FEATURES

Key challenges in using the ventricular response for AF detection are that the ventricular response may or may not change in presence of AF. So, in AF, RR can be either irregular or regular for example when an artificial ventricular pacer is applied RR interval gets regular. Besides that, AF irregular behaviour overlaps with the other arrhythmia like atrial flutter and multifocal atrial tachycardia [86]. To address this challenge atrial activity based features, e.g., for TQ interval, may be extracted as they are extracted for RR interval presented in Table VI.

Besides the popular methods mentioned above, some other advance techniques used for ECG feature extraction include power spectral density(PSD) [96], and Structural Co-Occurrence Matrix (SCM) [103], [104], Burg method, Short Time Fourier Transforms (STFT), Higher Order Statistics (HOS) [103], [104], Continuous Wavelet Transform (CWT). Some non-linear methods of feature extraction include Recurrence Plots, Sample Entropy (SampEn), Fractal Dimension, Approximate Entropy, Largest Lyapunov Exponent, Detrended Fluctuation Analysis, Correlation Dimension Analysis [84]. Methods of finding similarity between two waveform like wavelet coherence (WTC) method is also very effective method used for ECG features extraction [105]. Some techniques applied together improve the performance of the models as compared to when they are applied separately. For example SCM and HOS found to perform better when applied together [104].

From the futuristic perspective, low computational cost and robustness to noise are key requirement for the feature extraction techniques, to support low energy devices for AF auto-diagnosis. Authors in [106] share a smart modified version of Sequency Ordered Complex Hadamard Transform (SCHT) method, called Conjugate Symmetric Sequency Ordered Complex Hadamard Transform (CS-SCHT) for the efficient and effective feature extraction. This method outperforms other popular conventional and advance methods like adamard transform (NCHT), and natural-ordered complex Hadamard transform (NCHT) when applied with different classification algorithms like KNN, SVM and Levenberg Marquardt Neural Network (LMNN). The key advantages highlighted for this method, computationl efficiency, low memory consumption. Moreover, it produces strongly relevant features and avoids features redundancy unlike other feature extraction methods. Authors in [107] has also compared different versions of CS-SCHT namely natural order, Paley order, sequency order, and Cal–Sal order with LMNN classifier. It is found that CS-SCHT with Cal–Sal order outperforms other approaches n terms of sensitivity, specificity, and overall detection accuracy.

D. Feature Selection

From the discussion in preceding section, it is evident that too many features can be extracted from the ECG data for AF auto-detection. Use of all the features is neither practical nor efficient. So it is important to identify key features or re-engineer features to find fewer yet relevant features that encompass the maximum information needed for accurate prediction. To find the combination of features, that generates the optimal performance, different approaches are adopted. Features can be ranked based on correlation with the predicate, for this purpose different corelation methods can be applied. The top-ranked features, then can be used with different machine learning algorithms to develop a model. In this case features with high correlation may be selected but when they are used together in the model they may not yield better accuracy. Another possible approach is to re-engineer features in such a way that maximum information are compressed into fewer features, using feature engineering techniques like PCA. Model based heuristic approach is also an option which tries all the possible combinations of features with some ML algorithm and select the feature combination with best performance. Bottleneck here is that it is computationally very costly. Linear discriminant analysis is another popular approach used for feature selection in ECG based AF detection and prediction [16], [108]. Authors in [16] have used knowledge-based approach for add on information to select four combinations of features from the feature space of five features. Those feature combinations are further evaluated using discriminant function analysis to find the features that best characterize PeAF and PAF classes.

Some popular techniques of feature selection used for different type of medical data are reviewed in [109]. It discusses feature selection techniques like Correlation-Based Feature Selection, Consistency-Based Filter, INTERACT, Information Gain, ReliefF, Recursive Feature Elimination for Support Vector Machines, and Lasso regularization. Besides them some advanced Nature Inspired Optimization Algorithms (NIOA) are also getting popular for the selection of set of features with optimum performance. Authors in [110] group the NIOA in broad four categories namely, Evolutionary Algorithms (EA), Bio-inspired algorithms, algorithms inspired by Physics or Chemistry, and algorithms that do not fall in any of the preceding category but they are inspired some natural phenomenon like social-emotional optimization technique.

Evolutionary algorithms are further grouped into categories like Genetic Algorithm (GA) and Genetic Programming (GP) Evolution Strategies (ES) and Evolutionary Programming (EP), and Differential Evolution (DE). Popular Bio-inspired algorithms include Particle Swarm Optimizer (PSO), Ant Colony Optimization (ACO), Firefly Algorithm (FA), Cuckoo search (CS), Bat Algorithm (BA) etc. Harmony Search (SA), Big Bang Big Crunch (BBBC) and Gravitational Search Algorithm (GSA) are some of the Physics and chemistry inspired algorithms. For more detail about these algorithms please consult [110]. Optimal set of features can be selected using individual NIOA like GA [19], BA [105], PSO [111], or FA [111]. Their are some constraints associated with these algorithms e.g., implementation of GA is complex, defining of parameters is difficult and still it may not reach the optimal solution. Similarly FF is likely get stuck with the local optimum set. To overcome these challenges authors in [111] have proposed an hybrid approach called Fire Fly Particle Swarm Optimizer (FFPSO) for the optimization of ECG features. It is combination of PSO and FF. It takes advantage of the computational speed of PSO and effectiveness of Firefly that ultimately helps to reach global optimal set quickly.

V. Machine Learning for AF Diagnosis

Machine learning, in theory, focuses on mathematical algorithms and statistical models [112], [113] that help machines make decisions in an automated manner based on inference acquired from the data provided. The automatic detection of AF from the clinical ECG data has been researched for decades, and various algorithms have been proposed and implemented. However, the shift towards outpatient monitoring through low-power wearable devices and apps introduces additional challenging requirements. These requirements include real-time capability, the ability to cope with rather noisy and low-quality signals with various artefacts, harsh constraints on computational complexity and power consumption.

Conventionally machine learning is categorized as supervised learning and unsupervised learning. Supervised learning deals with problems where the predicate is known. For example use of machine learning on ECG data to find whether it is normal or it has an episode of AF, here the predicate class (i.e normal vs abnormal) is known. But in the case of unsupervised learning predicate is not known, clustering is a common example of unsupervised machine learning. Clustering can be used to identify important features or significant variations (arrhythmia types) in ECG. Machine learning algorithms, based on the nature of final predicate, are broadly grouped together as regression algorithms or classification algorithms. Regression algorithms can predict continuous values whereas the classification algorithms predict categorical variables.

Most of the algorithms discussed in the literature for the detection and prediction of AF are supervised learning classification algorithms. Use cases of AF related machine learning algorithms can be grouped in the following broad categories based on the implementation scheme or objective of of ML algorithm:

A. *Identification*

Machine learning based solution available in literature majorly perform classification to distinguish the normal heartbeat scenario from the existing AF scenario. As a second step, learning algorithms are also used to further categorize AF (e.g., PAF, PeF etc.). Most commonly used algorithms are Naive Bayes classification, linear discrimination analysis (LDA), K nearest neighbor (kNN), Hidden Markov Model (HMM) [114], artificial neural network (ANN), logistic regression, support vector machine (SVM), decision trees, sequential similarity algorithms, Graph theory algorithms e.g., optimum-path forest [115] and knowledge-based classification (KBC).

Most of the research has been on the topic of differentiating normal or sinus rhythm (SR) ECG from AF ECG segments when the AF is already present. For example, Physionet,

Ref	Method	Targets	Filter	Feature Domain	Features	Algorithm	Window Length	Sens. (%)	Spec. (%)	Acc. (%)	F1
[116]	Cl.	SR, AF	NA	AA & VR	Rhythm irregularity, Absence of P-wave	KB Algorithm	30 s	93	97	NA	NA
[16]	Cl.	PAF, PeAF	High pass (BLW); Low pass (EMG, PLI)	AA	Sub band sample entropies, dominant atrial frequency (DAF) & relative harmonics energy,	Minimum error rate classifier	10 s	92	80	NA	NA
[108]	Cl.	N,S,T, type AF	Band pass	AA & VR	DAF, HR-mean	Discriminant analysis	60 s	NA	NA	90	
[117]	Cl.	SR, PAF, PeAF, Other	High band pass	VR	ΔRR interval distribution difference	Kolmogorov Smirnov (K–S) test	50 HB	96.10	98.10	NA	NA
[100]	Cl.	SR, AF , Other, Noise	Median (BLW)	VR	122 RR time, frequency & distribution features	Linear and Quadratic discriminant analysis & Quadratic neural network (QNN)	60 s	NA	NA	NA	0.75
[20]	Cl.; Pred.	SR, PAF (p)	NA	VR	QRS width, amplitude & area; RR Interval	Autoregressive moving average, Fuzzy logic	30 m	NA	NA	80; 88	
[21]	Cl.; Pred.	NAF,FAF, Onset AF (P)	Morphological (BLW)	AA & VR	P-waves time & amplitude; RR interval time domain	k-NN, SVM;	5 m	96.20	98.10	NA	0.97
[48]	Cl.	SR, PAF	Low pass	AA & VR	Two PSPR features & six descriptive (i.e. mean, median, Kurtosis, Skewness)	PSPR, linear discriminant, logistic regression, decision trees, random forest	60 s	100	73.60	82	NA
[92]	Cl.	SR, AF	Inverse wavelet transform (BLW)	VR	RR interval; Mean stepping increment RR interval	Support vector machine for Cl.	60 s	91.40	92.90		NA
[15]	Pred.	Onset PAF	20% filter (ΔRR), Band pass (BLW), Median (PLI)	VR	ΔRR frequency & time domain features; Morphologic variability of QRS Complex	R peaks detection from ECG based on Pan-Tompkins algorithm	5 m	NA	NA	90	NA
[19]	Cl.	SR, AF , Noise, Other	Band pass (BLW, PLI)	VR	62 RR time & frequency features, linear, and nonlinear features	Random forest classifier	NA	NA	NA	82.70	0.74
[22]	Cl.; Clt.	SR, PAF & Types(S,N)	NA	VR	RR interval	Symbolic Pattern Recognition (SPR) Clustering	60 s	80	80	80	NA
[18]	Cl.	SR, PAF	NA	AA & VR	Raw ECG, Output of CNN	CNN, KNN, SVM, MLP	5 m	NA	NA	91	NA
[118]	Cl.	SR, AF	NA	VR	Symbolic sequence for RR interval	Shannon Entropy	NA	97.37	98.44	97.99	NA
[119]	Cl.; Pred.	SR, PAF (p)	Band pass (BLW, PLI, EMG)	AA	Spectrum & bi-spectrum features, sample entropy and Poincaré plot-extracted features, HRV, QRS Complex	SVM	NA	96.30	93.10	NA	NA
[50]	Cl.	SR, AF	Wavelet transform	AA & VR	1D time domain signal & 2D frequency-time pattern	Convolutional Neural Networks	5 HB	99.41	98.91	NA	99.23
[120]	Cl.	SR, AF	Butterworth band pass	AA	Six P-wave morphological features, Three statistical features (variance, skewness, and kurtosis)	Expectation Maximization (EM) multivariate Gaussian mixture model (GMM)	7 HB	98.09	91.66	NA	NA
[87]	Cl.	SR, AF	Band pass (BLW, PLI)	AA	Peak-to-average power ratio, log-energy entropy	SVM	10 s	97.00	97.10	99.50	NA

Table VII

USE CASES OF ML ALGORITHMS FOR FILTERING, CLASSIFICATION AND PREDICTION OF AF.
CL.: CLASSIFICATION, PRED.: PREDICTION, SR: SINUS RHYTHM, PAF: PAROXYSMAL AF, PEAF, PERSISTENT AF, NAF: NEAR FROM AF EPISODE, FAF: FAR FROM AF EPISODE, N: NON-TERMINATING, S: SUSTAINED, T: TERMINATING.

an online platform governed by Massachusetts Institute of Technology (MIT), has organized well accepted competition on this topic and provides an open access to relevant ECG databases to foster research in this area. They have also organized another competition on another common topic of research where classification is performed to differentiate AF, SR, Noise and the other types of arrhythmia. Other very common classification goals in research have been to differentiate the different types of AF like PAF, Persistent AF(PeAF) and permanent AF. Classification algorithms have also been used to evaluate the chances of other disease in the presence of AF. Example of such cases are presented in Table VII.

B. Prediction

Another important and challenging task for machine learning is to proactively predict PAF or episodes of AF before they occure. Most of the research available related to prediction focuses predicting the next possible episode of AF when AF is already present. Even predicting an onset of AF requires classifying the patterns that occur before PAF episodes and is often a challenging task due to their resemblance with the normal rhythm. Therefore for the prediction again mostly the same classification algorithms are used. But now the objective of these algorithms is different. In identification step they can differentiate between sinus rhythm from AF rhythm for the incident cases of AF (i.e., AF is already developed). Whereas for the prevalent cases (i.e., AF has not happend yet but their can be a risk of AF) classification algorithms can be used to predict if the PAF will happen or not. They can also be used to predict the next episode of AF before time. Though some researchers have worked to evaluate the risk of PAF in non-cardiac and cardiothoracic surgery [23], [24]. Prediction of PAF well before it happens is still an open research problem.

C. Real-time detection

Another challenging area is the real-time detection of AF, since most of the existing work rely on off-line processing of ECG signals. Existing ML models are developed or evaluated using ECG data already saved in databases. ECG data requires a lot of pre-processing, therefore, developing an algorithm that can detect or predict AF from streaming data is a challenging task. In the smart wearable space, there has been an ongoing research on real-time devices capable of detecting heart rhythm anomalies such as finger band developed by Apple [116]. However, efficacy of such devices still needs to be established. Another approach is to use anomaly detection algorithms which detects anomalous heartbeat patterns on real-time for initial alarm and data may be processed further for classification of arrhythmia as AF or any other type.

D. Features extraction based approaches

Machine learning approaches, in the context of application here, can also be grouped into two main categories.

1) With features as input: In this approach features extracted from the raw ECG data are used as input. Classical ML algorithms like SVM, KNN, Decision Trees, Naïve Byes etc., follow this approach. Implementation of such algorithms involve an extra computational step of feature extraction (fast, suitable for edge devices) and the information provided to algorithm are limited by the choice of features. Feature extraction and selection of right combination of feature is a challenging task here. But feature based algorithms are commonly computationally low cost in training and testing except few algorithms like SVM which is computationally expensive in training for the high number of features or KNN which performs in memory storage even for the testing phase. Otherwise feature based algorithm with right features are commonly low cost computationally for training and testing.

2) With raw data as input: The other approach of ML does not require the feature extraction and raw data can be used as it is in this approach. ML algorithms like Neural Networks (NN) their basic and advance versions use the raw data for model learning and diagnosis of AF. Intuitively such algorithms should perform faster than the first type of algorithms as they do not involve feature extraction step but it is not the case. It is because the algorithms crunch whole data to find important information for model learning which involves many nodes and layers of neurons (i.e computational units). It increase the computational cost. But these algorithm are more comprehensive and can extract important information and parameters that may not be exploited with the classical algorithms. The newer advance versions of ANN also known as deep learning are getting very popular for their robust approach and effectiveness. But the bottleneck is the computation cost which makes its implementation difficult on standalone small wearable devices. Cloud based deep learning solutions that sense data from the wearable devices but process and assess it in cloud are getting popular for always on Healthcare facilities [121]. An even more efficient method that can be used in some cases like at medical facilities is edge computing instead of the cloud computing. It can decrease the time of data transfer and computational cost remarkably [122].Besides that some advance optimization techniques like Adaptive Moment Estimation (ADAM) [123] can also increase the efficiency of the deep learning approach.

E. General Discussion

The Table VII presents some use cases of ML algorithms for the detection of the AF. ML algorithms that can be ported to smart wearable devices must not only be highly accurate but must needs to be computationally efficient. For this the algorithms need to be more robust to noise which is highly expected in low-energy wearable monitoring devices. Detection of QRS complex is mandatory preliminary step in all machine learning based solutions for AF diagnosis. But the presence of noise can impact the detection of QRS complex, and subsequently features extraction and ultimately the performance of ML model.

Authors in [124] have measured and compared the impact of noise on nine different algorithms for the detection of QRS. As input, they have used different types of signals like normal, single-channel, lead-II, and synthesized ECG. Five different types of synthesized noises (electromyographic interference, abrupt baseline shift, 60-Hz power line interference, abrupt baseline shift, baseline drift due to respiration, and a composite noise constructed from all of the other noise types) are added to synthesized ECG. They compared the performance of the algorithms based on the percentage of QRS complexes detected, time delay in detection, and the number of false positives. They found that at the highest noise level for all the noise types, no single algorithm could detect all the QRS complexes without any false positive. Different algorithm with specific feature sets performed better than others in the presence of certain noise type. An algorithm that used a digital filter performed better than all other algorithms in the presence of composite noise. Another algorithm with slope and amplitude based features showed the best performance in the presence of EMG noise.

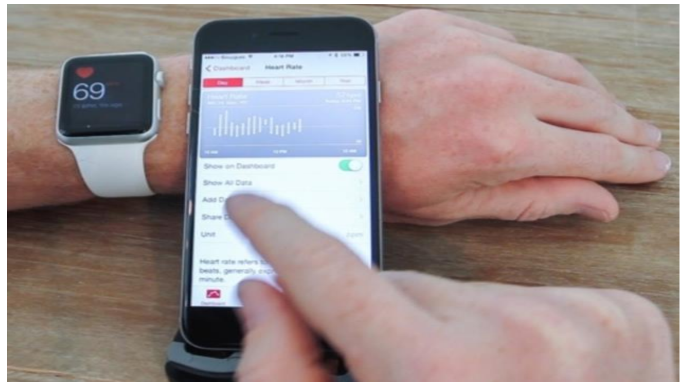


Figure 8. Apple watch and smartphone for cardiac monitoring

VI. Wearable, and Implantable Sensors for AF Detection

The number of connected wearable devices worldwide is expected to jump from an estimate of 325 million in 2016 to over 830 million in 2020 and to be specific, it is forecasted that smart watches would account for about half of all wearable unit sales worldwide in 2018 (Statista-Wearable). These promising predictions, along with the increased demands on user-specific contents and our desire to quantify ourselves, are fuelling the need for high-efficiency and adaptive wearable technologies beyond the existing capabilities. With the vision of 5G wireless communications and its associated novel applications becoming a reality, the proposed research conceives new theories, designs and experimental methodologies for the design and implementation of next generation wearable devices as part of the Internet of things (IoT).

Wearable and implantable technologies are the main driving force behind the modernization in the mobile health era. Smart healthcare is indeed envisioned as a revolutionary approach in various medical applications, in order to monitor, track, and record vital signs of critical patients' health conditions [125]. In addition to the substantial development in the fifth generation (5G) wireless networks, Internet of Things (IoT), and cloud radio access networks (C-RANs), rapid innovations in biomedical sensors, have led this vision to the verge of reality [126]. However, key challenges still remain to be addressed. This section focuses on presenting the recent development in wearable, and implantable technologies dedicated to medical application, such as AF detection.

A. Wearable Wireless Body Area Networks

AF outpatients enduring arrhythmias demanding heart monitoring for a long period of time have generally worn a Holter monitor for 24 hours, an apple watch or a smart phone, as shown in Figure 8 [102].

It captures and transmits ECG signals for post-processing. However, none of these techniques is ideal and an AF can be missed due to several technical reasons [127]. Moreover, various mobile cardiac telemetry systems are being developed in order to accurately detect AF such as Zio Patch, a non-invasive monitoring device. It is a single-use device, water resistant, cutaneous patch that regularly records single lead electrocardiography for up to 14 days. A detailed report of the cardiac electrical activity is finally released to the assigned physician [128]. Furthermore, advancements in sensor technologies have resulted in reducing the device's dimensions and improving power consumption. In fact, antenna design is a crucial player in wearable technology especially those dedicated to AF detection systems since a highly accurate and performant devices are required. Hence, the performance of the wearable antenna should take into account several considerations such as bending scenarios, mismatching, and most importantly ensuring minimum specific absorption rate (SAR) which is a measure of the rate at which the energy is absorbed by the human body tissues when exposed to an electromagnetic field [129]. In addition, the proposed prototype has to be low-profile, robust, and lightweight. In [130], a new wearable ECG device is developed as shown in Figure 9. The wearable ECG attached on the chest is composed of a pair of sensing electrodes, a transceiver and a detection circuit. The ECG data are collected and transmitted to a personal computer in real-time for AF detection. In the same study, results proved that the antenna bending has a significant impact on the gain and the radiation pattern compared to a flat antenna case. The overall gain is decreased by about 2 to 4 dB when the antenna is placed on the wrist and therefore a reduction of the radiation

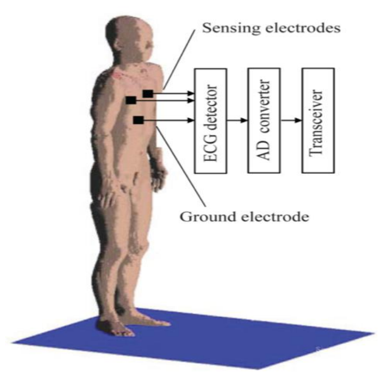


Figure 9. Wearable ECG on human body

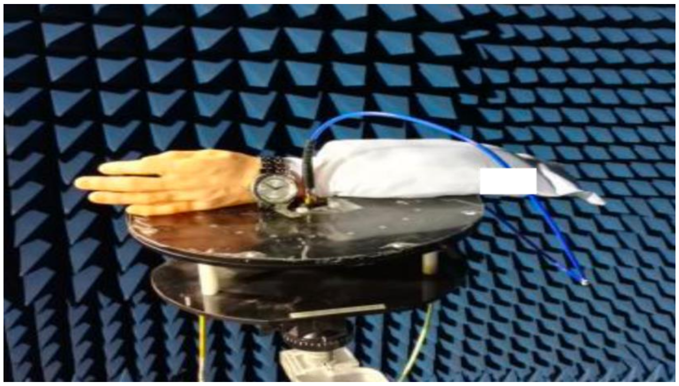


Figure 10. Radiation pattern measurement of the watch strap antenna in the anechoic chamber [131]

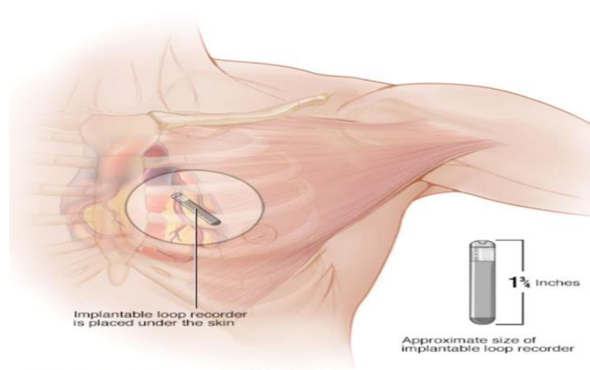


Figure 11. Implantable loop recorder [136]

front-to-back ratio ocuurs. However, the bandwidth remains unchanged across all measured cases. Moreover, a circular slot wearable antenna at 2.4 GHz based on a metal watch strap is proposed in [131]. The radiation patterns are measured in the anechoic chamber using a VNA, as shown in Figure 10 Results confirm that antenna bending on the wrist could significantly limit the antenna performance. Furthermore, it has been shown that the change of the feeding position would cause an alteration of the matching performance and resonance frequency. Another research study in [132] presents, a compact wearable antenna at 2.4 GHz using a novel miniaturized electromagnetic bandgap (EBG) structure. The design demonstrates a low-profile, compact, and robust solution to meet the requirements of medical applications. The EBG structure is used to reduce the back radiation and frequency shifting due to the human body effect [132]. In fact, electromagnetic bandgap (EBG) structures are integrated into the wearable sensor for the purpose of providing an acceptable degree of isolation from the human body and reduce the SAR in order to comply with the health and safety regulations. However, most EBG-based designs are electrically large [133]. Using EBG techniques, the proposed prototype has dimensions of 46 × 46 × 2.4 mm3, an impedance bandwidth of 27%, a gain improvement of 7.8 dBi and a reduction in SAR of more than 95%. Therefore, the antenna is considered as an outstanding candidate for deployment into wearable devices applied for biomedical applications.

B. Implantable Wireless Body Area Networks

Longer-term monitoring is recommended for patients experiencing occasional and unrecognized fainting periods. Therefore, implantable technologies are particularly attractive and have the potential to provide significant solutions [134]. A fully implanted cardiac pacemaker for patients suffering from cardiac anomalies was conceived in the 1960s, which was among the first implantable monitoring cardiac devices [135]. Since then, a lot of improvement is achieved using biocompatible devices and programmable circuitry. Today, Medtronic's insertable cardiac is the worlds smallest and most accurate monitor used for AF detection [136]. It consists of an implantable loop recorder as shown in Figure 11. It is inserted just below the skin of the chest in order to record permanently heart rhythm for up to three years and allowing remote monitoring. In fact, implantable medical devices are of paramount importance for in vivo monitoring, recording, and transmitting data [136]. The most crucial part of each implanted device is the integrated antenna. Because of the small package requirement, small planar antennas are considered to be the best candidates for medical implantable applications because of their thin profile [137]. Different research studies have investigated the integration of patch and planar inverted-F antennas (PIFA) [138], [139]. Planar dipole [140] and monopole [141] antennas have been also suggested. In [142], a loop antenna has been presented. Further, the rise of nanotechnology resulted in additional medical research advancements. Consequently, healthcare is developing quickly towards a future where smart medical implants could permanently monitor body conditions and autonomously respond to any cardiac anomaly such as AF. For more details on implantable or wearable sensing technologies in health care please consult [143]–[147]

VII. Challenges

In AF management, the most important and equally challenging task is its diagnosis. A machine learning based solution for AF diagnosis with high accuracy is desired which also need to be computationally efficient. In this section, we discuss the challenges related to the auto-diagnosis of AF.

A. Early detection or prediction

Detection of the potential risk of AF before it happens is an ideal scenario. Machine learning models in research mostly detect AF when it happens or when its episodes are about to happen. Two major bottlenecks in early auto-detection are the energy limitations of continuous monitoring equipment and lack of efficient ML based models for the prediction of AF. Such models are needed that can not only predict the possibility of PAF with high accuracy well before time but they are also required to be supportive for low energy monitoring devices. Development of monitoring devices with low energy consumption and capacity to harvest its own energy, can help to overcome energy related limitaitons. Data fusion of multi-source or multi-sensors patient specific data and the data from other healthcare records, can be very helpful in the development of efficient ML Models. Big data analytics can help in data fusion for the identification of important disease specific biomarkers from the multi-source data. Then this enriched data can be used in ML algorithms for developing models for the prediction of AF well before time.

B. Unique Biomarker

Biomarkers help to extract features that are used in ML models for AF detection and prediction. Common biomarkers used in research, so far, are based on atrial activity or ventricular response recorded with ECG. One main issue with such biomarkers is that they are common between AF and other types of arrhythmia. Hence, based on these biomarkers other type of arrhythmia may be confused with AF. For example incositent RR intervals can be diagnosed by a ML model as AF but actually it can be caused by Atrial Flutter. There is, therefore, need to identify unique and robust biomarkers exclusive to AF. For the identification of unique biomakers there is also need to look beyond the electrical activity of the heart. It means biological, chemical and physical changes should also be studied which by any mean can indicate occurrence of AF or patterns that can lead to AF. Moreover, instead of relying on single biomarker, combination of multiple biomarkers should also be explored with the help of ML models for AF auto detection and prediction. For example, some information about contributing factors highlighted in Figure 2 can also be used in combination to ECG based biomarkers for developing models, as they have been found correlated to AF [8]. Data fusion can also play important role in finding unique biomarkers.

C. Alternative Sensing Technologies

As in research and practice ECG is commonly used as the main tool for the diagnosis of AF. Similarly, therefore, main focus for data collection has been on ECG technologies e.g., patches, implantable, and ambulatory devices are getting popular. Admittedly, today ECG is the most reliable technique for the identification of AF among the available methods. But, Where there is a need to develop and adopt more sophisticated ECG techniques, there, exploration of new horizons for sensing technologies should also be considered. Technologies like IEGM [148], magnetic resonance angiography (MRA) [149], radio frequency and microwave sensing systems [150]–[157], Photopletysmography [158], echocardiography, augmented reality [159], accelerometry etc., should also be explored as they have been used in some healthcare issues of the same nature.

D. Low-cost Pre-processing

In the context of smart wearable devices, conventional preprocessing methods are not ideal since most of the noise removal techniques are not only computationally demanding but they are also not well suited for real-time processing. Advance methods are required to fulfill the stringent requirement of low-power devices and also able to meet the desired performance bounds. Assurance of QoS during data processing is also very critical. Artificial intelligence can play important role in the QoS optimization [122]. Algorithms like QoS computation algorithm (AQCA) [160] for the computation of QoS can help in monitoring performance indicators during data processing. Besides that, to meet the energy requirements in implantable or wearbale low energy devices, data processing steps should have very low computational cost. Moreover, adaptive energy-efficient transmission power control algorithms need to be developed like the ones proposed in [161], [162]. It should adapt the transmission according to the body postures and movement to conserve enrgy and also ensure quality of data.

E. Standardization

Another key requirement for the commercial viability of a machine learning solution for AF detection and prediction is its standardization. AF conditions may vary from patient to patient. So caution should be paid in the selection of biomarkers, collection of data, extraction of features and implementation of machine learning algorithm such that they perform equally good on the diverse range of the population. Development of such a solution which is highly accurate, computationally low-cost and works for the diverse population is a challenging task. Standardization is not only needed in the selection of biomarkers but also for the processing techniques and ML models important slso for the knowedge transfer.

F. Wearable Design

Although the substantial advancement are made in sensing technology, but still, implant processes can lead to infections or even implant failures, which makes patients cautious and hesitant to adopt them. Furthermore, several patients have expressed allergies and reactions to the materials containing the implant devices. The quality and robustness of wearable also demand further extensive enhancement. Wearable devices should be efficient in operating under different circumstances, such as in wet or humid environments and hot temperatures. This would allow adequate and continuous monitoring without losing performance during activities such as showering, swimming, or playing tennis. In addition, wearable systems fabricated from smart textiles and stretchable electronics should be possibly washable and dryable, and the electrodes should be strong and not break in case of bending or folding.

G. Privacy

Another very important and critical step in the development process of an auto-diagnosis solution for AF is to ensure the privacy of the subject under observation. It becomes even more critical when the data is transported over the Internet and saved in a shared database. Where the shared database helps to have access to added information valuable in developing more intelligent solutions there it becomes important to secure the personal information of each participant. Modern hacking techniques and big data analytic have many pros. But at the same time personal data or the identity of the participant can be revealed by the exploitation of these techniques. Therefore there is a need for more advance data encryption techniques like the one mentioned in [96] for the secure data transfer and storage. In addition to that anonymity schemes also need to be looked on cautiously. But a bottleneck connected to encryption is that even the simple arithmetic operations do not produce much accurate results for encrypted data. The algorithms that can pull off with encrypted data for higher accuracy can be computationally costly and require some memory as well. So advance encryption techniques like Homomorphic Encryption (HE) process [96] needed which not only secure data but also make data processing convenient.

VIII. Conclusion

Development of low-cost high accuracy machine learning based non-invasive solutions, for the auto-detection and prediction of AF and its types, has tremendous demand in smart health-care, particularly in AF management. In this paper, we review the research work about the detection of AF, we identify challenges associated with the processing of ECG data such as the noise removal techniques, the efficacy of various machine learning methods in conjunction with feature extraction techniques. Moreover, we provide a comparative study of various state-of-the-art solutions and highlighted the gaps that are needed to be addressed in order to envision a smart wearable solution for AF detection.

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References

[1] P. Kirchhof, S. Benussi, D. Kotecha, A. Ahlsson, D. Atar, B. Casadei, M. Castella, H.-C. Diener, H. Heidbuchel, J. Hendriks *et al.*, "2016 esc guidelines for the management of atrial fibrillation developed in collaboration with eacts," *European journal of cardio-thoracic surgery*, vol. 50, no. 5, pp. e1–e88, 2016.

[2] S. S. Chugh, R. Havmoeller, K. Narayanan, D. Singh, M. Rienstra, E. J. Benjamin, R. F. Gillum, Y.-H. Kim, J. H. McAnulty Jr, Z.-J. Zheng *et al.*, "Worldwide epidemiology of atrial fibrillation: a global burden of disease 2010 study," *Circulation*, vol. 129, no. 8, pp. 837–847, 2014.

[3] C. A. Morillo, A. Banerjee, P. Perel, D. Wood, and X. Jouven, "Atrial fibrillation: the current epidemic," *Journal of geriatric cardiology: JGC*, vol. 14, no. 3, p. 195, 2017.

[4] S. Nattel, "New ideas about atrial fibrillation 50 years on," *Nature*, vol. 415, no. 6868, p. 219, 2002.

[5] J. Oldgren, J. S. Healey, M. Ezekowitz, P. Commerford, A. Avezum, P. Pais, J. Zhu, P. Jansky, A. Sigamani, C. A. Morillo *et al.*, "Variations in cause and management of atrial fibrillation in a prospective registry of 15 400 emergency department patients in 46 countries: the re-ly atrial fibrillation registry," *Circulation*, vol. 129, no. 15, pp. 1568–1576, 2014.

[6] M. Alasady, N. J. Shipp, A. G. Brooks, H. S. Lim, D. H. Lau, D. Barlow, P. Kuklik, M. I. Worthley, K. C. Roberts-Thomson, D. A. Saint *et al.*, "Myocardial infarction and atrial fibrillation: importance of atrial ischemia," *Circulation: Arrhythmia and Electrophysiology*, vol. 6, no. 4, pp. 738–745, 2013.

[7] R. K. Sandhu, D. Conen, U. B. Tedrow, K. C. Fitzgerald, A. D. Pradhan, P. M. Ridker, R. J. Glynn, and C. M. Albert, "Predisposing factors associated with development of persistent compared with paroxysmal atrial fibrillation," *Journal of the American Heart Association*, vol. 3, no. 3, p. e000916, 2014.

[8] A. H. Hobbelt, J. E. Siland, B. Geelhoed, P. Van Der Harst, H. L. Hillege, I. C. Van Gelder, and M. Rienstra, "Clinical, biomarker, and genetic predictors of specific types of atrial fibrillation in a community-based cohort: data of the prevend study," *EP Europace*, vol. 19, no. 2, pp. 226–232, 2016.

[9] A. Brandes, M. D. Smit, B. O. Nguyen, M. Rienstra, and I. C. Van Gelder, "Risk factor management in atrial fibrillation," *Arrhythmia & electrophysiology review*, vol. 7, no. 2, p. 118, 2018.

[10] S. A. Lubitz, C. Moser, L. Sullivan, M. Rienstra, J. D. Fontes, M. L. Villalon, M. Pai, D. D. McManus, R. B. Schnabel, J. W. Magnani *et al.*, "Atrial fibrillation patterns and risks of subsequent stroke, heart failure, or death in the community," *Journal of the American Heart Association*, vol. 2, no. 5, p. e000126, 2013.

[11] X. Yang, D. Fan, A. Ren, N. Zhao, and M. Alam, "5g-based user-centric sensing at c-band," *IEEE Transactions on Industrial Informatics*, vol. 15, no. 5, pp. 3040–3047, 2019.

[12] S. A. Lubitz, E. J. Benjamin, J. N. Ruskin, V. Fuster, and P. T. Ellinor, "Challenges in the classification of atrial fibrillation," *Nature Reviews Cardiology*, vol. 7, no. 8, p. 451, 2010.

[13] V. Fuster, L. E. Rydén, D. S. Cannom, H. J. Crijns, A. B. Curtis, K. A. Ellenbogen, J. L. Halperin, J.-Y. Le Heuzey, G. N. Kay, J. E. Lowe *et al.*, "Acc/aha/esc 2006 guidelines for the management of patients with atrial fibrillation–excutive summary," *Revista portuguesa de cardiologia: orgao oficial da Sociedade Portuguesa de Cardiologia= Portuguese journal of cardiology: an official journal of the Portuguese Society of Cardiology*, vol. 26, no. 4, p. 383, 2007.

[14] M. Muzammal, R. Talat, A. H. Sodhro, and S. Pirbhulal, "A multi-sensor data fusion enabled ensemble approach for medical data from body sensor networks," *Information Fusion*, vol. 53, pp. 155–164, 2020.

[15] H. Costin, C. Rotariu, and A. Păsărică, "Atrial fibrillation onset prediction using variability of ecg signals," in *2013 8th International symposium on advanced topics in electrical engineering (ATEE)*. IEEE, 2013, pp. 1–4.

[16] R. Alcaraz, F. Sandberg, L. Sörnmo, and J. J. Rieta, "Classification of paroxysmal and persistent atrial fibrillation in ambulatory ecg recordings," *IEEE Transactions on Biomedical Engineering*, vol. 58, no. 5, pp. 1441–1449, 2011.

[17] M. Duarte, A. Restrepo, C. Tobon, K. Cardona, and J. Saiz, "Chloroquine effect on human atrial action potential under normal conditions and during paroxysmal and chronic atrial fibrillation. a simulation study," in *2013 Pan American Health Care Exchanges (PAHCE)*. IEEE, 2013, pp. 1–5.

[18] B. Pourbabaee, M. J. Roshtkhari, and K. Khorasani, "Deep convolutional neural networks and learning ecg features for screening paroxysmal atrial fibrillation patients," *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, no. 99, pp. 1–10, 2017.

[19] R. Mahajan, R. Kamaleswaran, J. A. Howe, and O. Akbilgic, "Cardiac rhythm classification from a short single lead ecg recording via random forest," in *2017 Computing in Cardiology (CinC)*. IEEE, 2017, pp. 1–4.

[20] W. Zong, R. Mukkamala, and R. Mark, "A methodology for predicting paroxysmal atrial fibrillation based on ecg arrhythmia feature analysis," in *Computers in Cardiology 2001. Vol. 28 (Cat. No. 01CH37287)*. IEEE, 2001, pp. 125–128.

[21] E. De Giovanni, A. Aminifar, A. Luca, S. Yazdani, J.-M. Vesin, and D. Atienza, "A patient-specific methodology for prediction of paroxysmal atrial fibrillation onset," in *2017 Computing in Cardiology (CinC)*. IEEE, 2017, pp. 1–4.

[22] O. Akbilgic, J. A. Howe, and R. L. Davis, "Categorizing atrial fibrillation via symbolic pattern recognition," *Journal of Medical Statistics and Informatics*, vol. 4, no. 1, p. 8, 2016.

[23] K. K. Joshi, M. Tiru, T. Chin, M. T. Fox, and M. S. Stefan, "Postoperative atrial fibrillation in patients undergoing non-cardiac non-thoracic surgery: a practical approach for the hospitalist," *Hospital Practice*, vol. 43, no. 4, pp. 235–244, 2015.

[24] D. Dobrev, M. Aguilar, J. Heijman, J.-B. Guichard, and S. Nattel, "Postoperative atrial fibrillation: mechanisms, manifestations and management," *Nature Reviews Cardiology*, p. 1, 2019.

[25] C. G. C. U. National, "Atrial fibrillation: the management of atrial fibrillation," 2014.

[26] M. Sampson, "Ambulatory electrocardiography: indications and devices," *British Journal of Cardiac Nursing*, vol. 14, no. 3, pp. 114–121, 2019.

[27] A. J. Camm, G. Corbucci, and L. Padeletti, "Usefulness of continuous electrocardiographic monitoring for atrial fibrillation," *The American journal of cardiology*, vol. 110, no. 2, pp. 270–276, 2012.

[28] N. J. Welton, A. McAleenan, H. H. Thom, P. Davies, W. Hollingworth, J. P. Higgins, G. Okoli, J. A. Sterne, G. Feder, D. Eaton *et al.*, "Screening strategies for atrial fibrillation: a systematic review and cost-effectiveness analysis," *Health Technology Assessment*, vol. 21, no. 29, 2017.

[29] M. A. Awal, S. S. Mostafa, and M. Ahmad, "Performance analysis of savitzky-golay smoothing filter using ecg signal," *International Journal of Computer and Information Technology*, vol. 1, no. 02, 2011.

[30] M. Zubaid, W. A. Rashed, A. A. Alsheikh-Ali, W. AlMahmeed, A. Shehab, K. Sulaiman, I. Al-Zakwani, A. AlQudaimi, N. Asaad, and H. Amin, "Gulf survey of atrial fibrillation events (gulf safe) design and baseline characteristics of patients with atrial fibrillation in the arab middle east," *Circulation: Cardiovascular Quality and Outcomes*, vol. 4, no. 4, pp. 477–482, 2011.

[31] G. Moody, "A new method for detecting atrial fibrillation using rr intervals," *Computers in Cardiology*, pp. 227–230, 1983.

[32] G. Moody, A. Goldberger, S. McClennen, and S. Swiryn, "Predicting the onset of paroxysmal atrial fibrillation: The computers in cardiology challenge 2001," in *Computers in Cardiology 2001. Vol. 28 (Cat. No. 01CH37287)*. IEEE, 2001, pp. 113–116.

[33] A. L. Goldberger, L. A. Amaral, L. Glass, J. M. Hausdorff, P. C. Ivanov, R. G. Mark, J. E. Mietus, G. B. Moody, C.-K. Peng, and H. E. Stanley, "Physiobank, physiotoolkit, and physionet: components of a new research resource for complex physiologic signals," *Circulation*, vol. 101, no. 23, pp. e215–e220, 2000.

[34] G. Moody, "Spontaneous termination of atrial fibrillation: a challenge from physionet and computers in cardiology 2004," in *Computers in Cardiology, 2004*. IEEE, 2004, pp. 101–104.

[35] S. Petrutiu, A. V. Sahakian, and S. Swiryn, "Abrupt changes in fibrillatory wave characteristics at the termination of paroxysmal atrial fibrillation in humans," *Europace*, vol. 9, no. 7, pp. 466–470, 2007.

[36] G. D. Clifford, C. Liu, B. Moody, H. L. Li-wei, I. Silva, Q. Li, A. Johnson, and R. G. Mark, "Af classification from a short single lead ecg recording: the physionet/computing in cardiology challenge 2017," in *2017 Computing in Cardiology (CinC)*. IEEE, 2017, pp. 1–4.

[37] J.-Y. Le Heuzey, G. Breithardt, J. Camm, H. Crijns, P. Dorian, P. R. Kowey, I. Merioua, E. N. Prystowsky, P. J. Schwartz, C. Torp-Pedersen *et al.*, "The recordaf study: design, baseline data, and profile of patients according to chosen treatment strategy for atrial fibrillation," *The American journal of cardiology*, vol. 105, no. 5, pp. 687–693, 2010.

[38] G. Schreier, P. Kastner, and W. Marko, "An automatic ecg processing algorithm to identify patients prone to paroxysmal atrial fibrillation," in *Computers in Cardiology 2001. Vol. 28 (Cat. No. 01CH37287)*. IEEE, 2001, pp. 133–135.

[39] C. Maier, M. Bauch, and H. Dickhaus, "Screening and prediction of paroxysmal atrial fibrillation by analysis of heart rate variability parameters," in *Computers in Cardiology 2001. Vol. 28 (Cat. No. 01CH37287)*. IEEE, 2001, pp. 129–132.

[40] K. Lynn and H. Chiang, "A two-stage solution algorithm for paroxysmal atrial fibrillation prediction," in *Computers in Cardiology 2001. Vol. 28 (Cat. No. 01CH37287)*. IEEE, 2001, pp. 405–407.

[41] A. Yang and H. Yin, "Prediction of paroxysmal atrial fibrillation by footprint analysis," in *Computers in Cardiology 2001. Vol. 28 (Cat. No. 01CH37287)*. IEEE, 2001, pp. 401–404.

[42] P. De Chazal and C. Heneghan, "Automated assessment of atrial fibrillation," in *Computers in Cardiology 2001. Vol. 28 (Cat. No. 01CH37287)*. IEEE, 2001, pp. 117–120.

[43] A. Rizwan, A. Zoha, R. Zhang, W. Ahmad, K. Arshad, N. A. Ali, A. Alomainy, M. A. Imran, and Q. H. Abbasi, "A review on the role of nano-communication in future healthcare systems: A big data analytics perspective," *IEEE Access*, vol. 6, pp. 41 903–41 920, 2018.

[44] J. P. Mueller and L. Massaron, *Machine learning for dummies*. John Wiley & Sons, 2016.

[45] I. H. Witten, E. Frank, M. A. Hall, and C. J. Pal, *Data Mining: Practical machine learning tools and techniques*. Morgan Kaufmann, 2016.

[46] T. T. Nguyen and Z. M. Yuldashev, "Methods and algorithms for atrial fibrillation episodes detection in condition of alternant premature contractions and atrial flutter," in *2018 Third International Conference on Human Factors in Complex Technical Systems and Environments (ERGO) s and Environments (ERGO)*. IEEE, 2018, pp. 173–176.

[47] A. C. V. Maggio, M. P. Bonomini, E. L. Leber, and P. D. Arini, "Quantification of ventricular repolarization dispersion using digital processing of the surface ecg," in *Advances in Electrocardiograms-Methods and Analysis*. IntechOpen, 2012.

[48] J. R. Sutton, R. Mahajan, O. Akbilgic, and R. Kamaleswaran, "Physonline: An open source machine learning pipeline for real-time analysis of streaming physiological waveform," *IEEE journal of biomedical and health informatics*, vol. 23, no. 1, pp. 59–65, 2019.

[49] S.-C. Pei and C.-C. Tseng, "Elimination of ac interference in electrocardiogram using iir notch filter with transient suppression," *IEEE transactions on biomedical engineering*, vol. 42, no. 11, pp. 1128–1132, 1995.

[50] R. He, K. Wang, N. Zhao, Y. Liu, Y. Yuan, Q. Li, and H. Zhang, "Automatic detection of atrial fibrillation based on continuous wavelet transform and 2d convolutional neural networks," *Frontiers in physiology*, vol. 9, p. 1206, 2018.

[51] H. Wan, R. Fu, and L. Shi, "The elimination of 50 hz power line interference from ecg using a variable step size lms adaptive filtering algorithm," *Life Science Journal*, vol. 3, no. 4, pp. 90–93, 2006.

[52] J. Joy and P. Manimegalai, "Wavelet based emg artifact removal from ecg signal," *Journal of Eng. Comp. & Appl. Sci*, vol. 2, pp. 55–58, 2013.

[53] M. Marouf, L. Saranovac, and G. Vukomanovic, "Algorithm for emg noise level approximation in ecg signals," *Biomedical Signal Processing and Control*, vol. 34, pp. 158–165, 2017.

[54] W. Jenkal, R. Latif, A. Toumanari, A. Dliou, O. El B'charri, and F. M. Maoulainine, "An efficient algorithm of ecg signal denoising using the adaptive dual threshold filter and the discrete wavelet transform," *Biocybernetics and Biomedical Engineering*, vol. 36, no. 3, pp. 499–508, 2016.

[55] I. I. Christov and I. K. Daskalov, "Filtering of electromyogram artifacts from the electrocardiogram," *Medical engineering & physics*, vol. 21, no. 10, pp. 731–736, 1999.

[56] A. N. S. Belgurzi and I. Elshafiey, "A power line interference canceler using wavelet transform and adaptive filter for ecg signal," in *2017 International Conference on Computer and Applications (ICCA)*. IEEE, 2017, pp. 206–210.

[57] C. Levkov, G. Mihov, R. Ivanov, I. Daskalov, I. Christov, and I. Dotsinsky, "Removal of power-line interference from the ecg: a review of the subtraction procedure," *BioMedical Engineering OnLine*, vol. 4, no. 1, p. 50, 2005.

[58] C. Mbachu and K. Offor, "Reduction of power line noise in ecg signal using fir digital filter implemented with hamming window," *International Journal of Science, Environment and Technology*, vol. 2, no. 6, pp. 1380–1387, 2013.

[59] D. Dobrev, T. Neycheva, V. Krasteva, and I. Iliev, "High-q comb fir filter for mains interference elimination," *Annual Journal of Electronics*, vol. 4, no. 2, pp. 126–129, 2010.

[60] S. Kocoń and J. Piskorowski, "Digital finite impulse response notch filter with non-zero initial conditions, based on an infinite impulse response prototype filter," *Metrology and Measurement Systems*, vol. 19, no. 4, pp. 767–776, 2012.

[61] G. J. Warmerdam, R. Vullings, L. Schmitt, J. O. Van Laar, and J. W. Bergmans, "A fixed-lag kalman smoother to filter power line interference in electrocardiogram recordings," *ieee Transactions on Biomedical engineering*, vol. 64, no. 8, pp. 1852–1861, 2016.

[62] J. J. Rieta, F. Castells, C. Sánchez, V. Zarzoso, and J. Millet, "Atrial activity extraction for atrial fibrillation analysis using blind source separation," *IEEE Transactions on Biomedical Engineering*, vol. 51, no. 7, pp. 1176–1186, 2004.

[63] A. K. Ziarani and A. Konrad, "A nonlinear adaptive method of elimination of power line interference in ecg signals," *IEEE transactions on biomedical engineering*, vol. 49, no. 6, pp. 540–547, 2002.

[64] Y.-D. Lin and Y. H. Hu, "Power-line interference detection and suppression in ecg signal processing," *IEEE Transactions on Biomedical Engineering*, vol. 55, no. 1, pp. 354–357, 2007.

[65] D. D. Taralunga, I. Gussi, and R. Strungaru, "Fetal ecg enhancement: adaptive power line interference cancellation based on hilbert huang transform," *Biomedical Signal Processing and Control*, vol. 19, pp. 77–84, 2015.

[66] J. A. L. Marques, P. C. Cortez, J. P. d. V. Madeiro, S. J. Fong, F. S. Schlindwein, and V. H. C. de Albuquerque, "Automatic cardiotocography diagnostic system based on hilbert transform and adaptive threshold technique," *IEEE Access*, 2019.

[67] P. S. Hamilton, "A comparison of adaptive and nonadaptive filters for reduction of power line interference in the ecg," *IEEE Transactions on Biomedical Engineering*, vol. 43, no. 1, pp. 105–109, 1996.

[68] G. Mihov, "Subtraction procedure for power-line interference removal from ecg signals with high sampling rate." *International Journal Bioautomation*, vol. 22, no. 2, 2018.

[69] G. Mihov, I. Dotsinsky, and T. Georgieva, "Subtraction procedure for powerline interference removing from ecg: improvement for non-multiple sampling," *Journal of medical engineering & technology*, vol. 29, no. 5, pp. 238–243, 2005.

[70] M. Tomasini, S. Benatti, B. Milosevic, E. Farella, and L. Benini, "Power line interference removal for high-quality continuous biosignal

monitoring with low-power wearable devices," *IEEE Sensors Journal*, vol. 16, no. 10, pp. 3887–3895, 2016.

[71] R. Von Borries, J. Pierluissi, and H. Nazeran, "Wavelet transform-based ecg baseline drift removal for body surface potential mapping," in *2005 IEEE Engineering in Medicine and Biology 27th Annual Conference*. IEEE, 2006, pp. 3891–3894.

[72] O. Sayadi and M. B. Shamsollahi, "Multiadaptive bionic wavelet transform: Application to ecg denoising and baseline wandering reduction," *EURASIP Journal on Advances in Signal Processing*, vol. 2007, no. 1, p. 041274, 2007.

[73] B. M. M. A. Tinati *et al.*, "Ecg baseline wander elimination using wavelet packets," *World academy of science, Engineering and technology*, vol. 3, no. 2005, pp. 14–16, 2005.

[74] Y. Luo, R. H. Hargraves, A. Belle, O. Bai, X. Qi, K. R. Ward, M. P. Pfaffenberger, and K. Najarian, "A hierarchical method for removal of baseline drift from biomedical signals: application in ecg analysis," *The Scientific World Journal*, vol. 2013, 2013.

[75] F. P. Romero, L. V. Romaguera, C. R. Vázquez-Seisdedos, M. G. F. Costa, J. E. Neto *et al.*, "Baseline wander removal methods for ecg signals: A comparative study," *arXiv preprint arXiv:1807.11359*, 2018.

[76] K. Park, K. Lee, and H. Yoon, "Application of a wavelet adaptive filter to minimise distortion of the st-segment," *Medical and Biological Engineering and Computing*, vol. 36, no. 5, pp. 581–586, 1998.

[77] S. Poungponsri and X.-H. Yu, "An adaptive filtering approach for electrocardiogram (ecg) signal noise reduction using neural networks," *Neurocomputing*, vol. 117, pp. 206–213, 2013.

[78] W. Hao, Y. Chen, and Y. Xin, "Ecg baseline wander correction by mean-median filter and discrete wavelet transform," in *2011 Annual International Conference of the IEEE Engineering in Medicine and Biology Society*. IEEE, 2011, pp. 2712–2715.

[79] W. T O'Neal, S. Venkatesh, S. T. Broughton, W. F. Griffin, and E. Z. Soliman, "Biomarkers and the prediction of atrial fibrillation: state of the art," *Vascular health and risk management*, vol. 12, p. 297, 2016.

[80] X. Du, N. Rao, M. Qian, D. Liu, J. Li, W. Feng, L. Yin, and X. Chen, "A novel method for real-time atrial fibrillation detection in electrocardiograms using multiple parameters," *Annals of Noninvasive Electrocardiology*, vol. 19, no. 3, pp. 217–225, 2014.

[81] H. Dang, M. Sun, G. Zhang, X. Qi, X. Zhou, and Q. Chang, "A novel deep arrhythmia-diagnosis network for atrial fibrillation classification using electrocardiogram signals," *IEEE Access*, 2019.

[82] F. Plesinger, P. Andrla, I. Viscor, J. Halamek, V. Bulkova, and P. Jurak, "Shape analysis of consecutive beats may help in the automated detection of atrial fibrillation," in *2018 Computing in Cardiology Conference (CinC)*, vol. 45. IEEE, 2018, pp. 1–4.

[83] E. A. Ashley and J. Niebauer, *Cardiology explained*. Remedica, 2004.

[84] H. W. Lim, Y. W. Hau, C. W. Lim, and M. A. Othman, "Artificial intelligence classification methods of atrial fibrillation with implementation technology," *Computer Assisted Surgery*, vol. 21, no. sup1, pp. 154–161, 2016.

[85] P. Sharma, T. W. Barrett, J. Ng, C. Knoten, A. J. Ferreira, and J. J. Goldberger, "Surface ecg f wave analysis at initial onset of paroxysmal and persistent atrial fibrillation," *Journal of cardiovascular electrophysiology*, vol. 28, no. 5, pp. 498–503, 2017.

[86] S. Petrutiu, J. Ng, G. M. Nijm, H. Al-Angari, S. Swiryn, and A. V. Sahakian, "Atrial fibrillation and waveform characterization," *IEEE engineering in medicine and biology magazine*, vol. 25, no. 6, pp. 24–30, 2006.

[87] S. Asgari, A. Mehrnia, and M. Moussavi, "Automatic detection of atrial fibrillation using stationary wavelet transform and support vector machine," *Computers in biology and medicine*, vol. 60, pp. 132–142, 2015.

[88] J. Park, C. Lee, E. Leshem, I. Blau, S. Kim, J. M. Lee, J.-A. Hwang, B.-i. Choi, M.-H. Lee, and H. J. Hwang, "Early differentiation of long-standing persistent atrial fibrillation using the characteristics of fibrillatory waves in surface ecg multi-leads," *Scientific reports*, vol. 9, no. 1, p. 2746, 2019.

[89] A. Petrenas, V. Marozas, L. Sornmo, and A. Lukosevicius, "An echo state neural network for qrst cancellation during atrial fibrillation," *IEEE Transactions on Biomedical Engineering*, vol. 59, no. 10, pp. 2950–2957, 2012.

[90] P. Guzik, J. Piskorski, T. Krauze, A. Wykretowicz, and H. Wysocki, "Heart rate asymmetry by poincaré plots of rr intervals," *Biomedizinische Technik*, vol. 51, no. 4, pp. 272–275, 2006.

[91] Ö. Yakut and E. D. Bolat, "An improved qrs complex detection method having low computational load," *Biomedical Signal Processing and Control*, vol. 42, pp. 230–241, 2018.

[92] J. Park, S. Lee, and M. Jeon, "Atrial fibrillation detection by heart rate variability in poincare plot," *Biomedical engineering online*, vol. 8, no. 1, p. 38, 2009.

[93] C.-C. Lin, H.-Y. Chang, Y.-H. Huang, and C.-Y. Yeh, "A novel wavelet-based algorithm for detection of qrs complex," *Applied Sciences*, vol. 9, no. 10, p. 2142, 2019.

[94] J. S. Lee, S. J. Lee, M. Choi, M. Seo, and S. W. Kim, "Qrs detection method based on fully convolutional networks for capacitive electrocardiogram," *Expert Systems with Applications*, vol. 134, pp. 66–78, 2019.

[95] J. Pan and W. J. Tompkins, "A real-time qrs detection algorithm," *IEEE Trans. Biomed. Eng*, vol. 32, no. 3, pp. 230–236, 1985.

[96] A. F. Hussein, M. Burbano-Fernandez, G. Ramírez-González, E. Abdulhay, V. H. C. De Albuquerque *et al.*, "An automated remote cloud-based heart rate variability monitoring system," *IEEE Access*, vol. 6, pp. 77 055–77 064, 2018.

[97] S. Francesca, C. G. Carlo, F. R. Di Nunzio Luca, and R. Marco, "Comparison of low-complexity algorithms for real-time qrs detection using standard ecg database," *International Journal on Advanced Science, Engineering and Information Technology*, vol. 8, no. 2, pp. 307–314, 2018.

[98] C. Vásquez, A. Hernandez, F. Mora, G. Carrault, and G. Passariello, "Atrial activity enhancement by wiener filtering using an artificial neural network," *IEEE Transactions on Biomedical Engineering*, vol. 48, no. 8, pp. 940–944, 2001.

[99] A. Bollmann, D. Husser, L. Mainardi, F. Lombardi, P. Langley, A. Murray, J. J. Rieta, J. Millet, S. B. Olsson, M. Stridh *et al.*, "Analysis of surface electrocardiograms in atrial fibrillation: techniques, research, and clinical applications," *Europace*, vol. 8, no. 11, pp. 911–926, 2006.

[100] N. Sadr, M. Jayawardhana, T. T. Pham, R. Tang, A. T. Balaei, and P. de Chazal, "A low-complexity algorithm for detection of atrial fibrillation using an ecg," *Physiological measurement*, vol. 39, no. 6, p. 064003, 2018.

[101] F. Shaffer and J. Ginsberg, "An overview of heart rate variability metrics and norms," *Frontiers in public health*, vol. 5, p. 258, 2017.

[102] M. J. Tadi, S. Mehrang, M. Kaisti, O. Lahdenoja, T. Hurnanen, J. Jaakkola, S. Jaakkola, T. Vasankari, T. Kiviniemi, J. Airaksinen *et al.*, "Comprehensive analysis of cardiogenic vibrations for automated detection of atrial fibrillation using smartphone mechanocardiograms," *IEEE Sensors Journal*, vol. 19, no. 6, pp. 2230–2242, 2018.

[103] L. B. Marinho, N. de MM Nascimento, J. W. M. Souza, M. V. Gurgel, P. P. Rebouças Filho, and V. H. C. de Albuquerque, "A novel electrocardiogram feature extraction approach for cardiac arrhythmia classification," *Future Generation Computer Systems*, vol. 97, pp. 564–577, 2019.

[104] N. M. M. Nascimento, L. B. Marinho, S. A. Peixoto, J. P. do Vale Madeiro, V. H. C. de Albuquerque, and P. P. Rebouças Filho, "Heart arrhythmia classification based on statistical moments and structural co-occurrence," *Circuits, Systems, and Signal Processing*, pp. 1–20, 2019.

[105] P. Kora and K. S. R. Krishna, "Ecg based heart arrhythmia detection using wavelet coherence and bat algorithm," *Sensing and Imaging*, vol. 17, no. 1, p. 12, 2016.

[106] P. Kora, A. Annavarapu, P. Yadlapalli, K. S. R. Krishna, and V. Somalaraju, "Ecg based atrial fibrillation detection using sequency ordered complex hadamard transform and hybrid firefly algorithm," *Engineering Science and Technology, an International Journal*, vol. 20, no. 3, pp. 1084–1091, 2017.

[107] A. Annavarapu and P. Kora, "Ecg-based atrial fibrillation detection using different orderings of conjugate symmetric–complex hadamard transform," *International Journal of the Cardiovascular Academy*, vol. 2, no. 3, pp. 151–154, 2016.

[108] F. Chiarugi, M. Varanini, F. Cantini, F. Conforti, and G. Vrouchos, "Noninvasive ecg as a tool for predicting termination of paroxysmal atrial fibrillation," *IEEE Transactions on Biomedical Engineering*, vol. 54, no. 8, pp. 1399–1406, 2007.

[109] B. Remeseiro and V. Bolon-Canedo, "A review of feature selection methods in medical applications," *Computers in biology and medicine*, p. 103375, 2019.

[110] K. G. Dhal, S. Ray, A. Das, and S. Das, "A survey on nature-inspired optimization algorithms and their application in image enhancement domain," *Archives of Computational Methods in Engineering*, pp. 1–32, 2018.

[111] P. Kora, "Ecg based myocardial infarction detection using hybrid firefly algorithm," *Computer methods and programs in biomedicine*, vol. 152, pp. 141–148, 2017.

[112] E. Alpaydin, *Machine learning: the new AI*. MIT press, 2016.

[113] K. P. Murphy, *Machine learning: a probabilistic perspective*. MIT press, 2012.
[114] F. Sandberg, M. Stridh, and L. Sornmo, “Frequency tracking of atrial fibrillation using hidden markov models,” *IEEE Transactions on Biomedical Engineering*, vol. 55, no. 2, pp. 502–511, 2008.
[115] E. J. D. S. Luz, T. M. Nunes, V. H. C. De Albuquerque, J. P. Papa, and D. Menotti, “Ecg arrhythmia classification based on optimum-path forest,” *Expert Systems with Applications*, vol. 40, no. 9, pp. 3561–3573, 2013.
[116] J. M. Bumgarner, C. T. Lambert, A. A. Hussein, D. J. Cantillon, B. Baranowski, K. Wolski, B. D. Lindsay, O. M. Wazni, and K. G. Tarakji, “Smartwatch algorithm for automated detection of atrial fibrillation,” *Journal of the American College of Cardiology*, vol. 71, no. 21, pp. 2381–2388, 2018.
[117] C. Huang, S. Ye, H. Chen, D. Li, F. He, and Y. Tu, “A novel method for detection of the transition between atrial fibrillation and sinus rhythm,” *IEEE Transactions on Biomedical Engineering*, vol. 58, no. 4, pp. 1113–1119, 2010.
[118] X. Zhou, H. Ding, W. Wu, and Y. Zhang, “A real-time atrial fibrillation detection algorithm based on the instantaneous state of heart rate,” *PloS one*, vol. 10, no. 9, p. e0136544, 2015.
[119] M. Mohebbi and H. Ghassemian, “Prediction of paroxysmal atrial fibrillation based on non-linear analysis and spectrum and bispectrum features of the heart rate variability signal,” *Computer methods and programs in biomedicine*, vol. 105, no. 1, pp. 40–49, 2012.
[120] S. Ladavich and B. Ghoraani, “Rate-independent detection of atrial fibrillation by statistical modeling of atrial activity,” *Biomedical Signal Processing and Control*, vol. 18, pp. 274–281, 2015.
[121] M. Hartmann, U. S. Hashmi, and A. Imran, “Edge computing in smart health care systems: Review, challenges, and research directions,” *Transactions on Emerging Telecommunications Technologies*, p. e3710, 2019.
[122] A. H. Sodhro, Z. Luo, G. H. Sodhro, M. Muzamal, J. J. Rodrigues, and V. H. C. de Albuquerque, “Artificial intelligence based qos optimization for multimedia communication in iov systems,” *Future Generation Computer Systems*, vol. 95, pp. 667–680, 2019.
[123] B. Hussain, Q. Du, S. Zhang, A. Imran, and M. A. Imran, “Mobile edge computing-based data-driven deep learning framework for anomaly detection,” *IEEE Access*, vol. 7, pp. 137 656–137 667, 2019.
[124] G. M. Friesen, T. C. Jannett, M. A. Jadallah, S. L. Yates, S. R. Quint, and H. T. Nagle, “A comparison of the noise sensitivity of nine qrs detection algorithms,” *IEEE Transactions on biomedical engineering*, vol. 37, no. 1, pp. 85–98, 1990.
[125] A. Kiourti, “Rfid antennas for body-area applications: From wearables to implants,” *IEEE Antennas and Propagation Magazine*, vol. 60, no. 5, pp. 14–25, 2018.
[126] K. N. Paracha, S. K. A. Rahim, P. J. Soh, and M. Khalily, “Wearable antennas: A review of materials, structures, and innovative features for autonomous communication and sensing,” *IEEE Access*, vol. 7, pp. 56 694–56 712, 2019.
[127] S. Majumder, L. Chen, O. Marinov, C.-H. Chen, T. Mondal, and M. J. Deen, “Noncontact wearable wireless ecg systems for long-term monitoring,” *IEEE reviews in biomedical engineering*, vol. 11, pp. 306–321, 2018.
[128] U. Satija, B. Ramkumar, and M. S. Manikandan, “A review of signal processing techniques for electrocardiogram signal quality assessment,” *IEEE reviews in biomedical engineering*, vol. 11, pp. 36–52, 2018.
[129] A. Y. Ashyap, Z. Z. Abidin, S. H. Dahlan, H. A. Majid, A. Waddah, M. R. Kamarudin, G. A. Oguntala, R. A. Abd-Alhameed, and J. M. Noras, “Inverted e-shaped wearable textile antenna for medical applications,” *IEEE Access*, vol. 6, pp. 35 214–35 222, 2018.
[130] W. Liao, J. Shi, and J. Wang, “Electromagnetic interference of wireless power transfer system on wearable electrocardiogram,” *IET Microwaves, Antennas & Propagation*, vol. 11, no. 3, pp. 330–335, 2016.
[131] G. Li, G. Gao, J. Bao, B. Yi, C. Song, and L.-a. Bian, “A watch strap antenna for the applications of wearable systems,” *IEEE Access*, vol. 5, pp. 10 332–10 338, 2017.
[132] A. Y. Ashyap, Z. Z. Abidin, S. H. Dahlan, H. A. Majid, S. M. Shah, M. R. Kamarudin, and A. Alomainy, “Compact and low-profile textile ebg-based antenna for wearable medical applications,” *IEEE Antennas and Wireless Propagation Letters*, vol. 16, pp. 2550–2553, 2017.
[133] G.-P. Gao, B. Hu, S.-F. Wang, and C. Yang, “Wearable circular ring slot antenna with ebg structure for wireless body area network,” *IEEE Antennas and Wireless Propagation Letters*, vol. 17, no. 3, pp. 434–437, 2018.
[134] Y. Li, L. Yang, W. Duan, and X. Zhao, “An implantable antenna design for an intelligent health monitoring system considering the relative permittivity and conductivity of the human body,” *IEEE Access*, vol. 7, pp. 38 236–38 244, 2019.
[135] A. K. Teshome, B. Kibret, and D. T. Lai, “A review of implant communication technology in wban: Progress and challenges,” *IEEE reviews in biomedical engineering*, vol. 12, pp. 88–99, 2018.
[136] R. Lee and S. Mittal, “Utility and limitations of long-term monitoring of atrial fibrillation using an implantable loop recorder,” *Heart rhythm*, vol. 15, no. 2, pp. 287–295, 2018.
[137] A. Smith, M. Perdue, J. Vojnika, and B. Pavri, “The diagnostic yield of implantable loop recorders stratified by indication:“real-world” use in a large academic hospital,” *Journal of the American College of Cardiology*, vol. 73, no. 9 Supplement 1, p. 384, 2019.
[138] Z. Shao and Y. P. Zhang, “Miniaturization of differentially-driven microstrip planar inverted f antenna,” *IEEE Transactions on Antennas and Propagation*, vol. 67, no. 2, pp. 1280–1283, 2018.
[139] K. N. Ketavath, D. Gopi, and S. S. Rani, “In-vitro test of miniaturized cpw-fed implantable conformal patch antenna at ism band for biomedical applications,” *IEEE Access*, vol. 7, pp. 43 547–43 554, 2019.
[140] R. Lesnik, N. Verhovski, I. Mizrachi, B. Milgrom, and M. Haridim, “Gain enhancement of a compact implantable dipole for biomedical applications,” *IEEE Antennas and Wireless Propagation Letters*, vol. 17, no. 10, pp. 1778–1782, 2018.
[141] Z. H. Jiang, Z. Cui, T. Yue, Y. Zhu, and D. H. Werner, “Compact, highly efficient, and fully flexible circularly polarized antenna enabled by silver nanowires for wireless body-area networks,” *IEEE transactions on biomedical circuits and systems*, vol. 11, no. 4, pp. 920–932, 2017.
[142] Z. Jiang, Z. Wang, M. Leach, Y. Huang, E. G. Lim, J. Wang, and R. Pei, “Wideband loop antenna with split ring resonators for wireless medical telemetry,” *IEEE Antennas and Wireless Propagation Letters*, 2019.
[143] A. Kiourti and R. M. Shubair, “Implantable and ingestible sensors for wireless physiological monitoring: A review,” in *2017 IEEE International Symposium on Antennas and Propagation & USNC/URSI National Radio Science Meeting*. IEEE, 2017, pp. 1677–1678.
[144] R. A. Khan and A.-S. K. Pathan, “The state-of-the-art wireless body area sensor networks: A survey,” *International Journal of Distributed Sensor Networks*, vol. 14, no. 4, p. 1550147718768994, 2018.
[145] N. Rishani, H. Elayan, R. Shubair, and A. Kiourti, “Wearable, epidermal, and implantable sensors for medical applications,” *arXiv preprint arXiv:1810.00321*, 2018.
[146] H. Elayan, R. M. Shubair, and A. Kiourti, “Wireless sensors for medical applications: Current status and future challenges,” in *2017 11th European Conference on Antennas and Propagation (EUCAP)*. IEEE, 2017, pp. 2478–2482.
[147] M. A. Santos, R. Munoz, R. Olivares, P. P. Rebouças Filho, J. Del Ser, and V. H. C. de Albuquerque, “Online heart monitoring systems on the internet of health things environments: a survey, a reference model and an outlook,” *Information Fusion*, vol. 53, pp. 222–239, 2020.
[148] N. Razzaq, S.-a. A. Sheikh, T. Zaidi, I. Akhtar, and S. H. Ahmed, “Automated differentiation between normal sinus rhythm, atrial tachycardia, atrial flutter and atrial fibrillation during electrophysiology,” in *2017 IEEE 17th International Conference on Bioinformatics and Bioengineering (BIBE)*. IEEE, 2017, pp. 266–272.
[149] M. Valinoti, G. V. Lozupone, P. Sabbatani, R. Mantovan, S. Severi, and C. Corsi, “Analysis of the electrical patterns and structural remodeling in atrial fibrillation,” in *2015 37th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*. IEEE, 2015, pp. 7035–7038.
[150] S. A. Shah and F. Fioranelli, “Rf sensing technologies for assisted daily living in healthcare: A comprehensive review,” *IEEE Aerospace and Electronic Systems Magazine*, 2019.
[151] X. Yang, S. A. Shah, A. Ren, N. Zhao, Z. Zhang, D. Fan, J. Zhao, W. Wang, and M. Ur-Rehman, “Freezing of gait detection considering leaky wave cable,” *IEEE Transactions on Antennas and Propagation*, vol. 67, no. 1, pp. 554–561, 2018.
[152] X. Yang, S. A. Shah, A. Ren, N. Zhao, D. Fan, F. Hu, M. U. Rehman, J. Tian *et al.*, “Wandering pattern sensing at s-band,” *IEEE journal of biomedical and health informatics*, vol. 22, no. 6, pp. 1863–1870, 2017.
[153] X. Yang, D. Fan, A. Ren, N. Zhao, S. A. Shah, A. Alomainy, M. Ur-Rehman, and Q. H. Abbasi, “Diagnosis of the hypopnea syndrome in the early stage,” *Neural Computing and Applications*, pp. 1–12, 2019.
[154] S. Shah, A. Ren, D. Fan, Z. Zhang, N. Zhao, X. Yang, M. Luo, W. Wang, F. Hu, M. Rehman *et al.*, “Internet of things for sensing:

A case study in the healthcare system," *Applied Sciences*, vol. 8, no. 4, p. 508, 2018.
[155] L. Liu, S. Shah, G. Zhao, and X. Yang, "Respiration symptoms monitoring in body area networks," *Applied Sciences*, vol. 8, no. 4, p. 568, 2018.
[156] X. Yang, S. A. Shah, A. Ren, N. Zhao, J. Zhao, F. Hu, Z. Zhang, W. Zhao, M. U. Rehman, and A. Alomainy, "Monitoring of patients suffering from rem sleep behavior disorder," *IEEE Journal of Electromagnetics, RF and Microwaves in Medicine and Biology*, vol. 2, no. 2, pp. 138–143, 2018.
[157] D. Fan, A. Ren, N. Zhao, X. Yang, Z. Zhang, S. A. Shah, F. Hu, and Q. H. Abbasi, "Breathing rhythm analysis in body centric networks," *IEEE Access*, vol. 6, pp. 32 507–32 513, 2018.
[158] J. L. Moraes, M. X. Rocha, G. G. Vasconcelos, J. E. Vasconcelos Filho, V. H. C. De Albuquerque, and A. R. Alexandria, "Advances in photopletysmography signal analysis for biomedical applications," *Sensors*, vol. 18, no. 6, p. 1894, 2018.
[159] J. D. Hemanth, U. Kose, O. Deperlioglu, and V. H. C. de Albuquerque, "An augmented reality-supported mobile application for diagnosis of heart diseases," *The Journal of Supercomputing*, pp. 1–26, 2018.
[160] A. H. Sodhro, A. S. Malokani, G. H. Sodhro, M. Muzammal, and L. Zongwei, "An adaptive qos computation for medical data processing in intelligent healthcare applications," *Neural Computing and Applications*, pp. 1–12, 2019.
[161] A. H. Sodhro, S. Pirbhulal, G. H. Sodhro, A. Gurtov, M. Muzammal, and Z. Luo, "A joint transmission power control and duty-cycle approach for smart healthcare system," *IEEE Sensors Journal*, 2018.
[162] A. H. Sodhro, Y. Li, and M. A. Shah, "Energy-efficient adaptive transmission power control for wireless body area networks," *IET Communications*, vol. 10, no. 1, pp. 81–90, 2016.

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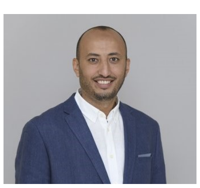

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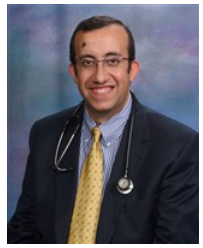

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