Smart Devices for Detection of Atrial Fibrillation - Literature Review

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Abstract:- The most commonly experienced cardiac arrhythmia and the most associated with significant clinical occurrences and expenses is Atrial fibrillation (AF) . Predominantly Due to advances in diagnosis methods, AF has been reported a greater and increasing frequency. By 2030, 14 – 17 million AF cases are anticipated in the European Union, with 120 000 – 215 000 newly diagnosed patients per year. Estimates suggest approximately 3% of adults aged 20 years or older are likely of contracting the condition. AF is independently associated with a two-fold a doubly increased risk of all-cause mortality in women and a 1.5-fold increase in men. The silent form of AF is incidentally diagnosed during routine physical examinations, pre-operative assessments, or population surveys. Unfortunately,, in certain cases, silent AF is revealed only after complications such as a stroke or congestive heart failure have transpired. New smart devices present impactful advantages in the detection of this cardiac arrhythmia. However, the widespread use of these devices, and the large number of free apps with varying degrees of certification, may lead to a great amount of misleading information causing anxiety about arrhythmic occurrences diagnosed by the devices but not professionally confirmed. The possibility of illegitimate or inaccurate results causing panic in the general population would merely convert a solution into a problem. Therefore, it is important to find the best smart device for detection of atrial fibrillation.

Keywords:- Atrial Fibrillation, Cardiac Arrhythmia, Smart Devices, Detection, Photoplethysmography, Electrocardiogram.

I. INTRODUCTION

Atrial fibrillation (AF) is the most common cardiac arrhythmia and is associated with increase of mortality and morbidity [1]. This type of heart rhythm disorder occurs in about 1-2% percent of the population [2]. It has been documented that in Europe alone, over 6 million people suffer from this cardiac arrhythmia, while the number of people affected worldwide is estimated between 30 and 100 million [3]. The older portion of population, 65 years and older, is most affected by this mostly asymptomatic disorder [3]. It is expected that during the next decade the prevalence of this arrhythmia will increase due to the ageing populations and an increase in risk factors [2]. It is estimated that 14-17 million people in the European Union will suffer from AF by 2030. Approximately 120,000–215,000 initial diagnoses are expected each year [4].

The biggest issue of AF is that it often appears paroxysmal or asymptomatic which makes detection and management of this disease utterly challenging. This means that AF will sometimes remain undetected until well overdo and some thrombotic event or a heart failure occurs, and the cause of which being the untreated arrhythmia. For decades, doctors were using the classic model, the gold standard for detection of AF, which are conventional methods such as doctor visits or short-term ECG monitoring, but these are not a solution due to the often-unpredictable occurrence of AF episodes. It is important to emphasize that conventional methods offer only a small insight into the disease's presence and implication [5, 6].

Smart devices such as smartphones and wearables, together with applications and algorithms for smart devices, have the potential to change this traditional way of AF detection and treatment, due to their availability, cost efficacy, applicability, feasibility, ability to provide a way for continuous rhythm monitoring. Smart devices have been successfully tested in several studies, proving their ability to detect AF accurately [7, 8, 9].

There is great potential for smart devices for detection of AF and their implementation into the healthcare system. These devices could be used as an assisting diagnostic tool or for follow-up reasons. If such a thing happens, patients suffering from AF, or probable to suffer from AF due to other indices, could purchase a smart device such as smartphone or smart watch approved to detect arrhythmias. This would give them the chance to monitor their rhythm disorder themselves, to check whether some of the symptoms they are feeling, such as stress, palpitations or dizziness, are caused by an AF episode or not, not to mention that this can relieve a substantial amount of stress since they would be able to know the exact reason of their symptoms without unnecessary panic. On the other hand, if the smart device happens to recognize AF, patients would have a chance to make an appointment with their physician on time and even show them the recording of their arrhythmia episode, all this can potentially prevent any further complications that could come with the disorder as it is AF.

This is a long process and a long road to go on because in order to successfully integrate a smart device arrhythmia detection system into the healthcare system, we need to be aware that the acceptance of this method by doctors and patients must be ensured. In addition, it must be guaranteed that the usability of the device meets the requirements of both parties. This carries great responsibility and requires substantial research and confirmation.

II.   MATERIALS AND METHODS

Google Scholar search engine, NCBI and PubMed databases as well as the social media platform ResearchGate were used for emerging information regarding atrial fibrillation and methods of detecting AF including both insight into current studies and previous work, all this with focus on smart devices for detection of AF, as well as background research conducted previously on the severity and problematics of AF and its challenging detection. Search terms included but were not limited to: atrial fibrillation, PPG, ECG, smart devices for detection of AF, methods for detection of atrial fibrillation, as well as the smart watches, smartphones, applications and algorithms for detection of paroxysmal or asymptomatic atrial fibrillation, and well known smart devices for detection of AF projects and products such as AliveCor Kardia-band, Huawei Heart study, FitBit study, Samsung Simband study, Apple Watch study and eHeart study. Sources were evaluated based on two criteria: whether the source was scientifically sound and not misinformative, and the relevance of the source to the AF and smart devices.

III.   RESULTS

The results will be presented based on the literature research concerning smart devices for detection of AF. A significant amount of research has been done in the field of using smart devices for detection of the AF. This chapter provide an overview of recent studies covering this topic and presents the assembly and sum of the collective information. Information will be categorized first by basic mode of function of discussing smart device used for the detection of AF (PPG, ECG, gyroscope and accelerometer based device); further branching into existing products.

A. PPG based smart devices for AF detection
PPG algorithm is the main factor that determines the predictive ability of PPG-based smart devices. These include: the quality of PPG signals in 'real-world' setting, the battery life of smart devices, measurement method (active or periodic measurement), and AF burden (monitoring time) [10]. The recent studies examining effectiveness of the PPG-based smart devices in detection of AF have involved the use of smart wristbands or smartwatches linked to a smartphone application [11], or the use of smartphone cameras [12]. Depending on different studies monitoring time using different smart devices for detection of AF changed from minutes to two weeks [10].

Furthermore, comparators were used in these studies with aim to confirm the accuracy of used devices. Most commonly used comparators were single-lead ECG devices and gold standard 12-lead ECG [10, 11, 12, 13]. Ideally, any studies using any other alternative device for detection of AF should use these comparators for confirmation of AF diagnosis [10].

Two recent significant large-scale studies employed mobile PPG technology for smart device for detection of AF in the US (the Apple Heart Study; n=419,297 participants) and Chinese (HUAWEI Heart Study; n=187,912 individuals) populations [14,15]. Patients with a history of AF as well as those taking anticoagulants were excluded from both studies [16].

To identify AF, the Apple Heart study evaluated the ability of an irregular pulse notification algorithm among consumers using an Apple Watch app. After receiving the notification, participants were supplied with an ECG patch to wear up to 7 days; subsequently 3-minute ECG strips from each patch were reviewed by clinicians. Overall, 0.52% of the participants received an irregular pulse notification, although it should be noted that this proportion was 6-fold higher in those older than 65 years at 3.2%. The ECG patch follow-up showed AF in 34% of the notified participants, and the positive predictive value for AF detection was 84% [14, 16].

In the HUAWEI Heart Study, 0.23% received a "suspected AF" notification, from which 87% were confirmed to have AF using ECG or 24-h Holter monitoring during subsequent clinical evaluation, with a positive predictive value for having AF being about 92% [14]. In addition, patients diagnosed with AF were added in integrated care program with an guideline-guided intervention for AF management. Overall, 95% of participants with identified AF entered further management programme, and those patients with 80% of high-risk were prescribed with oral anticoagulant therapy [16].

➢ WATCH AF
The WATCH AF trial compared the diagnostic accuracy of a smartwatch-based algorithm in detection of AF by a using PPG signals with cardiologists' diagnosis by ECG [11].

Data acquisition and measurements were obtained first from the wrist by the use of a PPG recording with Fit 2 Samsung Electronics sensors (Samsung Electronics Co) smartwatch paired with Samsung S5 mini smartphone and Heartbeats application (app) [11]. Second, a single-lead iECG using the AliveCor KardiaMobile system (AliveCor, USA) was paired with an iPhone 4s with the left index and middle fingers on the left electrode and the right index and middle fingers on the right electrode of the device [11]. Sensitivity and specificity for detection of AF by this novel smartwatch-based algorithm were 99.5% and 97.4%, with 96.1% overall accuracy [11].

➢ *Samsung Simband*

To deal with the challenges of AF detection with a smartwatch, Bashar [17] developed a novel method based on the wrist PPG signal for AF detection, which also accounts for motion and noise artifacts (MNA). This method was designed not only to detect AF from a smart wrist watch PPG signal, but also to determine whether the recorded PPG signal is corrupted by motion artifacts or not. After they determined the clean PPG signals, they distinguished AF from normal SR. Furthermore, they used a premature atrial and ventricular contraction detection algorithm to get more accurate AF identification and to reduce false alarms. Two separate data sets that have been used in this study to test the efficacy showed a combined sensitivity, specificity and accuracy of 98.18%, 97.43% and 97.54% across the data sets [17].

In their experiments, smart wristwatch provided by Samsung (also known as "Simband") was used to record the PPG signal. The Simband has 8 PPG sensors, an accelerometer with 3 axes, an ECG lead, a temperature sensor and other sensors [18].

In another study by Nemati et al., Samsung Simband was also used to record ambulatory pulsatile and movement data [19]. Single channel ECG, multi-wavelength PPG and tri-axial accelerometry were recorded simultaneously at 128 Hz from the non-dominant wrist using the Simband. Furthermore, a logistic model was made to differentiate of AF from non-AF. An accuracy achieved on out-of-sample data was 95%, with a sensitivity of 97%, specificity of 94%. This approached proved to provide a noise-resistant, accurate screening tool for AF from PPG sensors located in an ambulatory wrist watch [19].

➢ *Apple Watch vs Fitbit study*

Fitbit (FBT) calculates the pulse rate by taking the average of the pulse signals captured between 2 and 5 seconds [21], while Apple Watch has 2 functional modes with different algorithm settings: on S mode, the pulse rate (average of pulse signals) is computed roughly every 6 min, and on W mode, the rate is calculated every 5 to 6 seconds. Additionally, Apple Watch has an automatic optimization function that increases the luminance of the light-emitting diode and sampling rate to compensate for low signal levels (eg, dark skin tones)[20,21].

Furthermore, in Cross-Correlation Analysis, Innui et al. noted that for data validation for detection of AF with PPG devices, the pulse rate data from the PPG devices was compared with the heart rate data from telemetric ECG[20]. Additionally, the main findings of their validation studies were as follows: pulse rates based on PPG measurements can be matched with heart rates from ECG with sufficient accuracy, however some adjustments might be required (eg, during tachycardia); and the detection precision of AF and measurement accuracy during AF were both proven to be better with Apple Watch W mode than with FBT[20].

➢ *Cardiogram application (Cardiogram Inc., USA)*

Health eHeart Study at the University of California did a trial with a commercially available Apple Watch and the Cardiogram mobile application (Cardiogram Inc., USA). This deep neural network for detecting AF using data from smartwatches was developed and validated by Tison et al. [9]. This app functions on principle of detecting a heart rate via PPG sensor and from the accelerometer it gets access to pedometer data. The validation of the developed neural network was carried out in two cohort groups. Within this population, the deep neural network was evaluated with the reference gold standard 12-lead ECG. Results showed 98% sensitivity, 90% specificity, and 94% overall accuracy in identification of AF against the reference standard [9].

➢ *Apps for processing multiple physiological parameters*

Krivoshei et al. used a novel approach to improve accuracy of the already existing McManus et al. method for detection of an irregular pulse in patients with AF [22, 23]. In both studies, the iPhone 4S (Apple, Inc., Cupertino, CA, USA) was used for signal acquisition, with data acquired by positioning the index fingertip on the camera lens and LED light [22, 23]. Extraction of peripheral pulse wave was done from the green light spectrum of the signal during the recording of a 5 min video file [22]. Furthermore, in order to discriminate between AF and SR, they tested three different statistical methods. Those were: normalized root mean square of successive difference of RR intervals (nRMSSD), Shannon entropy (ShE), and SD1/SD2 index extracted from a Poincare´ plot. When all these methods added they resulted in a sensitivity and specificity of 95% [22].

The major difference that Krivoshei et al. made in their study when compared to McManus et al. involves the pulse waveform analysis [22, 23]. This algorithm was recently validated with yield of 99% accuracy, compared with RR intervals from standard ECG recordings [24].

➢ *PULSESMART*

In PULSESMART study, McManus et al. tested whether an enhanced smartphone app for AF detection and use of out-of-the-box smartphone camera can discriminate between SR, AF, premature atrial contractions (PACs) and premature ventricular contractions (PVCs) [25, 26]. For their study they used an iPhone 4S. In order to enhance accuracy and correct motion/noise artifacts, the PULSESMART app conducted pulse analysis using 3 methods: nRMSSD, ShE and Poincare plot[26]. Furthermore, they examined the sensitivity, specificity, and accuracy of the app using the 12-lead ECG or 3-lead telemetry as the referent gold standard [25]. This study was based on their previous work with certain modifications and improvements [27].

Regarding the AF detection, results of this study showed 97% sensitivity, 93.5% specificity, and 95.1% accuracy, when compared to the gold-standard 12-lead ECG [25].

> *Pilot Study (Pre-mAFA II Registry) algorithm*

In this pilot study, Fan et al. investigated the feasibility and accuracy of a mobile phone and smart band for AF detection using pulse data measured by PPG [28]. In their study participants were concurrently tested using mobile phones (HUAWEI Mate 9, HUAWEI Honor 7X), smart bands (HUAWEI Band 2), and 12-lead ECG. In their results, it was noted that the sensitivity and specificity of the smart band PPG were 95.36% and 99.70%, respectively. Overall accuracy of smart band was 97.72%, while overall accuracy of mobile phones with PPG for AF detection was over 94% [28].

B. ECG based smart devices for AF detection

ECG based smart devices for detection of AF are usually smartphone-based devices equipped with 2 electrodes that enable obtaining a single-lead ECG. Furthermore, a deep neural network is trained for signal acquisition and analysis.

> *AliveCor (AliveCor, USA)*

In their multinational cardiovascular remote cohort study, Tison et al. demonstrated that a commercially available smartwatch can passively detect AF through utilizing a available mobile application using a deep neural network [9]. The device used in this study was the AliveCor Kardia (AliveCor Inc), smartphone-based device equipped with 2 electrodes that enables remote participants to obtain a single-lead ECG [9]. Following this, validation was performed against the reference standard 12-lead ECG. In external validation, algorithm performance achieved 97% accuracy. Furthermore, the accuracy of detecting self-reported AF in an ambulatory setting was 72% [9].

> *Kardia Mobile*

Kardia Mobile (Alivecor, Inc., USA) device is a example of a smartphone software and hardware which is able to record a high-quality single lead ECG for heart rhythm monitoring [1, 29]. Kardia Mobile is a portable smartphone compatible accessory which contains two electrodes and transmits the signal to a downloadable mobile application for smart phones, known as Kardia Mobile app. This works by placing fingers of right and left hands on the two electrodes, automatically starting the recording[1]. Kardia Mobile App has an automated algorithm which evaluates the heart rhythm analyzing RR wave and gives a "diagnosis", which is followed by citation with three possible outcomes: "no abnormalities detected", "possible AF" or "this ECG could not be interpreted" [1].

It is important to mention that this is the algorithm with 97% sensitivity, 98% specificity and 97.5% overall accuracy in AF detection; it is FDA-validated and there is recent data which supports its clinical use [1].

> *The Kardia Band*

In recent years, this technology was rapidly advancing as was that of smart watches. Alivecor recently introduced the Kardia Band (AliveCor, Mountain View CA, USA), the Kardia Band (KB) was the first FDA-approved Apple Watch accessory (Apple, Cupertino CA, USA) [8], which can record, store, and transfer single channel ECGs for 30 seconds. This novel technology records an ECG rhythm strip which is interpreted by an algorithm – either as AF or SR. It also displays ECG rhythms during recording and, with the aid of artificial intelligence, recognizes the occurrence of AF and normal SR. KB has automated algorithm for rhythm diagnosis of AF and, if AF detected, can further transmit essential information to the patient's physician, in this manner the physician is automatically updated and has insight in the latest information about a patient's condition. The accuracy of this device in distinguishing SR from AF was compared with 12-lead ECG and KB recordings. The KB showed 93% sensitivity, 84% specificity in detection of AF. Physician's review of KB recordings showed 99% sensitivity, 83% specificity when compared to 12-lead ECG recordings [1, 8].

> *Real-time algorithms on a wearable ECG device*

Previous studies have proposed detecting AF by analyzing ECG and P-wave morphology, the ventricular interval (RR) series, or a combination of the two [30].

Marsili et al. implemented optimized algorithms for AF detection on a wearable ECG monitoring device and assessed their performance [30]. The signal processing framework was composed of two main modules: 1) a QRS detector based on a finite state machine, and 2) an AF detector based on the ShE of the symbolic word series obtained from the instantaneous heart rate [30].

The first module, the QRS detector, was based on the algorithm proposed by Gutiérrez-Rivas et al. which yields the heart rate (HR) series as output [31]. The second module, the SF detector, was based on the algorithm by Zhou et al., which classifies heart beats as 'AF' and 'non-AF'[32, 33].

Regarding the results of their study, with the implementation of the QRS detector, overall accuracy was 99% on the MIT-BIH Arrhythmia Database. Furthermore, the implementation of the optimized AF algorithm gave an overall accuracy of 98.1% on the MIT-BIH AF Database, with 99.2% sensitivity and 97.3% specificity [30].

> *Handheld ECG devices*

Another way smartphones can be used as ECG monitors is by interfacing with peripherals, such as a special smartphone case with embedded electrodes to acquire, store, and transfer single-channel ECG rhythms. Examples of this include AliveCor Heart Monitor (AHM), which has already been US Food and Drug Administration cleared and Conformite Europeenne (CE) marked, and My Diagnostick handheld ECG stick [34].

In Raja et al. study, sensitivity and specificity of the automated algorithms were overall 85.65% and 94.95% for MyDiagnostick; 66.77% and 97.7% for AliveCor, when evaluated against a 12-lead or 6-lead ECG [34].

Furthermore, in their study, using the Kardia application, AHM was paired with an iPhone 6-Plus smartphone. Three consecutive 30-second single-lead iECG recordings were obtained with finger placement on the 2 electrodes at the back of the iPhone. The AHM demonstrated reduced sensitivity (77%) and specificity (76%) [34].

➤ *Kardia Mobile Case and ECG Check Smarphone device*
The aforementioned Kardia Mobile case was also used in Garabelli, Stavrakis & Po study and had excellent correlation with a 12-lead ECG [35].

Garabelli, Stavrakis & Po mentioned another ECG based product for detection of AF [35]. The name of this product is ECG Check from Cardiac Designs, Inc. and it is also FDA approved, just as the previously mentioned Kardia Mobile Case from AliveCor did. In 2013, ECG Check was the first device that was compatible with both the iPhone 4S and 5 via Bluetooth [35].

C. ECG/PPG Combination studies
These are the studies in which the combination of two methods for AF detection such as PPG and ECG are integrated in one with help of algorithm or application in order to perfect recording and results.

➤ *SMART-India-pulse based app*
Soni et al. used a single-lead ECG and a pulse-based application to screen each individual for AF. Their team developed a novel pulse-based approach for detecting arrhythmias that does not require additional hardware. They named this application ANAND after their study site in India; ANAND stands for Automated Novel Atrial fibrillation Noninvasive Detection [36]. Participants were asked to hold the mobile phone in their hand, with their right index or middle finger over the standard camera and lamp. The flashlight illuminates the finger and the pulse waveform is recorded. After the recording was made, the ANAND algorithm performs two calculations to approximate a person's cardiac rhythm based on nRMSSD and ShE [23]. The results from this automated algorithm's calculation on the waveform are classified as normal SR, possible AF or indeterminate [25]. When compared with reference 12-lead ECG, ANAND application (app) demonstrated a 97% sensitivity, 94% specificity and overall accuracy of 95.5% for the detection of AF [36].

D. Inertial measurement unit (IMU) based smart devices
Lahdenoja et al. approach was also based on smartphone, similar to previous PPG camera lens flash based studies [37], however the alternative method was used for acquisition of the heart signal [38]. This alternative

method utilizes the built-in accelerometer and gyroscope sensors in the detection, known as inertial measurement unit (IMU). This noninvasive recording needed no external sensors and would be made by placing the smartphone on the chest of the patient in a laying down position [38]. In this way, IMU, typically is for determining the orientation of smartphone, is now used namely for registering the tiny cardiogenic micromovements of the patient's chest. They used both a gyroscope and an accelerometer for signal acquisition, since the gyroscope alone could add robust information to the heart signal which can further affect accuracy [38, 39]. Following this, the application determines whether the patient suffers from AF or not. They obtained 93.8% sensitivity, 100% specificity and 97.4% accuracy in AF detection. Due to the wide availability of smart devices/sensors with embedded IMU, they proposed that this method could potentially also help with general improvement in fields such as embedded body-sensor networks [38].

E. Results Overview
All aforementioned modes of function (PPG, ECG, ECG/PPG and IMU) are summarized in tables and figuress based on sensitivity, specificity and overall accuracy when compared to gold standard 12-lead ECG as a reference. According to given tables and figures, insight into results is given. Table 1 presents all aforementioned devices based on their mode of function. These modes are PPG, ECG, combined PPG and ECG devices (ECG/PPG) and IMU. Further, after being classified in one of the mode of function categories, app/algorithm/statistical method on which the device operates is presented, together with sensitivity, specificity and overall accuracy of each device in detection of AF.

Table 1 presents a comparison of all devices based on Table 2. Mean, minimum and maximum of sensitivity, specificity and accuracy of all devices. These are presented for PPG, ECG, ECG/PPG and IMU based devices separately and at the end, total accuracy of all devices in detection of AF in general is proposed.

According to Figure 1, mean overall sensitivity in detection of AF is highest for PPG based devices (97.15%) and lowest for ECG based devices (86.81%). According to Figure 2, overall specificity in detection of AF is highest for IMU devices (100%) and lowest for ECG based devices (90.55%). According to Figure 3, overall accuracy in detection of AF is highest for IMU based devices (97.40%) followed by PPG based devices (95.78%) and ECG/PPG combination based devices (95.50%), and ECG based devices with lowest accuracy of 88.59%.

	Sensitivity			Specificity			Accuracy		
	Mean	Max.	Min.	Mean	Max.	Min.	Mean	Max.	Min.
ECG	86.81%	99.00%	66.70%	90.55%	99.20%	76.00%	88.59%	98.10%	76.50%
PPG	97.15%	99.50%	95.00%	95.29%	99.70%	90.00%	95.78%	97.72%	94.00%
IMU	93.80%	93.80%	93.80%	100%	100%	100%	97.40%	97.40%	97.40%
ECG/PPG	97%	97%	97%	94%	94%	94%	95.50%	95.50%	95.50%
TOTAL	92.90%	99.50%	66.70%	94.0%	100.0%	76.0%	92.40%	98.10%	76.50%

Table 1:- Mean, Maximum And Minimum Value Of Sensitivity, Specificity And Overall Accuracy Of Ecg, Ppg, Imu And Ecg/Ppg Devices Derived From

Mode of function	Type of device	App, Algorithm or Statistical method	Sensitivity	Specificity	Accuracy	References
PPG	Samsung smartwatch (Samsung Electronics Co.)	Heartbeats application Preventicus GmbH	99.50%	97.40%	96.10%.	[11]
PPG	Samsung Simband (Samsung Electronics Co.)	MNA removal algorithm	98.18%	97.43%	97.54%	[17]
PPG	Samsung Simband (Samsung Electronics Co.)	Elastic Net logistic model	97%	94%	95%	[19]
PPG	Apple Watch (Apple, Cupertino CA, USA)	Cardiogram application (Cardiogram Inc., USA)	98%	90%	94%	[9]
PPG	iPhone 4S (Apple, Inc., Cupertino, CA, USA)	nRMSSD, ShE and SD1/SD2 index extracted from a Poincaré plot	95%	95%	95%	[22,24]
PPG	iPhone 5S (Apple, Inc., Cupertino, CA, USA)	PULSESMART app	97%	93.50%	95.10%	[25]
PPG	mobile phones (HUAWEI Mate 9, HUAWEI Honor 7X)	mAFA II registry	>94%	>94%	>94%	[28]
PPG	smart bands (HUAWEI Band 2)	mAFA II registry	95.36%	99.70%	97.72%	[28]
ECG	AliveCor Kardia (AliveCor Inc)	deep neural network			85%	[9]
ECG	Kardia Mobile (Alivecor, Inc., USA)	Kardia Mobile app	97%	98%	97.50%	[1]
ECG	Kardia Band (AliveCor, Mountain View CA, USA)	KB algorithm	99%	83%	91%	[1,34]
ECG	Unspecified wearable ECG device	Optimized algorithm	97.30%	99.20%	98.10%	[30]
ECG	AliveCor Heart Monitor (AHM)	Built in	66.70%	97.70%	82.20%	[34]
ECG	AHM paired with an iPhone 6-Plus smartphone	Kardia application	77%	76%	76.50%	[34]
ECG	My Diagnostick handheld EKG stick	Built in	85.65%	94.95%	90.30%	[34]
ECG/PPG	AliveCor device; mobile phone with standard camera and lamp	ANAND application	97%	94%	95.50%	[36]
IMU	smartphone-only	Google Android OS (required)	93.80%	100%	97.40%	[38]

Table 2:- All Smart Devices For Detection Of Af Mentioned In Results. Sorted By Mode Of Function With Presented Type And Overall Accuracy
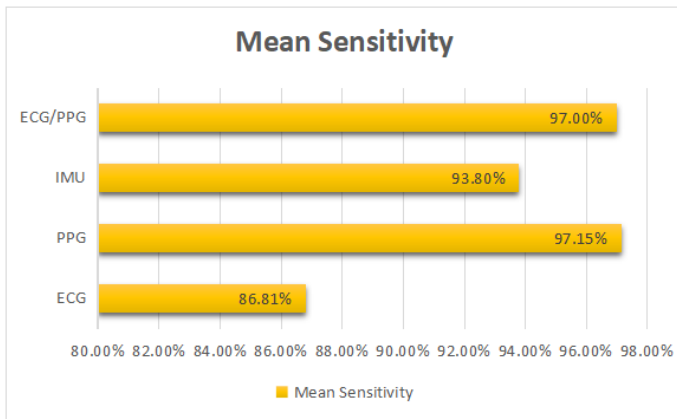
Fig 1:- Mean Sensitivity of Ecg, PPG, Imu An Ecg/PPG Devices In Detection of AF
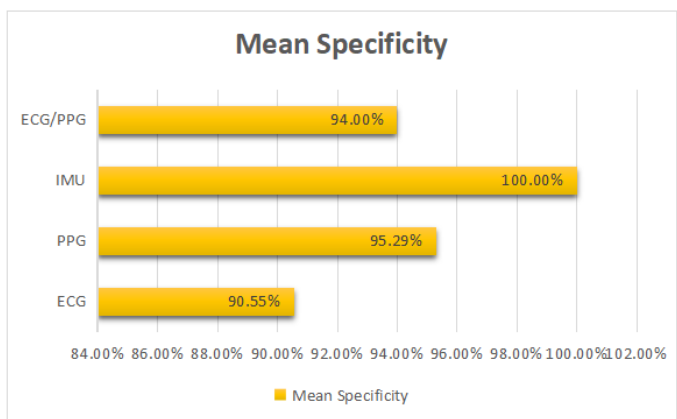

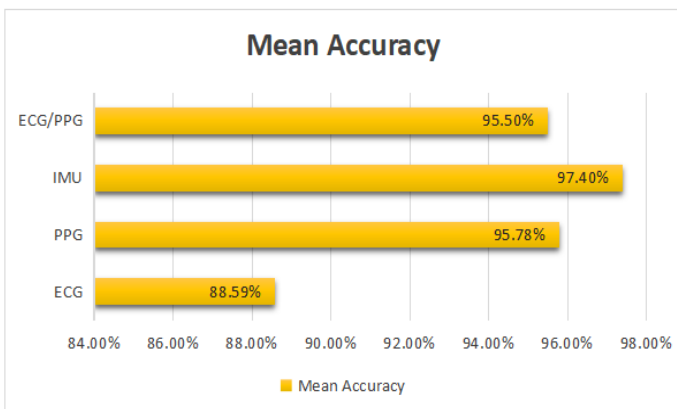Fig 2:- Mean Specificity of ECG, PPG, IMU an ECG/PPG devices in detection of AF

Fig 3:- Mean Accuracy of ECG, PPG, IMU an ECG/PPG devices in detection of AF

IV. DISCUSSION

According to the results, IMU based devices have shown the highest accuracy. However, regarding the fact that a greater amount of data is required to get a statistically significant mean to conclude that IMU based devices are devices with a highest accuracy in detection of AF. Due to lack of studies, it is safer to say that PPG based devices are devices with the highest accuracy, and due to multiple aforementioned studies in the Results chapter, it is with the highest efficacy as well.

PPG-based smart devices are accurate in the continuous detection of AF outside the hospital. The accuracy is similar between the active and periodic measurements [40]. Additionally, this method is simple and accessible for asymptomatic patients with low AF burden, prolonged continuous monitoring time might increase the detection rate of AF. This technology can extend the diagnosis, monitoring, and risk assessment of AF beyond the hospital, providing a new way for doctors and patients to manage AF together [40].

One of the biggest challenges is creating a device which will constantly track physiological parameters which might indicate AF, without any other anxiety causing false positive nor false negative results. These results need to be managed by isolating all inside and outside factors that might decrease accuracy of such devices.

The major advantage of smart devices is continuous monitoring which is possible with these devices being wearable and having it to record patient condition by carrying it with you at all times. However, with this comes one of the main limitations of these devices - motion artifacts. Isolating factors that affect accuracy such as those that come with necessary motion presents a big challenge. Another limitation is the fact that certain patients lack knowledge for proper use of these devices which can also affect accuracy and patient education for these device would be neccessary. Furthermore, false positives that can cause anxiety to the user and drive up health costs with unwarranted ER visits. The system of irregular rhythm notification in people without a known diagnosis of AF supported by physician review can help in uncovering the sub-clinical AF population.

V. CONCLUSION

Detection of AF with a commercially available smartwatch is feasible in principle, with relatively high sensitivity and specificity, and very high diagnostic accuracy. This indicates that smartwatches and smart devices, in general, have a potential for AF screening and monitoring. Achieving a sufficient signal quality is still a challenge that has to be resolved through technological improvements and more advanced algorithms. In light of the increasing use of smartwatches, their consistent availability, and the possibility of a user-independent continuous application, this technology could raise smart device–based rhythm screening to the next level compared to previous approaches with smartphones and become a widely applicable, convenient, and potentially cost-effective tool for large-scale AF screening or extended rhythm monitoring in high-risk individuals. According to different statistical studies, every year, the economy suffers due to high numbers of stroke patients and their treatment, this could simply be prevented by use of smart devices for early detection of AF. In this way, patients would receive adequate management of AF on time and strokes which leads to great economical costs that could be avoided. Nevertheless, further investigation involving broad

population screening is the next necessary step to determine the acceptance and effectiveness of these devices.

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