Detection of Atrial Fibrillation from Commercial Smartwatches Data: A Survey

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Abstract
Atrial fibrillation (AF) is a common and important disturbance of the electrical system of the heart. It is one of many disorders in which the heart beats with an abnormal rhythm. If it is not recognised and treated, it can result into significant health problems such as stroke and heart failure. Detection of AF may require several measurements and tests including electrocardiogram (ECG), holter monitor, echocardiogram, blood tests, stress test and chest X-ray etc. The number of smartwatches dramatically increased in recent years. Most of the smartwatches are capable of collecting real-time and continuous photoplethysmography (PPG) data with high accuracies. This capability has led several academic studies and researches focusing on detecting, diagnosing or screening AF. In the literature, several algorithms are developed that can identify abnormalities in the PPG data, detect AF and even predict stroke with some accuracy. In this study, we have surveyed the machine learning related researches that can detect atrial fibrillation using the commercial smartwatch data. We have tried to describe the pros and cons of all algorithms systematically.

Keywords: Atrial Fibrillation, Smartwatch data analysis, photoplethsmography data.

1. INTRODUCTION

Heart pumps the blood to the body by electrical message signal that produced in the sinus node. These electrical signals are regular in a healthy subject and they give heart the message that the blood should be pumped to our body. Atrial fibrillation occurs as beside the sinus node, the points located in the atrium or around the atrium produce uncoordinated electrical signal [1]. In summary, atrial fibrillation is an irregular heartbeat that interrupts the normal blood flow. Tiredness, dizziness, weakness, a fluttering heartbeat can be symptoms of atrial fibrillation sometimes. However, atrial fibrillation generally does not show any symptoms and in the long term it causes heart attack or strokes [2]. %0.5 of the world population suffer from atrial fibrillation according to World Health Organization [3].
Atrial fibrillation is an anomaly that come up when the routine health control of a patient. In the first stage it couldn't be noticed since it generally does not affect the daily life. Blood tests, electrocardiography (EKG), holter monitoring, stress tests must be observed to diagnosis of atrial fibrillation.
As known, anomaly detection is the task of identifying unusual patterns that do not conform to the expected behavior of the data. Abnormal patterns observed in physiological data are significant in the medical field. Studies have been carried out in [4] to identify unusual patterns in health dataset and to enable health professionals to make correct decisions in a short time. Anomaly detection techniques have generally been developed based on a classification method to divide the data set into normal classes and outliers [5]. Different methods such as support

vector machine [6], Markov models [7] and Wavelet analysis [8] have been used for anomaly detection in health monitoring applications.

Smartwatch usage rose rapidly along with emerging technology. According to IDC's data, 172.2 million smartwatches were sold in 2018, whereas 135 million smartwatches were sold in 2017 [9]. At the first quarter of 2019, sales amount of smartwatch was remarked as 49.6 million. By means of proliferation of smartwatch use, collecting personal health information gets easier. There are many sensors used in smart watches such as; accelerometer, gyroscope, magnetometer, barometric pressure sensor, ambient temperature sensor, heart-rate monitor, oximetry sensor, skin conductance sensor, skin temperature sensor, GPS etc.

Cardiac rhythm can be non-invasive measured with optical sensors by means of the smart watches included photoplethysmographic (PPG) technology. A PPG sensor gauges the volume transition of blood in microvascular vein by low intensity light [10]. There are many medical devices based on PPG technology such as clinical physiological monitoring, blood oxygen saturation, blood pressure, heart rate etc. Since PPG signal is continuous and cheaper than ECG, it can be considering the diagnosis of atrial fibrillation and it makes machine learning methods popular for this problem. In this study, general machine learning structure for diagnosis of atrial fibrillation with PPG data and some other works in literature are shown comprehensively.

2. MACHINE LERNING MODELS TO DETECT ATRIAL FIBRILLATION

In the last two decades, there were many methods which were proposed for automatic diagnosis of atrial fibrillation. However, real time diagnosis became possible as smart watches became popular. As known, there are two basic methods in machine learning such as supervised and unsupervised. Since using both of them is suitable for atrial fibrillation detection, supervised methods are more popular. Supervised methods need to label information for learning data set. Hence, data set is formed by labelling with ECG while it is collected from PPG sensor. Because medical doctors are accustomed to ECG signal. PPG signal is a form of sinusoidal in healthy person. Variation in amplitude and periodicity is regular but it can be varied from person to person and from time to time. A general block diagram of atrial fibrillation from smart watches using supervised learning is illustrated in Figure 1.

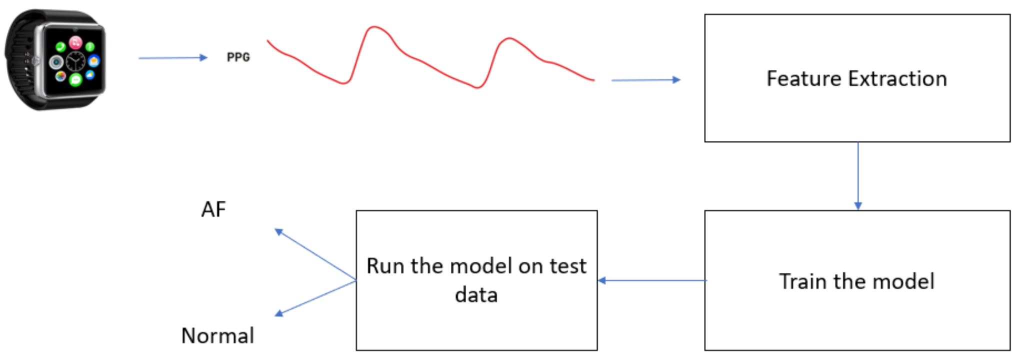

Figure 1 Block Diagram of Atrial Fibrillation Detection using Machine Learning Algorithms

2.1 Performance Evaluation

There are many performance evaluations for machine learning techniques such as accuracy, sensitivity, specificity, f-measure etc. The calculation of these metrics generally depends on the confusion matrix of the classification method. The elements of the confusion matrix can be described as,

- **True Positives (TP):** Number of the patients we predicted as they have AF and also, they have AF.
- **True Negatives (TN):** Number of the patients we predicted correctly as they have no disease.
- **False Positives (FP):** Number of the patients we predicted as they have AF however they are healthy.
- **False Negatives (FN):** Number of the patients we predicted as they are healthy but they actually have the disease.

Also, calculation of the sensitivity and specificity values are shown in Equation 1 and Equation 2.

Table 1. Confusion Matrix Diagram

Real Condition / Estimated Condition	Patient has AF	Patient is healthy
Patient has AF	True positive (TP)	False positive (FP)
Patient is healthy	False Negative (FN)	True negative (TN)

$$\text{Sensitivity} = TP / (TP+FN) \tag{1}$$

$$\text{Specificity} = TN / (TN+FP) \tag{2}$$

2.2 Deep Learning Neural Networks

Tison, Geoffrey H., et al. have designed an experiment with 9750 participants between February 2016 and March 2017. The experiment group includes 347 participants with AF (3.5%), 6143 of the all participant were male and the average age of the participants was 42$\pm$12. They have

trained a deep neural network model using with heuristic pretraining without manual labelling. They represent the data using time between the peak to peak heartrate. The sensitivity, specificity for the algorithm to detect AF were calculated based on the reference standard of 12-lead ECG–diagnosed AF and the results show that they have identified AF with 98.0% sensitivity and.0% and 90.2% specificity [11].
Another study on detection of AF using deep neural networks had studied by Dörr, Marcus, et al. They have used Gear Fit-2 with 508 subjects (mean age 76.4 years, 225 women, 237 with AF). The sensitivity value of the model was 93.7% and specificity was 98,2% [12].
Poh, Ming-Zher, et al. have collected PPG data from several devices and public datasets and train a deep convolutional neural network architecture with %95.2 sensitivity and %99 specificity [13].

2.3 Hidden Markov Models

Bonomi, Alberto G., et al. used CM3 Generation-3 device for collecting to data and with 60 minutes duration. They have collected photoplethysmography and acceleration data from wrist from 2 cohorts of AF patients: AF patients (n=20) undergoing electrical cardioversion (ECV) and AF patients (n=40) that were prescribed for 24 hours ECG Holter in outpatient settings (HOL). They have used first order 11-states Markov model and got 97% sensitivity and 100% specificity [14].

2.4 Long-Short Term Memory Networks

Gotlibovych, Igor, et al. have designed a study to detect AF using Apple watch with 180 hours duration data (36 hours include AF). They have developed a model based on the convolutional-recurrent neural network architecture to classify the raw time series data while the recurrent long short-term memory (LSTM) layer added to get a variable receptive field of each output. Their algorithm has 99% sensitivity and 99% specificity [15].

3. CONCLUSIONS

Use of data collected from wearable technologies rapidly increases in both commercial field and biomedical area. For big voluminous data processing, it is made use of signal processing algorithms and machine learning methods. In this study, some works which use AF detection on PPG signals collected from smart watches are examined. PPG signal capturing is cheaper and data collection is easier than ECG. PPG signal has advantages over portable ECG because it is continuous. PPG signal is well enough to train a supervised learning method to detect AF. The literature shows that deep neural networks are very successful to detect AF from PPG data. The studies show that models based on neural networks are considerably successful on AF detection from PPG data. In the years ahead, it can take an important role in early diagnosis of this illness by real time analyses.

4. REFERENCES

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