A smart sleep apnea detection service

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Abstract

Over the last decades, sleep apnea has become one of the most prevalent healthcare problems. Diagnosis and treatment monitoring are key elements when it comes to addressing this public health crisis. A problem for diagnosis and treatment monitoring is a chronic lack of specialized lab facilities which results in long waiting times or the absence of such services. This can delay appropriate treatment which might prolong living with sleep apnea and thereby leading to health issues due to poor sleep.
We address this problem with a smart sleep apnea detection service based on Heart Rate Variably (HRV) analysis. The service incorporates Internet of Medical Things (IoMT), mobile technology (MT), and advanced Artificial Intelligence (AI). The measured signals are relayed by a smart phone into a cloud server via IoMT protocols. Once the data is stored in the cloud server, a deep learning (DL) algorithm is used to detect sleep apnea events. Detecting these events can trigger a warning message which is sent to care givers.
The smart sleep apnea detection service is beneficial for patients who find it difficult to access specialized lab facilities for diagnosis or treatment monitoring. Furthermore, the system prolongs the observation period, which can improve the diagnosis accuracy. The resource requirements for the proposed service are lower when compared to clinical facilities, this might lead to significant cost savings for healthcare providers.
Keywords Sleep Apnea, Computer Aided Diagnosis, Internet of Medical Things, Heart Rate Variability.

1. Introduction

Sleep apnea is a significant public health concern with an estimated 62.5% to 91.2% rise in global prevalence [1,2]. Both prevalence and incidence of sleep apnea increases with age [3]. Recent US and European estimates show that approximately 14% to 49% of middle-aged people are affected by sleep apnea [4]. In 2003, about 4% of the US population suffered from sleep apnea. In 2008, the global prevalence was calculated to be at 6% [5]. Demographics indicate that up to 24% of the adult population suffer from daily sleep problems [6]. Sleep apnea is a kind of sleep disruption that can dramatically reduce quality of life [7]. The American Academy of Sleep Medicine (AASM) defines the condition as a delay in respiratory flow for more than 10s [8]. A less severe form of sleep apnea is hypopnea, which is defined as a decrease in respiration that lasts for more than 10s during sleep [9,10]. Symptoms include excessive snoring, exhaustion, weak sleep, daytime sleepiness and breathing collapse during sleep [8]. Apart from that, both sleep apnea and hypopnea increase the risk for cardiovascular diseases which can lead to morbidity and mortality if not treated [11,12]. Haoyu et al., estimated that undiagnosed sleep apnea costs the United States economy $70 billion in losses and $11.1 billion in damage, and leading to 980 deaths per year [13]. These figures suggest that sleep apnea affects a large proportion of the population [14]. In the US, only 25% of sleep apnea sufferers were aware of their condition [13] and 70% to 80% lacked a formal diagnosis [15]. Even if patients are aware of their condition, the waiting times for clinical tests range from 2 to 10 months in the UK to 7 to 60 months in the USA [16]. The combination of high prevalence together with a low awareness and long waiting times suggests that current diagnostic procedures fail to protect patients [17]. A more effective system for diagnosis and treatment monitoring is required.

Many physicians still diagnose sleep apnea only by recording disruptive, noisy snoring [17]. Unfortunately, analysing these recordings leads to subjective results which suffer from intra- and inter-observer variability. The Polysomnography (PSG) method incorporates a wide range of measurements which reduces the subjectivity of the analysis [16]. However, PSG signals are acquired with heavy sensors and an expert technician must do the analysis, which is known as scoring [18] [9] [19] [20]. PSG tools are costly expensive, with costs ranging up to 10,000 dollars [21]. Furthermore, PSG strategies are only available at sleep centres. The demand for these specialized facilities outstrips the supply which results in long waiting times [21]. Nevertheless, PSG is the gold standard approved tool for sleep studies [22]. Many patients highlight the inconvenience of traveling to a sleep lab and the cumbersome equipment as drawbacks of the PSG method [18]. These issues accumulate when attempting to track a patient over many nights [22]. In addition, PSG recordings are also difficult to analyse manually [23].

With this paper we introduce a smart sleep apnea detection service for sleep monitoring in the home environment. The patient data is sent to the IoMT cloud server by using the heart health app we developed. The cloud server stores and analyses the measurement signal. A deep learning (DL) algorithm is used to detect sleep apnea periods. Having information about time and extend of sleep apnea periods allows the cloud server framework to send emergency tweet messages to healthcare professionals in case a dangerous condition was detected. The proposed service platform is illustrated in Figure 1. The smart sleep apnea detection service can be conducted in the home setting with an electrode connected to the body during sleep. Therefore, at anytime and anywhere doctors can access both measurement signals and DL results. Considering these advantages, we put forward that a smart apnea detection service can be more cost-effective, because the materials used are not consumable and the service is scalable which enables us to harvest the economies of scale. DL was chosen for this study because it can detect disease based on hidden information in physiological signals and it does not require feature engineering. The physician may use the Heart Rate Variability Analysis Program (HRVAS) to validate the DL results. In this workflow scenario, the smart sleep apnea detection service does real time analysis, and human experts only confirm or indeed reject the machine findings. Such a hybrid approach, in which machines and humans collaborate, increases cost efficiency while ensuring diagnostic safety and reliability and helps with adoption and trust amongst clinicians.

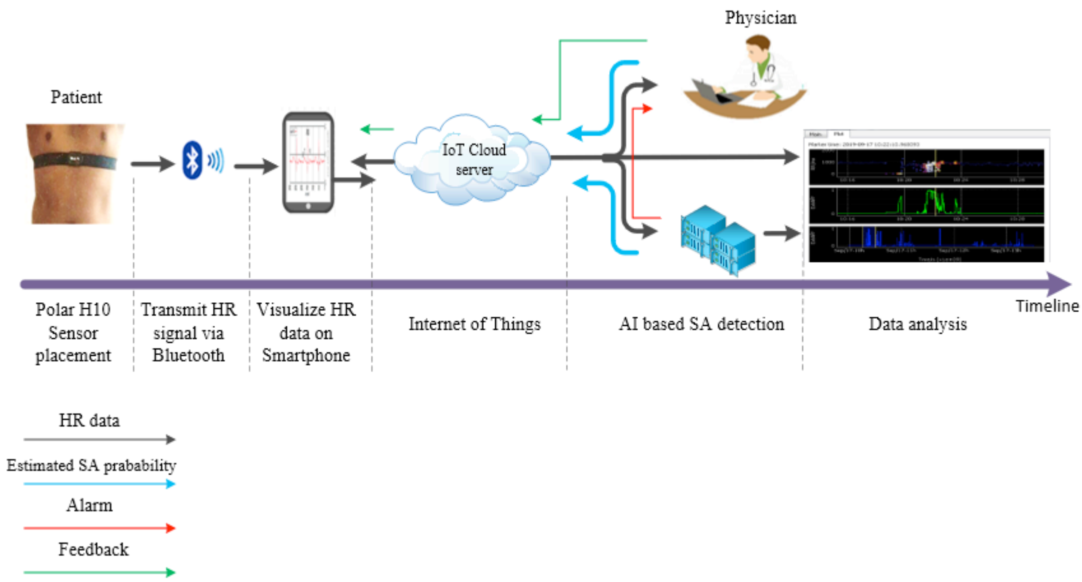

Figure 1. The diagnostic system architecture.

The remainder of the article has been organized as follows: The proposed system is described in Section 2. The findings are discussed in Section 3. Section 4 provides a discussion which relates our service idea to the wider research field. Section 5 concludes the paper with a summary and potential future research directions.

2. Methodology

In this paper, we propose a hybrid scheme for detecting sleep apnea by combining a Polar H10 sensor with AI technology. The main goal of the smart apnea detection service is to monitor sleep health in real time and report the results through a smartphone-based application. Figure 2 depicts the six implementation phases, which are described in the following subsections. The implementation incorporates IoMT, MT, and advanced AI. A DL algorithm is used for sleep apnea detection. The measurement environment, which includes the Polar H10 sensor, is extended by the DL algorithm. Signals from the patient are obtained in real time using a Polar H10 sensor and the data is communicated via low power Bluetooth to a smart phone. The smart phone technology relays the data via WiFi to an IoT cloud server. Physicians will receive automatically generated alerts in the event of an emergency or if any abnormalities are discovered. The Polar H10 sensor is a chest strap that is connected to the patient's body, as shown in Figure 3. The Polar H10 sensor has the following advantages: it is simple to use, lightweight, and there are no technical limitations to the observation time. Not only would such a scheme benefit the elderly and chronically ill, but it would also assist families in providing high-quality treatment.
These components were chosen to meet all the project's key objectives. The equipment has small dimensions which ensures user convenience. The proposed smart sleep apnea detection service consists of the following components: Polar H10 sensor, smartphone, IoMT system, DL, and physician.

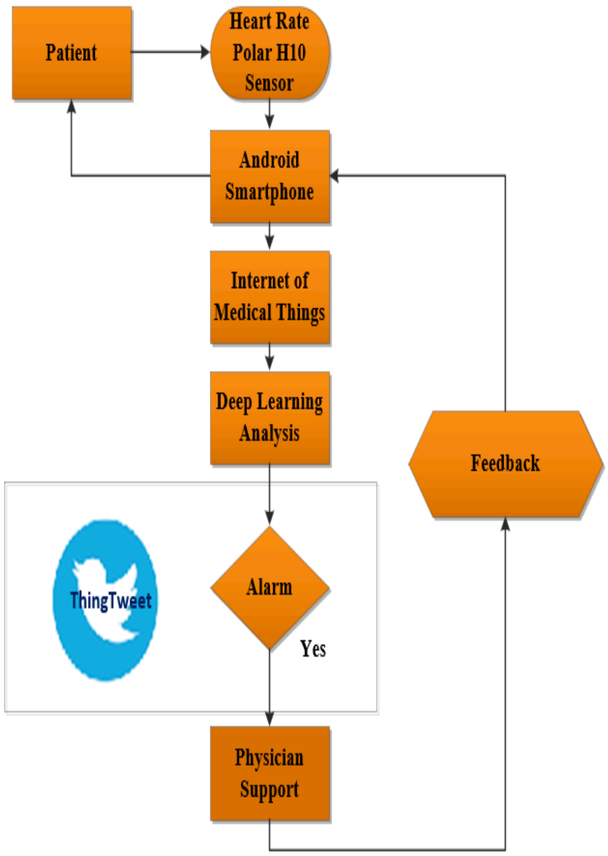

Figure 2. Program flowchart of the smart sleep apnea detection service.

2.1 Heart Rate Polar H10 sensor

Wearable sensors are instruments which are attached to a patient's body [24], such as body sensors, watches, smart glasses, smart belt, etc. Wearable devices need to be practical and easy to use. Hence, they should be simple to set up and operate, inexpensive, comfortable to wear, have a long battery life, a user friendly interface on a mobile application or computer programme and they should not need technical skill to understand and use the results [22].

We have used a Polar H10 sensor in our system to monitor a patient's sleep health status. Polar H10 features a chest strap. It is commercially available (www.polar.com/uk-en), the position of the Polar H10 sensor is shown in Figure 3. The measurement setup for the data acquisition is straightforward. The heart beats are picked up in real time. Low power Bluetooth is used to transfer data from the HR sensor to an Android smartphone in real time.

Figure 3. The Polar H10 sensor is placed on the body.

2.2 Android smartphone

Nowadays, many technologies are being built to track and improve the lives of patients suffering from various illnesses [25]. Therefore, the number of applications and solutions developed for mobile phones is growing [25]. The number of users of smart mobile phones is increasing, particularly among healthcare professionals [26]. In 2021, close to 3 billion people worldwide are using smartphones [27]. Smartphone technology is described in this work as one of the most suitable solutions that can help with diagnosis and treatment monitoring for patients with sleep apnea. Our smart sleep apnea detection service connects the Polar H10 sensor to a smartphone via Bluetooth. The collected HR data is sent to an IoMT system via an Android smartphone. IoMT enables us to access data from anywhere at any time and interpret signals using machine or human expertise [28].

2.3 Internet of Medical Things

More precision and screening tools are required to better diagnose the presence of sleep apnea. In 2011, Mobile health (mHealth) was described by the World Health Organization (WHO) as medical practices that have been enabled by MT such as cell phones, tracking devices and wearables. mHealth establishes a new bridge between patients and physicians that can help underserved populations to overcome barriers to healthcare. Up to 500 million people worldwide access at least one mHealth app with their private cell phone [27]. The number of health app publications continues to expand. For example, 350,000 health apps from 84,000 health publishers were available in 2017, and around 78,000 apps were added only in the last year [29]. Up to 4.5 million applications are commonly available in the Google & Apple store. For the approximate 3000,000 of these applications, a patient's disease is automatically diagnosed and this diagnosis might lead to treatment [27]. In today's life, real time monitoring is one of the most critical and clinically applicable activities in medical settings [30]. Smart device services were developed to fix these issues. These services can track patients at home using less sensors. The systems incorporate IoMT, MT and advanced AI for measurement, recording and transmission of data. The smart sleep apnea detection service is a hospital extension system which recognizes critical conditions automatically. Therefore, using such a service, doctors will help to provide patients with a more accurate and customised decision [31]. IoMT has a lot of impact in the medical field, it provides versatility and quick operating speed to achieve anticipated outcomes. IoMT is a useful technique for tracking and updating patient data. Visualizing this data might help physicians during diagnosis and treatment monitoring [32]. It also provides an environment where parameters can be transmitted to the cloud server using modern technology, such as body sensors to store, display, assemble and analyse the information. The signals are transmitted to patients via WiFi, and thus provide physicians with real-time monitoring. Prior to the revolutionary implementation of IoMT in hospitals, the following were the key issues: Patients did not receive timely medical attention, which can have serious consequences for their health. Many factors contribute to the delay, including a lack of available hospital rooms, traffic on the route, a lack of extra doctors, and a delay in disease diagnosis. In healthcare, IoMT is a cost-effective service that provides a solution. The doctor examines and verifies data from the cloud and advises patients and relatives on what to do. This kind of cloud can store millions of patient details that can be recovered and analysed in the future [33].

Rapid technology growth and smart systems, such as IoMT, Smart Devices, and Big Data have enabled integration into healthcare services [34]. IoMT makes medical equipment more effective, enabling patients to track and analyse their data in real time, which extends the observation duration and reduces human analysis errors. IoMT thus, provides a solution for efficient monitoring of patient conditions by lowering costs and lowering the trade-off between patient outcome and disease management [32]. Furthermore, IoMT brings out a real solution for linking patient and health care facilities. The use of IoMT devices will benefit multiple medical conditions including elderly patients, chronic disease monitoring and private health management. In addition, innovative services based on IoMT can be integrated into home environment to assist and monitor sleep apnaa patients. IoMT has been the most effective healthcare system for the well-being, safe ageing and disease prevention of the elderly [13].

2.4 Deep learning analysis

With this study we put forward an effective framework which can operate directly on wearable devices. The method, as shown in Figure 4, is based on the concept of providing an offline and online framework [35]. The programme consists of the online and offline parts where all sections are linked such that they work together to attain the ultimate goals. The main objective here is to limit the details and assist the specialist in making the right decisions. The offline framework consists of four stages which were used to design the algorithm's structure based on labelled HR data, pre-processing, DL and performance evaluation while the online system is made up of algorithms which make the various parts operational. The DL was used in this study because it has the potential to detect disease based on hidden information in HR signals while requiring no function engineering [28].

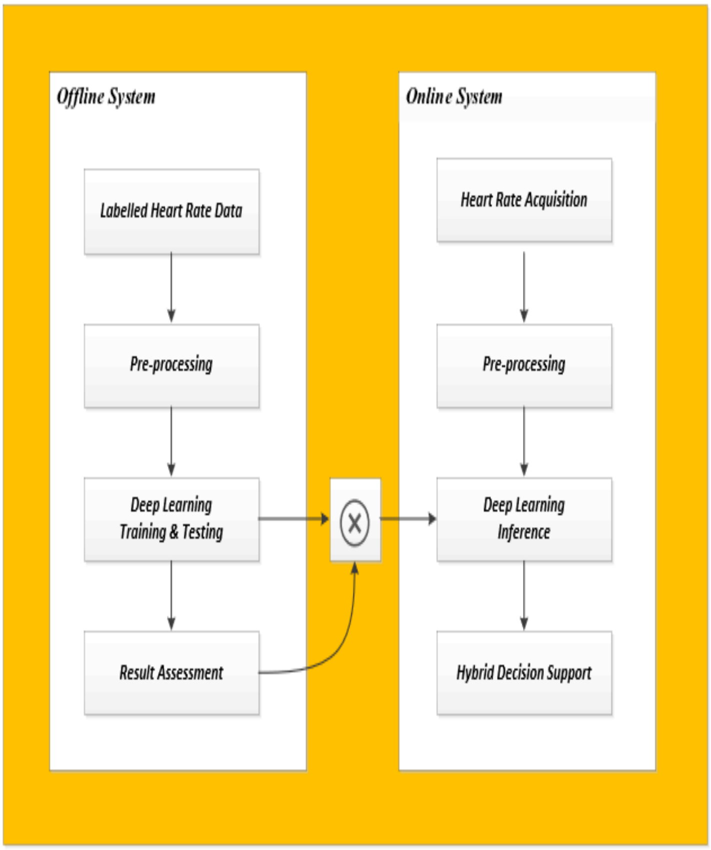

Figure 4. Block diagram of a Heart rate signal-based decision support device.

2.5 Alarm messages

A unique feature of this proposed system is the Thingtweet platform which offers alarm notifications. This functionality allows the proposed service to send emergency tweet messages. This facility has the potential to minimise human error and it allows the doctor timely intervention when a patient is in a critical condition. Figure 2 shows the information flow which enables this functionality.

2.6 Physician Support

We are suggesting a hybrid diagnosis method involving decision taking by humans and machines. A DL algorithm analyses the data concerning HR in real time. If an abnormality is detected, the system will transmit a warning message to physicians. In response, the physician may use the extended HRVAS program to verify the DL result. Figure 5 displays a screenshot of the extended HRVAS program for the physician support module with the SA. The extended HRVAS programme has a number of features, including a drop-down menu that allows users to choose the HR signal from a specific patient [36]. The automated decision support from the DL module is visualized on the left-hand side of the figure. The HRV signal features on the right-hand side were designed to assist the assigned physician in validating the DL data. After pressing" Fetch Data," the name of the patient with number 10 was selected due to an alert message, as shown in Figure 5. In the figure's upper left corner, the DL results are shown as approximate SA probability over time.

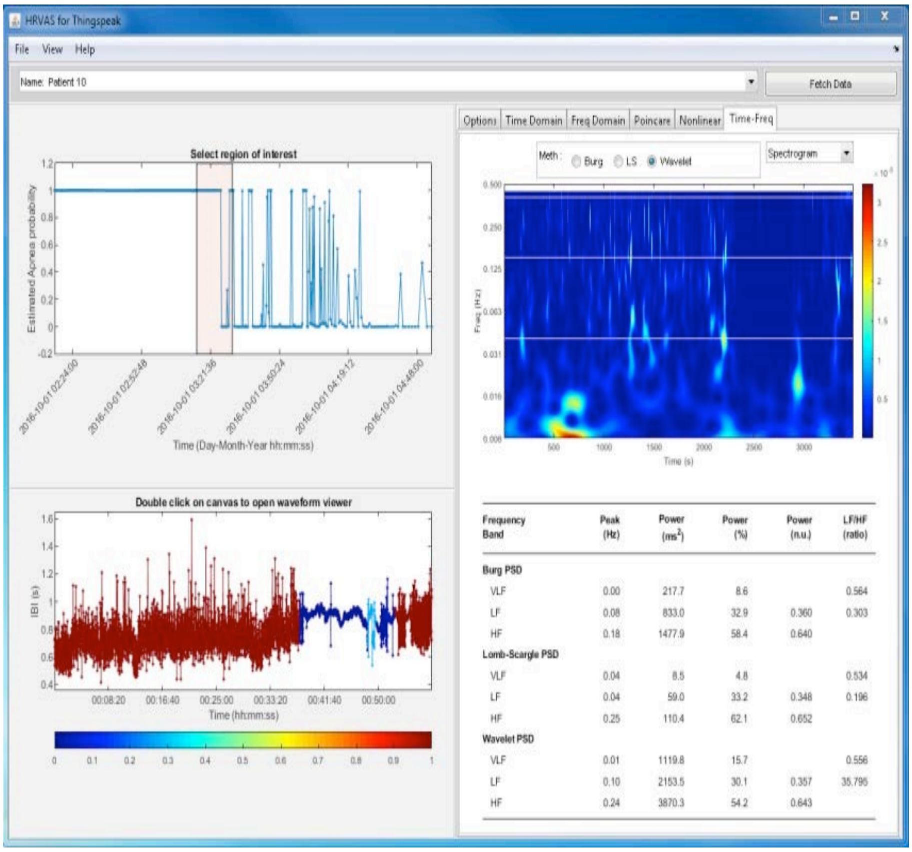

Figure 5. The report sheet captured from the HRVAS software.

2.7 Feedback

In this scenario, the feedback module is used to connect with the patient after the appointed physician has reached a diagnosis. Feedback can be provided via social media, such as e-mail, or personal phone calls.

3. Results

This segment will include a summary of the study findings obtained to diagnose sleep apnea and will also cover some of the results obtained from our algorithm.

Diagnosing sleep apnea through a low-cost approach has been the most important findings in our study. A Polar H10 sensor was used to track sleep apnea episodes in real time. The embedded Polar H10 sensor is continuously collecting the HR parameters while the subject carries a normal life with the chest strap. After that, the data is forwarded through Bluetooth to the user's smartphone. The smartphone will then show the signal to decide whether the user is in normal or anomalous condition, see Figure 6. From there, the data will be processed on the DL network and the data will be visualised as a graphic to the doctor on his computer in real-time.

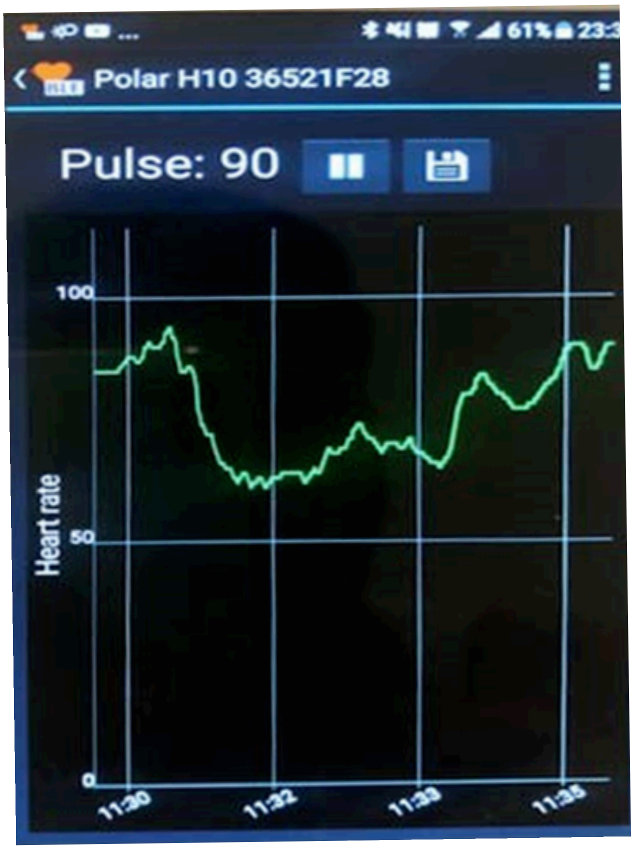

Figure 6. HR signals appear on the smartphone screen.

In this scenario users must build an account in the ThingSpeak platform (https://thingspeak.com/) as cloud server to accomplish that. The user will create an account to test and measured data, after effective registration. Five channels have been developed to store HR data values in our proposed version. The measurement data is stored in the RR interval data channel. When the heart health app relays the HR signals, the material is updated. Figure 7 displays a screenshot of each of the five channels.

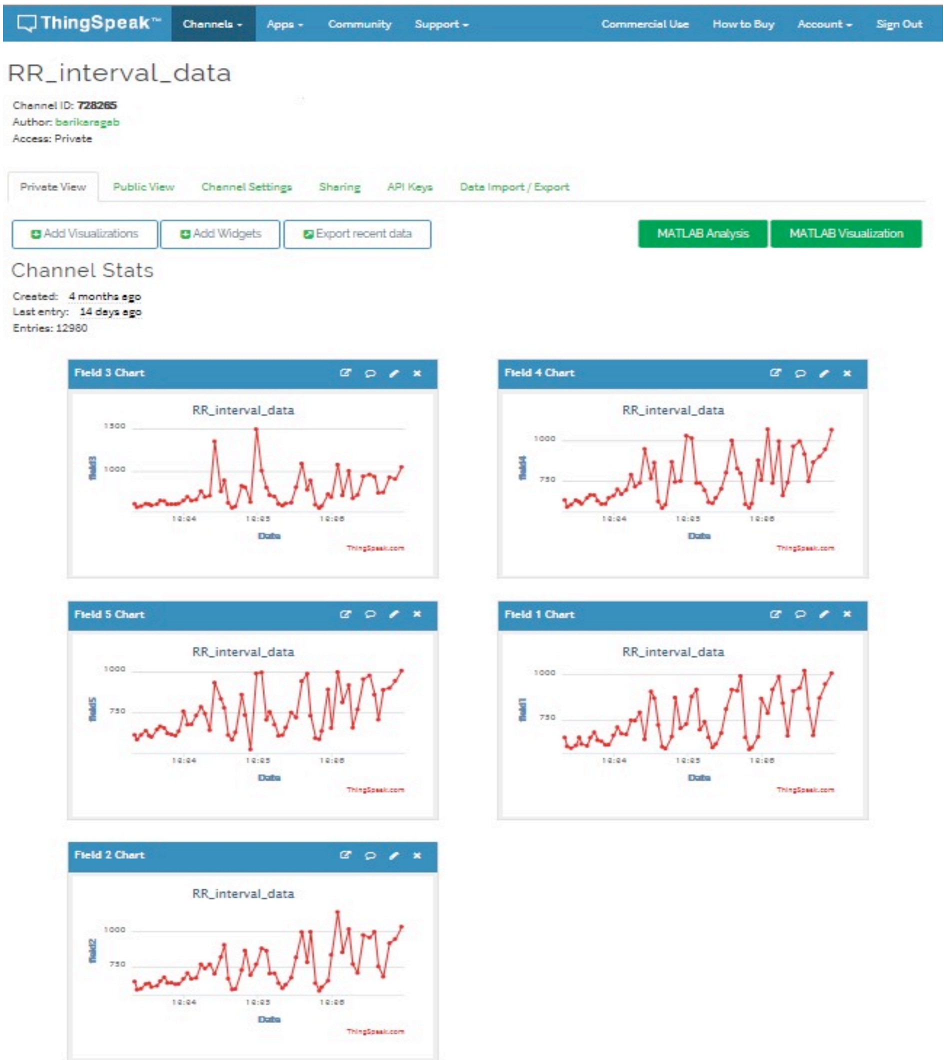

Figure 7. HR signal screenshot from the ThingSpeak website.

This system continues to monitor the patient in real time when he or she is wearing a sensor. If an apnea episode occurs, the unit alerts the attending physician. In response, the physician should verify the system decision using the software for HRV analysis. The doctor will then advise the patient whether the condition is usual or irregular to attend by submitting his suggestions when they are smartphoning. Furthermore, such a system would reduce the need for patients to attend hospitals daily. Additionally, because medical hospital bills can be very large, it will save millions of dollars. Through this viewpoint, it is now clear that our proposed model varies from the others, and as a full end-to-end system has strong potential.

4. Discussion

In this paper, we propose a cost-effective service framework that can be used to detect and monitor sleep apnea in the home environment. The sleep apnea detection service might even improve both diagnosis and treatment monitoring by extending the observation duration. Sleep disorders currently have distinct diagnosis and treatment tracking processes. Measurements taken in a clinical setting are used to diagnose sleep apnea. As a result, if measurements are needed, the patient must travel to a clinic. These measurements are analysed by doctors to establish a diagnosis. For the patient, this procedure is inconvenient, and the cost is high. The proposed service platform incorporates a DL algorithm which can distinguish between disease and non-disease in real time. This study indicates that when applied to the diagnosis and monitoring of sleep apnea cases, a state-of-the-art smart sleep service will attain expert human output. The most important contribution of the methods which underpin the apnea detection service is the ability to generate an alarm message. This property is necessary if the doctors are to alert the patients and their relatives. Methods of monitoring and detecting sleep apnea by incorporating an IoMT, MT and advanced AI tend to offer a scalable, efficient, and, at least potentially, better solution than most other methods of sleep apnea recording. Besides, the combination of using an IoMT, MT and Advanced AI helps to improve detection performance and thereby reduce case risk. Such solutions may extend the independent life of individuals in their home environment and they may provide more protection. Finally, this study shows that it is possible to diagnose sleep apnea using HRV analysis by combining IoMT, MT, and Advanced AI. Table 1 provides a list of different methods used to diagnose sleep apnea.

Table 1. The various approaches used to diagnose sleep apnea

Sleep apnea		
Authors	**Devices**	**Results / Findings**
Yüzer et al., 2020 [21]	Acceleration sensor	This devise is a reliable method of sleep apnea and economical, comfortable, convenient than existing system.
Heima et al., 2018 [37]	Physiological signal Electrocardiogram (ECG)	The overall efficiency is 90.5%
Sabil et al., 2019 [38]	Tracheal Sound sensor (TS)	TS sensor was a good quality, can be easily placed on patients, and does not disturb sleep
Ferrer et al., 2019 [9]	Sleepwise	SW was found a highly accuracy to compared to PSG technique to diagnosis OSA in both labs and home
Crinion et al., 2020 [39]	SleepMinderTH	Sen 50% Spe 72% Acc 92%
Jen et al., 2020 [18]	WatchPaT	Sen 95.85% Spe 92.3% Acc 88.95%
Schätz et al., [40]	PSG and Depth sensors	Sen 89.1% Spe 98.8% Acc 92.2%
Taran, 2020 [7]	Artificial Bee Colony	Sen 99.47% Spe 99.58% Acc 99.53%
Wange et al,.2019 [41]	Residual network	Sen 93.0%. Spe 94.9% Acc 94.4%
Faust et al., 2020 [5]	10-fold Hold out	Sen 99.85 % Spe 99.73% Acc 99.80% Sen 59.90% Sep 91.75% Acc 81.30%

4.1 Limitations

The proposed service has numerous limitations. First, we failed to distinguish between the three types of sleep apnea. In future, we will need to collect data from all these types of apnea and create a new model to distinguish them. Second, there are certain drawbacks to wearable sensors. One is that proper sensor positioning is critical for the quality of data collected, as the sensor's sensitivity is determined by its location. Another possible problem arises when the sensor itself impacts negatively on the sleep quality by being uncomfortable. Third, while some systems have been developed to detect sleep apnea in patients, these technologies are not geared toward assisting with sleep apnea care. Moreover, these solutions still have some technical limitations, such as the use of invasive devices and technologies, limited wireless technologies support, a lack of interoperability of them, processing delays, a limited integration with other data sources, and other requirements. The proposed smart sleep apnea detection service does not address all these limitations. However, it provides the ability or indeed the technical framework to address them. It gathers more information to track, assess, and direct sleep apnea patients.

5. Conclusions and future work

Sleep apnea affects a large portion of the world's population. Unfortunately, many people are not aware of its symptoms which extends the time needed for diagnosis and treatment. Developing high quality sleep apnea equipment is critical because such equipment provides useful feedback to patients, clinicians, and researchers. We aim to improve existing technologies and create new wearable sleeping devices that provide valuable input and help sleepers to increase their sleep quality. The proposed smart sleep apnea detection service translates laboratory sleep research findings into the patient's home environment.

Through this paper, a new intelligent service is introduced which detects sleep apnea automatically. This functionality has the potential to aide physicians during sleep apnea diagnosis. The proposed service is based on a combination of IoMT, MT, and Advanced AI for detecting sleep apnea. The service might also be useful in emergency situations because it can be tracked, registered, and processed in real time. This service allows the doctor to keep track of important parameters, such as the heart rate, while the patient is away from the hospital. If any parameter becomes abnormal, the machine can alert physicians and other caregivers.

There is tremendous potential for future research in mHealth based sleep monitoring. We aim to diagnose sleep apnea disorders to aid early detection of health problems which require prompt intervention. We intend to apply possible solutions to older people, since many of them are unaware of the sleep apnea symptoms.

Abbreviations

AASM	American Academy of Sleep Medicine
Acc	Accuracy
AI	Artificial Intelligence
DL	Deep learning

ECG	Electrocardiogram
EEC	Electroencephalogram
EMG	Electromyogram
HR	Heart Rate
HRV	Heart Rate Variability
HRVAS	Heart Rate Variability Analysis Software
IoMT	Internet of Medical Things
MT	Mobile Technology
PSG	Polysomnography
Sen	Sensitivity Spe Specificity
Spe	Specificity
WHO	World Health Organization

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All authors approved the version of the manuscript to be published.

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