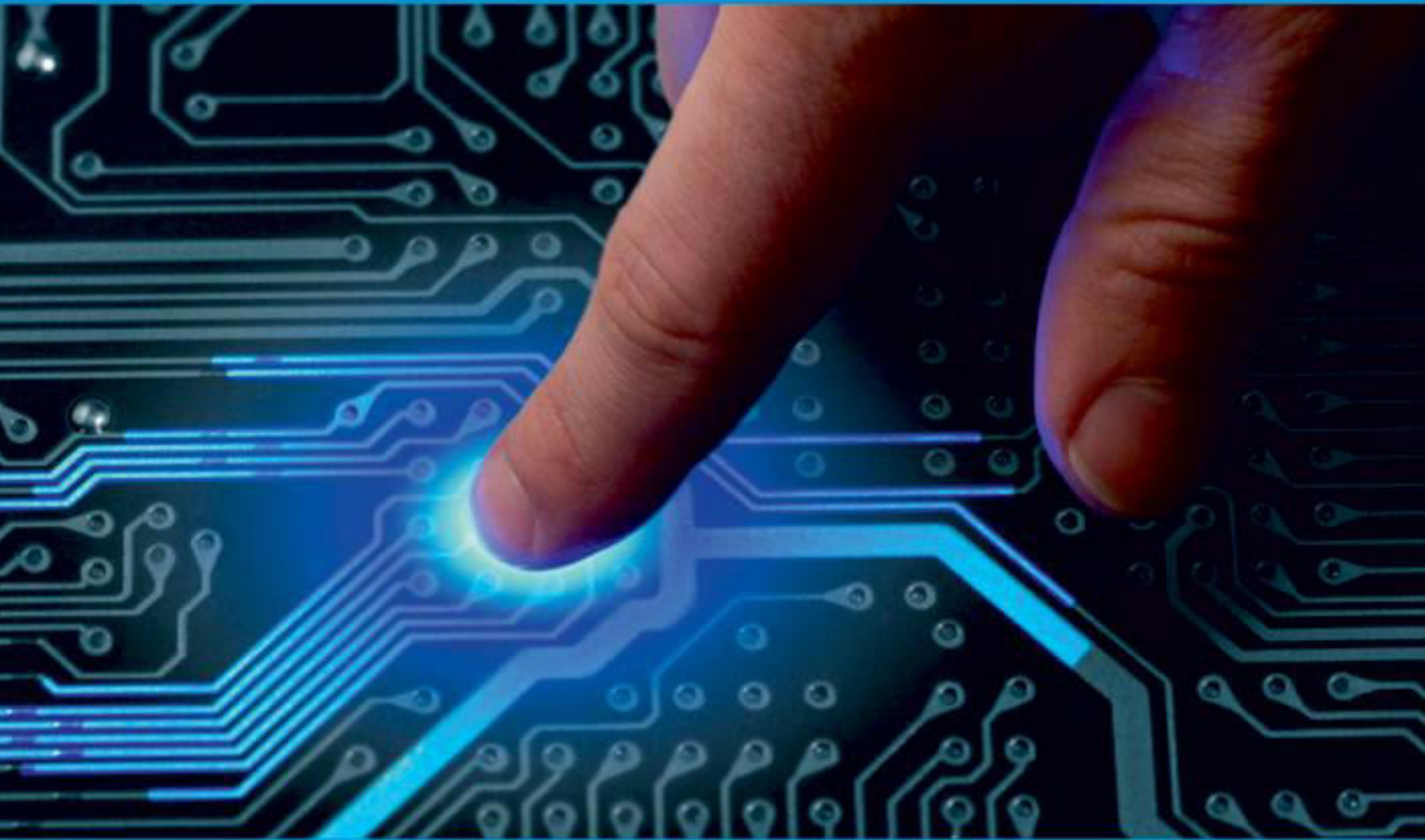
IJIRCCE

e-ISSN: 2320-9801 | p-ISSN: 2320-9798



INTERNATIONAL JOURNAL OF INNOVATIVE RESEARCH

IN COMPUTER & COMMUNICATION ENGINEERING

Volume 12, Issue 3, March 2024

INTERNATIONAL STANDARD SERIAL NUMBER INDIA

Impact Factor: 8.379

International Journal of Innovative Research in Computer and Communication Engineering

| e-ISSN: 2320-9801, p-ISSN: 2320-9798| www.ijircce.com | |Impact Factor: 8.379 | Monthly Peer Reviewed & Referred Journal |

|| Volume 12, Issue 3, March 2024 ||

| DOI: 10.15680/IJIRCCE.2024.1203030 |

IOT-Assisted ECG Monitoring Framework with Secure Data Transmission for Health Care Applications

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ABSTRACT: Heart disease remains a leading cause of mortality worldwide, emphasizing the critical need for innovative technologies for early detection and prediction. This abstract presents a novel wearable cardio-respiratory monitoring device designed to predict heart disease risk. The device integrates advanced sensors for continuous monitoring of key physiological parameters including heart rate variability, respiratory rate, oxygen saturation, and physical activity levels. The wearable device offers several advantages over traditional monitoring methods, including non-invasiveness, continuous monitoring capability, and real-time data analysis. By tracking subtle changes in cardio-respiratory parameters, the device can detect early signs of cardiovascular dysfunction and predict potential cardiac events. Furthermore, the device incorporates user-friendly features such as wireless connectivity and a smartphone application for seamless data visualization and remote monitoring. Initial testing of the wearable device has shown promising results in predicting heart disease risk factors and identifying individuals at higher risk. Future developments aim to refine the rule-based algorithms and incorporate additional physiological parameters for improved accuracy. Thus improving patient outcomes and reducing healthcare burdens.

KEYWORDS: wearable devices, cardiovascular disease, CVD, monitoring, risk reduction, behavioral economics

I. INTRODUCTION

Healthcare has always been one of the most important issues that people have cared about. Given the prevalence of diseases and their impact on people's lives, researchers are always looking for methods to improve medical services and promote public health. In addition, the aging population, shortage of medically trained personnel, lack of equity in services, epidemic planning, and a host of other problems hinder the growth of public health worldwide [1]. However, advances in information and communication technology (ICT) offer effective answers to these challenges. In this context, artificial intelligence (AI) is considered the most promising tool for improving healthcare, as it has the potential to be used in virtually all areas of medicine [2] and will transform healthcare for patients and communities [3]. This enormous contribution is not due to magic, but to AI's data-processing capabilities, which surpass those of humans, especially when large computations are performed in a short period of time. Even though the majority of AI applications in healthcare were developed after 2008 [4], their importance is obvious. First, AI has improved the learning capabilities of computers and humans, leading to improved diagnostic and healthcare procedures [5]. In addition, AI technologies are able to accept common sense, extract information from raw data, use human-like thought processes, deal with inaccuracies, adapt to a rapidly changing environment, and even act on their knowledge [2]. These characteristics enable AI tools to think and behave similar to humans at a virtually unparalleled level, allowing them to articulate clinical patterns and visions beyond human capabilities [3]. Combining AI capabilities with human intelligence, sometimes referred to as augmented intelligence, is probably the most effective way to improve healthcare services

Cardiovascular diseases (CVDs) are the leading cause of death and are hence recognized as the most dangerous disease in the world. According to the most recent World Health Organization (WHO) statistics on heart disease, the number of CVD patients worldwide has increased from 271 million to 523 million between 1990 and 2019, and the number of deaths caused by this disease has increased from 12.1 million to 18.6 million during the same period, accounting for 32% of global mortality in 2019 [6]. For example, in the United States, a person dies from heart disease at least every 34 s [7], and in Canada, a person dies at least every 5 min [8]. Moreover, cardiovascular disease is a major cause of

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both health conflict and economic suffering. According to the Medical Expenditure Panel Survey, the total cost of CVDs in the United States between 2017 and 2018 was estimated at USD 378.0 billion, including USD 226.0 billion in expenditures and USD 151.8 billion in lost future productivity.

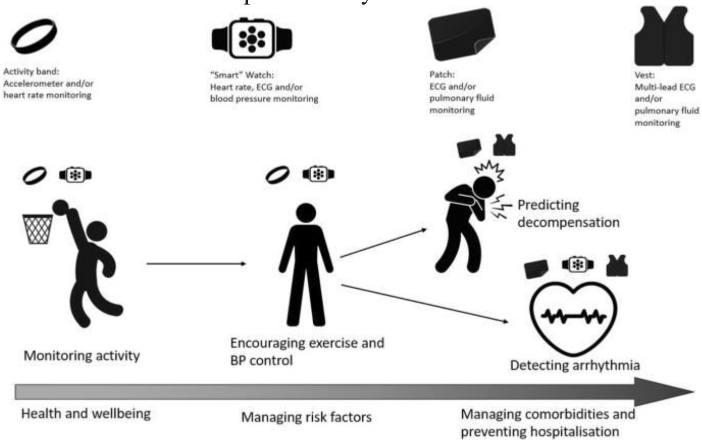

Fig 1: The Role of Wearables in Heart Failure

Due to their potentially fatal nature, cardiovascular diseases need the development of efficient solutions that allow early diagnosis and, ideally, prediction of their onset. The predictive power of modern technologies could help reduce the global prevalence of CVDs. Traditional methods for diagnosing these diseases include electrocardiogram, echocardiography, coronary angiography, stress testing, magnetic resonance imaging, or intracoronary ultrasonography. However, new technologies are improving health services and facilitating the detection of cardiovascular disease, particularly information and communication technologies (ICTs) and the development of artificial intelligence (AI) and its derivatives. The novel approaches of AI in cardiology have proven to be successful in providing fast, accurate, and less erroneous patient care, which has significant medical and financial implications. It is more effective and widely used, as the tools and applications offered are at the level of an expert using real-world data. In general, AI has fantastic potential to transform cardiology in the near future and is often seen as the next revolutionary step in the field due to its potential to accelerate and improve patient care.

II. RELATED WORK

Interest in machine learning applications such as health care and medical science is growing considerably [14]. For instance, Ellaji et al. design an architecture of a narrowband IoT system to integrate wearable devices to improve medical health care. The main benefits of using narrowband IOT are its low and low power consumption. Therefore, it provides a novel mechanism for linking all the smart devices, which requires a very less amount of data and long-range intervals. This improves hospital data transmission and accomplishes data processing in real time. The narrowband IoT system includes an application server, NB-IoT devices, cloud stage, and customer applications. First, NB-IoT devices send sensing data to the cloud platform and it stores the data. Different applications process data subsequently clients can access this information through a user interface [15].

The Internet of Things and artificial intelligence are emergent fields where researchers are developing methods and techniques to reduce human effort [1, 2]. While IoT is relying on communication technology, sensors, and data processing technics [3]; classification algorithms are used to recognize a hidden pattern in the input data and identify the class where it belongs [4].

It is possible to apply this technology in fields such as industry, farming, meteorology, or medicine. For instance, a medical cyber-physical system (MCPS) is a concept where software, sensors, and networks interacting with physical human signals in order to improve the effectiveness of the patient's medical care. In this way, sensors capture biological signals and send them through a network to be processed by software algorithms that extract useful information and take actions, such as emitting an alert, diagnosis, or even providing treatment in order to easily improve the patient's health care [5]. Due to the high costs associated with in-hospital care, alternatives including home care, assisted living, telemedicine, and sport-activity monitoring, have drawn more interest. Likewise, mobile monitoring and home monitoring of vital signs and physical activities allow health to be assessed remotely at all times [5].

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On the other hand, according to the World Health Organization, cardiovascular disease is the leading cause of death with an estimated 32% of all deaths worldwide [6]. Similarly, sudden cardiac death (SCD) and arrhythmia represent between 15% and 20% of all deaths in the world.
Sometimes arrhythmias are detected when complications appear; knowledge of the characteristic ECG changes may provide early clues to the presence of these disorders, the prompt recognition of which can be lifesaving [7]. Therefore, continuous heart monitoring is required for early detection in order to give a suitable treatment for patients with cardiac arrhythmias [8].

In order to detect and diagnose heart diseases, the electrocardiogram (ECG) is an indispensable tool for monitoring the electrical activity of the heart [9]. The ECG has allowed for studying and classifying different arrhythmias types according to their particular characteristics. Based on this typology, different studies have proposed using machine learning in order to extract ECG data patterns for the early identification of arrhythmias. In this way, machine learning algorithms such as k-nearest neighbors (KNN), convolutional neural networks (CNNs), and random forest has shown interesting result in arrhythmia classification [10–12].

III. METHODS

Convolutional Neural Network (CNN): CNN is a kind of deep neural network used to analyze visual images. These neural networks are modeled after the neural networks of the human visual system. Neurons are the basic computational unit of a neural network, just as they are the basic functional unit of the human nervous system. In the case of convolutional neural networks, instead of normal matrix multiplication, convolution is used, a special form of mathematical operation. In addition to the input and output layers, a convolutional neural network has numerous hidden layers (a neural layer is a stack of neurons in a single row). A neuron in the input layer receives an input, analyzes it, and performs computations on it, and then transmits a nonlinear function called an activation function to produce the final output of a neuron.

ong Short-Term Memory (LSTM): LSTM networks are a type of recurrent neural network (RNN) that can learn sequence dependence in sequence predictions. RNNs contain cycles that use network activations from a previous time step as inputs to influence predictions at the current time step. These activations are stored in the internal states of the network, theoretically preserving long-term contextual timing information. This method allows RNNs to use a contextual window that changes dynamically over the course of the input sequence. Complex problem domains such as machine translation, speech recognition, and others require this behavior.

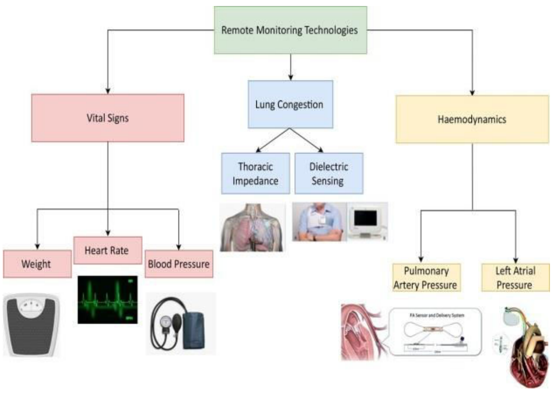

Fig 2: Work Flow

Decision Trees (DTs): A decision tree is a type of supervised machine learning used to make classifications or predictions based on answers to a prior set of questions. The model is a type of supervised learning, meaning that it is trained and evaluated on a dataset that contains the desired classification. Occasionally, the decision tree may not provide a definitive answer or conclusion. Instead, it may suggest possibilities from which the data scientist can make an informed choice. Because decision trees replicate human thought processes, it is often easy for data scientists to understand and explain the results.

On the other hand, the electrocardiogram (ECG) is considered the most effective indicator of cardiovascular disease due to its high accuracy in recording the presence of such disease and its practicality and reliability in detecting it.

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Conventional ECG signal acquisition relies on electrodes, which can be uncomfortable to wear during normal daily activities. Smart watches and wristbands, on the other hand, are quite effective at capturing ECG signals and are also convenient for a number of other reasons. They are available to everyone and are the best option as they combine a variety of useful features with accurate monitoring of heart rate and other vital signs. Commercially available smart watches and wristbands are cheap and have simple user interfaces. They are small, are not in the way, and do not limit people's options. In addition, they are equipped with reliable power sources that allow them to last for a long time. Finally, their ability to record a wide range of biometric data makes them an excellent, if not ideal, option for ECG capture devices and thus for predicting CVD parameters.

IV. RESULT ANALYSIS

PPG is based on measurement of changes in microvascular blood volumes. Pulses of photons are sent from an emitter which pass through the skin, reflected photons are received by a photodetector which measures variable intensity of reflected photons, which can be translated into a tachogram recording.One of the commonly used PPG-based devices is the Apple Watch which uses green and infrared LED lights and photodiodes to detect the amount of blood flowing through the wrist. With a sampling frequency in the 0.1–1 kHz range, variations during the cardiac cycle are used to detect each systolic event, then to calculate the heart rate. The optical sensor supports a range of 30–210 bpm. The sensor can also compensate for low signal levels by increasing both LED brightness and sampling rate. The infrared sensor is used for background/baseline measurements and heart rate notifications, the green LED uses a higher sampling rate to during workout or "breathe sessions" to calculate walking average and HRV. Another commercial device, the FitBit wrist monitor uses similar LED PPG-based technology.

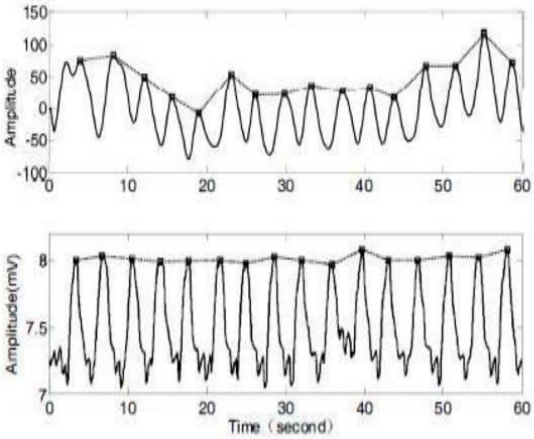

Fig 3: Result Analysis

Simple PPG-based devices may be adequate for heart rate detection, however, validation for HRV measures is lacking (see the discussion on wearable consumer grade devices). Consumer grade devices using PPG shown good correlation of accuracy with ECG measurements. Medical grade devices using PPG have superior accurac. PPG works best when there is good contact between the device and the skin which can be challenging when used with watch and wrist band straps, especially with activity [28]. Skin color, tattoos and moisture have also been known to affect PPG accuracy [29]. A significant limitation of PPG-based heart rate measurement is the underestimation of HR in arrhythmias, especially atrial fibrillation, where early contractions generate a weaker pulse which may not be detected. Despite significant advantages in terms of accuracy and ease of use, PPG based devices still have limitations.

V. CONCLUSIONS

Recently, the use of smart wearables in the diagnosis and prediction of cardiovascular disease has received increasing attention. This is partly due to the technological potential of smart wearables and partly due to the data processing power of artificial intelligence and its derivatives, machine learning and deep learning. In this research, we thoroughly investigated the use of smart wearables to treat fatal heart diseases. The review of the research area showed the high practicality and effectiveness of such methods, reflecting the growing interest that has surged in recent years. However, given the challenges and limitations discussed in this review, there is a large window for improvement that smart wearables should undergo to prove their feasibility and reliability. Increasing accuracy, automating noise

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reduction, solving privacy issues, dealing with heterogeneity, and improving explainability are interesting topics that should be considered when trying to promote the use of smart wearables in the management of CVDs. As a result, this review provides a brief overview of a number of relevant topics that can be used as recommendations for further research.

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