
ISSN: 2321-2152
IJMECE
International Journal of modern
electronics and communication engineering
E-Mail
editor.ijmece@gmail.com
editor@ijmece.com
www.ijmece.com

IJMECE
ISSN2321-2152
www.ijmece .com
Vol 12, Issue 2, 2024

PUPILHEART HEART RATE VARIABILITY MONITORING VIA PUPILLARY FLUCTUATIONS ON MOBILE DEVICES

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ABSTRACT

Heart disease has now become a very common and impactful disease, which can actually be easily avoided if treatment is intervened at an early stage. Thus, daily monitoring of heart health has become increasingly important. Existing mobile heart monitoring systems are mainly based on seismocardiography (SCG) or photo plethysmography (PPG). However, these methods suffer from inconvenience and additional equipment requirements, preventing people from monitoring their hearts in any place at any time. Inspired by our observation of the correlation between pupil size and heart rate varaiability (HRV), we consider using the pupillary response when a user unlocks his/her phone using facial recognition to infer the user's HRV during this time, thus enabling heart monitoring. To this end, we propose a computer vision-based mobile HRV monitoring framework-PupilHeart, designed with a mobile terminal and a server side. On the mobile terminal, PupilHeart collects pupil size change information from users when unlocking their phones through the front-facing camera. Then, the raw pupil size data is pre-processed on the server side. Specifically, PupilHeart uses a one-dimensional convolutional neural network (1D-CNN) to identify time series features associated with HRV. In addition, PupilHeart trains a recurrent neural network (RNN) with three hidden layers to model pupil and HRV. Employing this model, PupilHeart

infers users' HRV to obtain their heart condition each time they unlock their phones. We prototype PupilHeart and conduct both experiments and field studies to fully evaluate effectiveness of PupilHeart by recruiting 60 volunteers. The overall results show that PupilHeart can accurately predict the user's HRV.

1.INTRODUCTION

HEART is the most important organ of the human body, pumping blood to tissues and organs throughout the body and maintaining normal metabolism [1]. Heart disease can bring significant impacts on the safety of human life. According to the World Health Organization (WHO), about 17.5 million people die of heart disease each year, accounting for 30% of mortality [2]. Therefore, monitoring heart health in one's everyday life is of great importance to human beings.

A typical indicator used to evaluate heart health is heart rate variability (HRV) [3], [4], also known as heart rate volatility, which is simply a measure of the variation in time between each heartbeat [5]. On the other hand, it also contains the implicit information on the regulation of cardiovascular system by neuro-humoral factors, and thus can be used to diagnose or prevent cardiovascular and other diseases. Moreover, according to [6], measurements of HRV and the quantification of its spectral components are powerful predictors of cardiovascular morbidity and mortality. Therefore, it may help assess the return to work of patients with ischemic heart disease. Clinical analysis of HRV can reflect activity and balance of the cardiac autonomic nervous system (ANS) and related pathological states, etc [7]. In general, low HRV is considered a sign of current or future health problems because it shows your body is less resilient and struggles to handle changing situations. It's also more common in people who have higher resting heart rates. That s because when your heart is beating faster, there less time between beats, reducing the opportunity for variability. This is often the case with conditions like diabetes, high blood pressure, heart arrhythmia, asthma, anxiety and depression. In other words, heart health monitoring can be achieved by monitoring HRV.

Currently, there are two main categories of heart rate monitoring systems: medical and consumer heart rate monitors

[8]. Medical heart rate monitors used in hospitals are usually wired and use multiple sensors, such as commonly used electrocardiogram machines in hospitals [9]. Meanwhile, portable medical devices also have been developed, which are called Holter monitors [10]. On the other hand, consumer heart rate monitors are designed for everyday use and are wireless. Specifically, there are two types of consumer heart rate monitors: electrical-based and optical-based [11]. The electrical monitors consist of two parts: a monitor/transmitter worn on a chest strap, and a receiver. When a heartbeat is detected, a radio signal is transmitted, which is used by the receiver to display/determine the current heart rate [4], [12]. Instead, the optical-based heart monitoring system measure the heart rate by shining light from an LED light across the skin and evaluating how it scatters off blood vessels, such as the popular smart watches [13], [14]. However, all these existing methods either require professional guidance or additional equipment, which is inconvenient for daily heart rate monitoring and increases cost of devices.

In this context, we raise a question: can we monitor users' HRVs through some daily activities and without additional equipment and professional guidance? Recent studies have shown that both pupils and heartbeat are controlled by same nerves, i.e. sympathetic and parasympathetic nerves [15], [16].Thus changes in the pupil are correlated with variations in the heartbeat. For example, when a person is frightened, the sympathetic nerve strengthens while the parasympathetic nerve weakens, resulting in a faster heartbeat and a smaller pupil diameter. Based on this principle, we explore the quantitative correlation between pupil size and HRV. In addition, with the development of modern technology, the smart phone owner ship is growing, and the number of smart phones based on facial recognition unlocking is also increasing. According to [17],[18], more than 800 million users around the world have smartphones with the function of face recognition and users unlock their phones 50 times on average per day. Therefore, we consider using the front-facing camera of mobile phones to record the change of user's pupils while he/she unlocks the phone with facial recognition while obeying the privacy policy, so as to achieve HRV monitoring of the user. If it works, pupil-based mobile

HRV monitoring can bring some unique advantages over existing methods:

• Convenience. Monitoring HRV on mobile devices is much more portable than professional equipment and does not require special instruments or professional guidance.

• Accuracy. HRV monitoring based on mobile device unlocking involves different time periods and different physiological and mental states of users, which provides more samples and thus guarantees the accuracy of HRV monitoring.

In our study, we first investigate the initial qualitative relationship between the heartbeat and the pupil size captured by the front camera of mobile phones. Based on this, we do a further job of inferring HRV from papillary response more comprehensively and accurately. Achieving this goal entails several key technical challenges. First, the physiological process of papillary response is intricate: it is possible to extract some features from this process, but it is difficult to identify features that are relevant to HRV. Moreover, having found the features of papillary response, it is hard to correspond directly to HRV. Last but not least, in mobile scenarios, certain specific challenges are posed. For example, changes in light intensity or shaking may have a serious impact on the recorded face images.

2. LITERATURE SURVEY

Heart Rate Variability (HRV) is a critical indicator of autonomic nervous system function and overall cardiovascular health. Traditional methods of measuring HRV typically involve electrocardiograms (ECG) or photoplethysmography (PPG). However, recent advances in mobile technology and biometric monitoring have opened up novel avenues for non-invasive HRV assessment. One such innovative approach involves monitoring pupillary fluctuations, a method that can potentially be integrated into mobile devices for continuous and convenient HRV tracking.

Key Concepts and Methods:

1.Heart Rate Variability (HRV):

Definition and Importance: HRV refers to the variation in time intervals between consecutive heartbeats. It is an important marker of autonomic nervous system function, reflecting the balance between sympathetic and parasympathetic activity.

2. Pupillary Fluctuations:

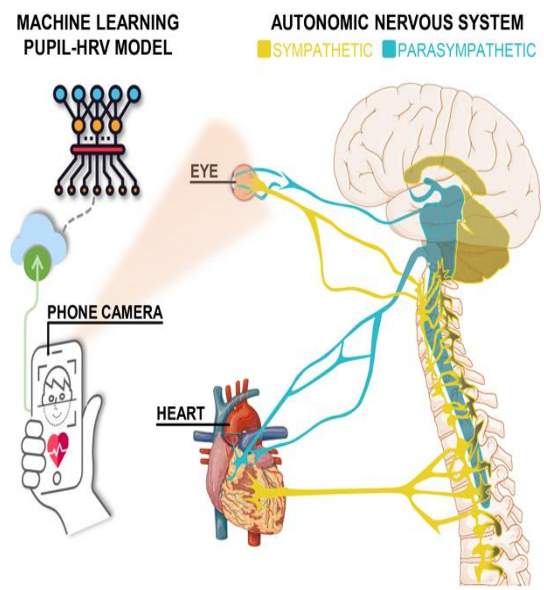
Physiological Basis: Pupillary light reflex and fluctuations in pupil size are influenced by autonomic nervous system activity. The parasympathetic nervous system constricts the pupil, while the sympathetic nervous system dilates it.

3. Mobile Device Integration:

Technological Feasibility: Modern smartphones are equipped with advanced cameras and sensors capable of high-resolution imaging, which can potentially be utilized for pupillometry.

SoftwareAlgorithms:Image processing and machine learning algorithms can be developed to analyze pupillary changes and infer HRV metrics.

The integration of pupillary fluctuation monitoring into mobile devices presents a promising frontier for non-invasive HRV assessment. While preliminary research shows potential, significant work remains in refining the technology, ensuring measurement accuracy, and validating the approach against established HRV measurement methods. Future studies should focus on algorithm development, real-world testing, and standardization to make this innovative method a reliable tool for cardiovascular and autonomic health monitoring.



3. EXISTING SYSTEM

In recent years, researchers have paid more attention to monitor people's HRV in mobile scenarios. We roughly categorize those methods into two groups.

Methods in the first group exploit photoplethysmography (PPG) to measure HRV [19]–[25]. Specifically, the mechanism mentioned in [19] works by placing a finger on the phone camera while turning on its flash and calculating the amount of light absorbed by the finger tissues by taking photos from the phone camera to calculate heart rate. Moreover, Bolkovsky et al. [20] use both Android phones and iPhones to capture RR intervals and then derive HRV through a complex algorithm. In addition, the effect of sampling rate between Android phones and iPhone on the accuracy of HRV measurements is also explored. Mobile phone PPG is also advocated by Plews et al. [21], showing that PPG correlated almost perfectly with ECG, with acceptable technical error in estimation and minimal differences in standard deviations. The rolling shutter camera mechanism has been utilized to extract CIS-photoplethysmography (CPPG) data points from CMOS image sensor (CIS) pixel rows, enabling the extraction of high frame rate CPPG signals from a common built-in low frame rate smartphone's CIS [25]. As for the specific applications, PPG is utilized as a tool to estimate HRV in patients with spinal cord injury (SCI) [24].

As to the methods of the second group, they measure HRV by seismocardiography (SCG), a simple and non-invasive method of recording cardiac activity from the body movements caused by heart pumping. In a preliminary study, J. Ramos-Castro et al. use a smartphone to record this movement and estimate heart rate [26]. Lei Wang et al. [27] use chest vibrations due to heartbeat as a biometric feature to authenticate users on mobile devices. Moreover, M. Scarpetta et al. describe a method based on simultaneous measurement of heartbeat and respiratory intervals with a smartphone [28].

Specifically, a commodity accelerometer of the smartphone is used to measure SCG signal generated by heart activity and the acceleration generated by respiratory movements. In addition, Mirella Urzeniczok et al. present a mobile application for measuring heart rate in real time based on SCG, where the heartbeat is detected using a modified version of the Pan-Tompkins algorithm [29]. All of the above methods measure HRV based on PPG or SCG. In this work, we used a different strategy to measure HRV based on features of pupillary response, breaking the limitation that measurement from PPG and SCG requires the user to be in a steady state all the time or with help of additional equipment. To our knowledge, this is the first work to monitor user's HRV by pupil information on mobile devices.

Disadvantages

1.In the existing work, the system did not implement Connecting Pupil with HRV model which leads less effective.

2.This system is less performance due to lack of Graph Neural Network and other ml classifiers.

4. PROPOSED SYSTEM

1) We conduct an in-depth study of the relationship between HRV and pupil size in mobile scenarios. To the best of our knowledge, this is the first work to explore the quantitative relationship between people's papillary response and HRV on mobile devices.

2) High-dimensional time-series features associated with user's HRV are identified by using a 1-D CNN to excavate the general physiological processes of papillary responses.

ISSN2321-2152

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Vol 12, Issue 2, 2024

3) We use RNN to train the high-dimensional time-series features extracted by 1-D CNN so as to model the relationship between pupil and HRV.

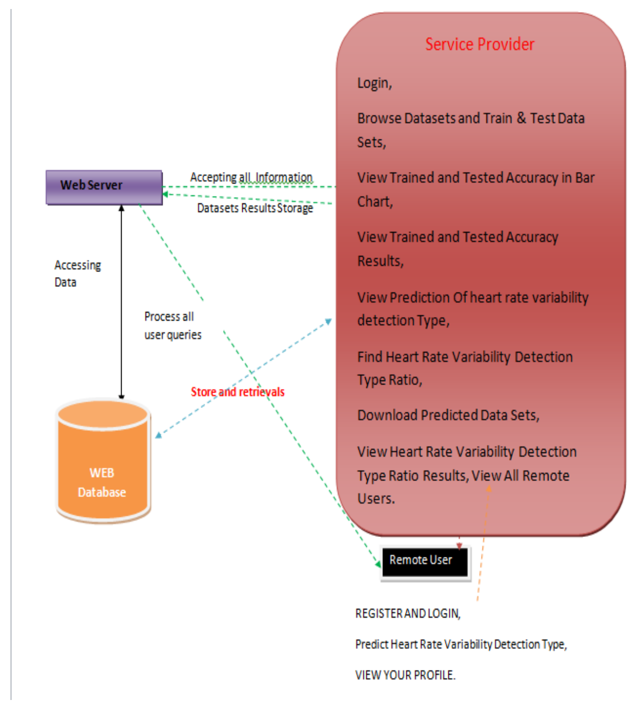
4) We validate the effectiveness of PupilHeart through an extensive trial by recruiting a total of 60 volunteers.1 The results show that the accuracy of PupilHeart achieves up to 91.37% on average.

Advantages

- Convenience. Monitoring HRV on mobile devices is much more portable than professional equipment and does not require special instruments or professional guidance.
- Accuracy. HRV monitoring based on mobile device unlocking involves different time periods and different physiological and mental states of users, which provides more samples and thus guarantees the accuracy of HRV monitoring.

4. SYSTEM ARCHITECTURE

Designing a system architecture for PupilHeart involves several components to ensure the accurate monitoring of heart rate variability (HRV) via pupillary fluctuations. The architecture needs to support data acquisition, processing, storage, and user interaction efficiently and securely. Here's a high-level overview of the system architecture:



Login: Here we can login with Username and Password

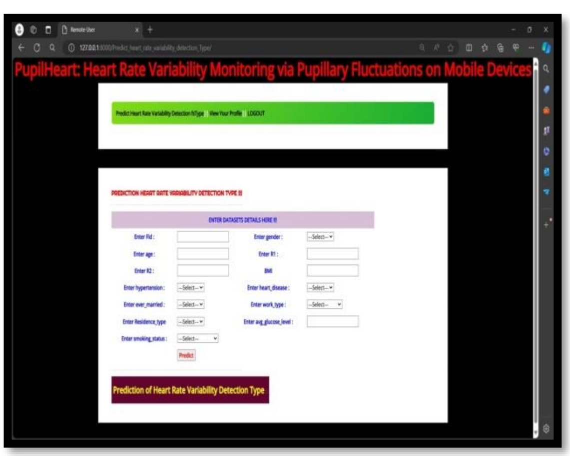
1.Browse IOT Datasets and Train and Test Data Sets : Here, We browse the dataset and it will train the data set and test the data set

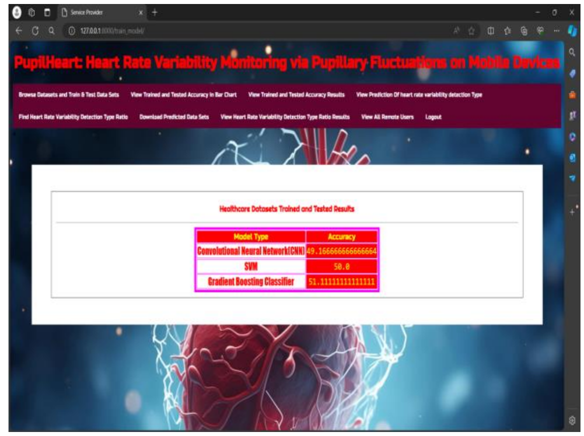
2.View Trained and Tested Accuracy in Bar chart: Here, after trained and tested the accuracy of the data the result will be displayed by bar charts.
3.View Trained and Tested Accuracy Results: Here, it will check the accuracy of the trained and tested data.
4.View Prediction of Heart Rate Detection Status: It will view the prediction of the HeartRate detection status
5.View HeartRate Detection Status Ratio: It will view the HeartRate detection status by the ratio analysis. It display the ratio of HeartRate is Predicted

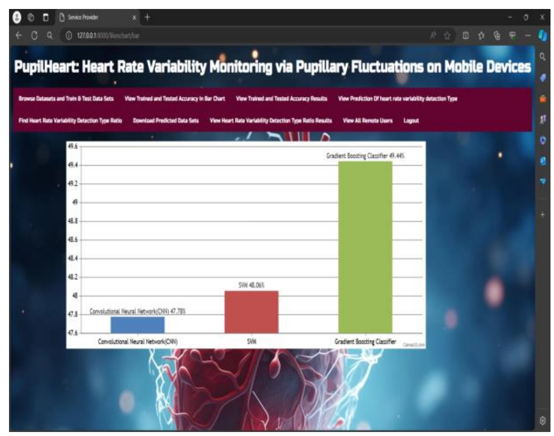
6.Download Predicted Data Sets: It will automatically download the Predicted datasets. It will perform after predicting the data.

7.View All Remote Users: Here, we can see the list of all the remote users who are registered and their status.

5. OUTPUT SCREENS







5. CONCLUSION

In this paper, we have proposed Pupil Heart as a computer vision- based mobile HRV monitoring system, including a mobile terminal and a server side. On the mobile terminal, during face recognition, Pupil Heart has collected pupil size information through the front facing camera on mobile phones. On the server side, after preprocessing the raw pupil size data, Pupil Heart has extracted high-dimension features using 1DCNN, and based on this, has built a pupil-HRV model by RNN. On that basis, Pupil Heart has achieved daily HRV monitoring. We have prototyped Pupil Heart and conducted experimental and field studies to thoroughly evaluate the efficacy of it by recruiting 60 volunteers. The overall results have shown that Pupil Heart can accurately predict a user's HRV when unlocking phones using face recognition. In general, Pupil- Heart provides us with a prototype for exploring pupil size and HRV, shedding lights on a viable yet innovative idea for realizing mobile HRV monitoring systems. In future works, we will expand the diversity of experiments in terms of devices, subjects, and environment conditions to further improve our Pupil Heart system.

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