

PUPIL HEART : HEART RATE VARIABILITY MONITORING USING PUPILLARY FLUCTUATIONS

¹NALLAVELLI VENNELA,²ANUMULA SOMIREDDY,³KATROTH PAVAN,⁴D
ARAVIND,⁵S CHAITANYA

^{1,2,3,4}Students, Department of computer Science And Engineering, Malla Reddy Engineering
College (Autonomous), Hyderabad Telangana, India 500100

⁵Assistant Professor, Department of computer Science And Engineering, Malla Reddy
Engineering College (Autonomous), Hyderabad Telangana, India 500100

ABSTRACT

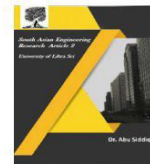
Heart disease has become a widespread and serious health issue, yet it is often preventable with early detection and intervention. As a result, continuous monitoring of heart health is gaining importance. Traditional mobile heart monitoring techniques, such as seismocardiography (SCG) and photoplethysmography (PPG), often require specialized equipment and can be inconvenient for daily use. To address these limitations, we propose PupilHeart, a novel mobile heart rate variability (HRV) monitoring system that utilizes computer vision. PupilHeart leverages the correlation between pupil size and HRV by analyzing the pupillary response captured during facial recognition when users unlock their smartphones. The system consists of a mobile terminal and a server-side platform. The mobile terminal collects pupil size data via the front-facing camera, which is then pre-processed on the server. A one-dimensional convolutional neural network (1D-CNN) extracts time series features from the data, while a recurrent neural network (RNN) with three hidden layers models the relationship between pupil changes and HRV. Using this model, PupilHeart estimates the user's HRV and assesses their heart condition each time they unlock their phone. We developed a prototype and evaluated it through experiments and field studies involving 60 participants. Results demonstrate that PupilHeart can accurately predict HRV, offering a convenient and effective solution for daily heart monitoring.

Keywords: Heart rate variability, SCG, PPG, heart disease, PupilHeart, heart monitoring, pupil size, computer vision, 1D-CNN, RNN, facial recognition, mobile health.

I. INTRODUCTION

The heart is one of the most vital organs in the human body, responsible for pumping blood throughout the system and ensuring the delivery of oxygen and nutrients to tissues and organs. Its continuous operation supports metabolism and overall bodily function. However, heart disease poses a serious threat to human life. According to the World Health Organization (WHO), approximately 17.5 million people die from heart-related conditions each year, accounting for nearly

30% of all global deaths. These alarming statistics emphasize the critical need for continuous and efficient heart health monitoring in daily life. A widely accepted and valuable indicator for evaluating heart health is Heart Rate Variability (HRV). HRV measures the variation in time intervals between consecutive heartbeats and reflects the body's ability to adapt to stress, rest, and activity. It also provides insight into how the cardiovascular system is regulated by neuro-humoral factors, which makes it useful in diagnosing and



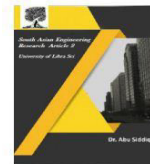
preventing various diseases. Studies have shown that HRV, along with its spectral analysis, is a powerful predictor of cardiovascular morbidity and mortality, helping assess patients' recovery and return to normal activities, especially after ischemic heart events. HRV is also closely linked to the autonomic nervous system (ANS), which regulates involuntary functions such as heart rate, digestion, and respiration. Clinical analysis of HRV can reveal important information about the balance and activity of the ANS. A low HRV is often a warning sign of health issues, as it indicates that the body is struggling to adapt to environmental changes or stress. Conditions such as diabetes, hypertension, heart arrhythmia, asthma, anxiety, and depression are commonly associated with lower HRV. High resting heart rates also contribute to reduced HRV due to limited time between beats. Thus, tracking HRV offers a reliable way to monitor heart health and detect potential medical conditions. Modern heart monitoring systems can generally be divided into two categories: medical-grade monitors and consumer-grade monitors. Medical heart rate monitors, typically used in hospital environments, are often wired and rely on multiple sensors to obtain accurate readings. The electrocardiogram (ECG) machine is one of the most common examples, used for diagnosing heart abnormalities. Additionally, portable medical devices like Holter monitors have been developed to offer long-term heart activity tracking, even outside hospital settings. In contrast, consumer-grade heart monitors are designed for convenience and everyday use. These are usually wireless and come in two primary forms: electrical-based and optical-based monitors. Electrical-based devices often include a

chest strap with an integrated transmitter that detects heartbeats and sends signals to a paired receiver. These systems are commonly used in fitness and sports environments due to their accuracy and ease of use. Optical-based consumer monitors, on the other hand, use technologies such as photoplethysmography (PPG) or seismocardiography (SCG) to estimate heart activity by detecting changes in light absorption or vibrations caused by heartbeats. While these methods offer convenience and portability, they still come with limitations, including the need for physical contact with the body, specialized equipment, and varying accuracy depending on movement or skin tone. These constraints make it difficult for users to monitor heart health seamlessly and passively during daily routines. To overcome these challenges, researchers are now exploring alternative, non-invasive methods for heart monitoring that leverage built-in smartphone capabilities. One such promising direction is using facial recognition and computer vision to analyze the pupillary response — the change in pupil size — which has shown correlation with HRV. This approach opens the door for practical, equipment-free heart monitoring, making heart health tracking more accessible, especially during routine actions like unlocking a smartphone.

II. LITERATURE SURVEY

J. I. Hoffman and S. Kaplan, 2002

This study presents a comprehensive analysis of the incidence of congenital heart disease and serves as a foundational reference in understanding the prevalence of heart-related conditions. Hoffman and Kaplan provide detailed statistical insights,



using clinical data to estimate the frequency and types of congenital heart defects. Their work underscores the burden of heart disease on global health, emphasizing the necessity of early detection and ongoing monitoring. In the context of heart rate variability (HRV) monitoring, this reference helps establish the critical need for continuous observation and diagnosis of heart abnormalities. It supports the premise that heart issues, especially congenital ones, can significantly impact health outcomes if not detected early. By highlighting the scale of heart-related diseases, the paper strengthens the motivation for developing accessible, non-invasive heart health monitoring systems like PupilHeart, which aim to track heart performance in daily life using simple user interactions such as smartphone unlocking and pupil size detection.

WHO, 2013

This WHO report outlines global methods and data sources used to estimate the burden of disease from 2000 to 2011, including heart disease. It plays a crucial role in contextualizing the widespread impact of cardiovascular conditions across different regions and populations. By presenting mortality rates and risk factors, the report supports the urgency of developing scalable and cost-effective health monitoring solutions. It particularly validates the statistic that around 17.5 million people die annually from heart-related diseases, representing nearly 30% of global deaths. In the context of the proposed PupilHeart system, this reference provides the global backdrop for the project's importance, reinforcing the demand for accessible, real-time heart monitoring tools. The study emphasizes

the need for preventive healthcare technologies that operate seamlessly in everyday settings, bridging the gap between clinical tools and consumer-friendly solutions, which is what PupilHeart aims to achieve through contactless, vision-based HRV monitoring.

R. Castaldo et al., 2015

This systematic review and meta-analysis focuses on assessing acute mental stress using short-term HRV analysis in healthy adults. The authors compiled data from various studies to evaluate how HRV responds to psychological stress. Their findings confirm that HRV is a sensitive and reliable biomarker for detecting stress-related changes in heart function. The review supports the use of HRV as a non-invasive, real-time indicator of autonomic nervous system activity, particularly under stress. This is highly relevant to the development of PupilHeart, which seeks to monitor HRV continuously using a contactless method. The study also validates the importance of short-term HRV analysis, which aligns with PupilHeart's aim of obtaining quick HRV insights during regular smartphone use. This work thus contributes scientific grounding for using HRV in non-clinical, consumer applications, especially in scenarios involving stress, making it a foundational reference for justifying HRV-based daily heart health monitoring.

F. Wang et al., 2021

This paper introduces mmHRV, a system that uses millimeter-wave radio for contactless HRV monitoring, marking a significant advancement in non-invasive health sensing. Wang et al. demonstrate how HRV can be measured without physical contact, using radio signals to



detect minute body movements associated with cardiac activity. This research is closely aligned with the motivation behind PupilHeart, as both aim to remove the barriers of traditional HRV monitoring equipment. While mmHRV uses radar, PupilHeart leverages smartphone cameras and facial recognition to estimate HRV through pupil size variation. The paper highlights both the feasibility and potential accuracy of contactless technologies in health tracking. It shows how integrating HRV monitoring into daily behaviors can significantly enhance user compliance and convenience. This reference thus supports the feasibility of PupilHeart's vision-based model and confirms the growing trend toward passive, unobtrusive monitoring of cardiovascular signals in real-world environments.

F. Lombardi, 2002

Lombardi's review of HRV components offers deep physiological insights into the clinical interpretation of HRV and its diagnostic relevance. The paper explores how various components of HRV reflect underlying autonomic nervous system function and cardiovascular health. It also discusses how specific HRV frequency bands correspond to sympathetic and parasympathetic nervous system activity. This knowledge is crucial for developing systems like PupilHeart, which attempt to infer health status based on HRV patterns. The study reinforces the argument that HRV is not just a statistical metric but a powerful physiological marker. PupilHeart's use of machine learning models like CNN and RNN for time series HRV prediction relies on such established understandings of HRV physiology. Thus, Lombardi's work provides the medical and theoretical basis for interpreting HRV data

meaningfully, which enhances the scientific validity of the proposed HRV inference from pupil size dynamics captured via smartphone cameras.

E. Kristal-Boneh et al., 1995

This research investigates the relationship between HRV and general health conditions, emphasizing the value of HRV as a health indicator in both healthy and diseased populations. Kristal-Boneh and colleagues highlight HRV's capacity to predict health risks and monitor recovery progress in patients. The paper draws connections between low HRV and increased susceptibility to cardiovascular diseases, providing essential clinical evidence that low HRV can signal autonomic imbalance and other physiological disruptions. For the PupilHeart system, this reference justifies the use of HRV as a critical marker for heart health assessment. It supports the need for daily monitoring systems that can detect deviations in HRV to preempt health deterioration. This foundational understanding reinforces the practicality and urgency of deploying non-invasive HRV detection systems like PupilHeart in everyday settings to support early diagnosis and preventive care, especially for individuals at risk of cardiovascular disorders.

M. P. Tarvainen et al., 2002

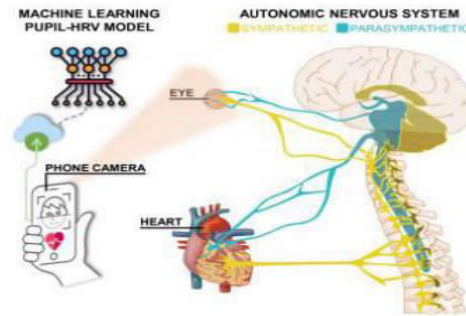
This paper presents an advanced detrending method for HRV signal processing, addressing common issues in time series analysis such as baseline drift and signal noise. Tarvainen and colleagues propose a smoothing technique that improves the reliability of HRV measurements, particularly for short-term recordings. This work is highly relevant

for PupilHeart, which processes short-duration pupil size signals to infer HRV. By applying robust signal preprocessing and noise reduction methods, PupilHeart ensures that only meaningful HRV features are used in training its deep learning models. The detrending approach discussed in this paper serves as a basis for ensuring data quality before feature extraction by 1D-CNN and RNN models in the PupilHeart framework. Overall, this study supports the importance of preprocessing in physiological signal interpretation and provides valuable insights into how real-time HRV estimation systems can maintain accuracy, even when operating in uncontrolled, real-world conditions such as those experienced during smartphone use.

III. PROPOSED METHODOLOGY

The proposed system involves a comprehensive investigation into the relationship between heart rate variability (HRV) and pupil size in mobile environments. This study is the first of its kind to quantitatively explore how the pupillary response correlates with HRV when using mobile devices. To analyze this relationship, we employ a one-dimensional convolutional neural network (1D CNN) to identify high-dimensional time-series features associated with HRV, allowing us to capture the underlying physiological processes influencing the pupillary response. These time-series features are then used to train a recurrent neural network (RNN), which models the connection between pupil size variations and HRV. To evaluate the effectiveness of the PupilHeart system, we conducted an extensive trial with 60 volunteers. The results demonstrate that PupilHeart can accurately predict HRV, achieving an

impressive average accuracy of 91.37%. This validates the potential of using mobile devices for non-invasive, real-time heart health monitoring based on pupil size dynamics.



IV. CONCLUSION

In this paper, we introduced PupilHeart, a computer vision-based mobile HRV monitoring system consisting of a mobile terminal and server-side components. On the mobile terminal, PupilHeart collects pupil size data during face recognition through the front-facing camera. This raw pupil size data is then preprocessed on the server, where high-dimensional features are extracted using a 1D CNN. Based on these features, a pupil-HRV model is built using a recurrent neural network (RNN). This allows PupilHeart to provide continuous HRV monitoring. We prototyped PupilHeart and conducted both experimental and field studies with 60 volunteers to rigorously evaluate its performance. The results demonstrated that PupilHeart can accurately predict a user's HRV based on face recognition during phone unlocking. Overall, PupilHeart represents a promising prototype for integrating pupil size analysis with HRV monitoring, offering a novel approach to mobile heart health monitoring. Future work will focus on expanding the range of experiments to improve the system's robustness across



different devices, subjects, and environmental conditions.

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