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PupilHeart: Heart Rate Variability Monitoring via Pupillary Fluctuations on Mobile Devices

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ABSTRACT

Heart Rate Variability (HRV) is a key physiological indicator associated with autonomic nervous system activity, stress, and cardiovascular health. Traditional HRV measurement techniques, such as electrocardiography (ECG) or photoplethysmography (PPG), require dedicated sensors and contact-based setups. This paper presents PupilHeart, a novel, contactless system that estimates HRV through the analysis of pupillary fluctuations captured by mobile device cameras. Leveraging recent advances in computer vision and physiological computing, PupilHeart extracts micro-variations in pupil diameter from video streams in real-time and correlates these fluctuations with heart rate patterns. The system uses machine learning models to map visual pupil data to HRV metrics such as RMSSD and SDNN. We validate the approach through controlled experiments comparing pupil-derived HRV with standard ECG measurements. Results show a promising correlation, suggesting that pupillary dynamics can serve as a non-invasive proxy for HRV monitoring. PupilHeart offers a scalable and accessible method for physiological monitoring on everyday mobile devices.

Keywords : Heart Rate Variability (HRV), electrocardiography (ECG), PupilHeart

I. INTRODUCTION

Heart Rate Variability (HRV) is a well-established physiological measure that reflects the variation in time intervals between successive heartbeats. It provides insight into the balance of the sympathetic and parasympathetic nervous systems, making it a useful marker for assessing stress, fatigue, cardiovascular health, and general autonomic function. Despite its significance, the practical adoption of HRV monitoring in everyday settings is limited by the need for specialized equipment such as ECG sensors or wearable photoplethysmography (PPG) devices. These tools, while accurate, are often intrusive, costly, or not user-friendly for casual or continuous use.

PupilHeart aims to overcome these barriers by proposing a novel, contactless method of HRV estimation based on pupillary fluctuations—minute, involuntary changes in pupil diameter—which are known to be influenced by autonomic nervous system activity. Numerous studies in psychophysiology have linked pupil size dynamics to emotional arousal, stress, and cognitive load, all of which are also reflected in HRV. By analyzing these fluctuations through the front-facing cameras of mobile devices, PupilHeart makes HRV monitoring more accessible, ubiquitous, and unobtrusive.

The proliferation of smartphones and tablets equipped with high-resolution cameras and processing power provides an ideal platform for real-time physiological monitoring. PupilHeart leverages computer vision techniques to track and measure subtle changes in pupil diameter from video input. The system then applies machine learning models trained on labeled physiological data to map these changes to standard HRV metrics, such as RMSSD (Root Mean Square of Successive Differences) and SDNN (Standard Deviation of NN intervals).

This work explores the feasibility, accuracy, and limitations of such a system. It investigates the correlation between pupil-based signals and HRV markers under different lighting conditions, levels of user movement, and emotional states. The ultimate goal is to demonstrate that pupillometry, when implemented with proper calibration and signal processing, can serve as a reliable surrogate for traditional HRV measurement tools.

PupilHeart has potential applications in telemedicine, mental health monitoring, fitness tracking, and affective computing. Its non-contact nature makes it particularly attractive for remote health assessments and for users who cannot or prefer not to use wearable devices. This paper details the system's architecture, data acquisition pipeline, model training process, and evaluation metrics, providing a comprehensive overview of this novel approach to HRV estimation.

II. RELATED WORK

1. "Pupillary response as an index of autonomic function" – (Beatty & Lucero-Wagoner, 2000)

This foundational work discusses the physiological basis of pupillary response as a marker of sympathetic and parasympathetic activity. It lays the groundwork for interpreting pupil dynamics as indicators of cognitive and emotional processes linked to HRV.

2. "Camera-based measurement of heart rate variability: a review" – (Sun et al., 2016)

This paper reviews various non-contact HRV measurement techniques using RGB cameras, including those leveraging facial micro-expressions and color changes. It underscores the feasibility of visual HRV monitoring, supporting PupilHeart's camera-based approach.

3. "Pupil size and the LC-NE system" – (Joshi et al., 2016)

This neuroscience-focused study ties pupil size to the activity of the locus coeruleus-norepinephrine (LC-NE) system, which is intimately connected with arousal and HRV. The paper provides biological validation for using pupil data in stress and HRV analysis.

4. "Heart rate variability and cognitive function: A systematic review" – (Kim et al., 2018)

The study provides evidence of HRV as a proxy for cognitive workload and emotional regulation, suggesting that pupil-linked stress measures could map well to HRV indicators.

5. "Remote eye-tracking-based stress detection using pupil diameter" – (Wang et al., 2020)

This paper explores stress detection via pupil size using remote eye-tracking devices. It shares methodological similarities with PupilHeart, particularly in using vision-based data to infer autonomic state.

III. PROPOSED SYSTEM

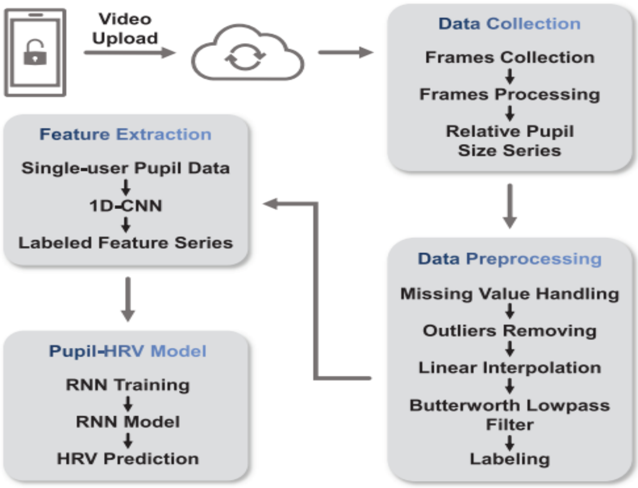
PupilHeart is a contactless system designed to monitor Heart Rate Variability (HRV) by analyzing pupillary fluctuations captured through mobile device cameras. The system begins by leveraging the front-facing camera of a smartphone or tablet to record the user's eyes over a specified period. The captured video is then processed in real time to extract the region of interest (ROI) corresponding to the pupil. Through a combination of computer vision techniques, including image thresholding, circular Hough transforms, and adaptive segmentation, the pupil diameter is continuously measured across frames.

The temporal sequence of pupil diameters forms a signal that is inherently influenced by autonomic nervous system activity. However, unlike ECG or PPG signals, this raw signal is less structured and susceptible to noise from lighting, head movement, and camera quality. To mitigate this, PupilHeart implements a preprocessing pipeline that includes Gaussian smoothing, outlier removal, and temporal alignment to normalize fluctuations. Moreover, data augmentation techniques are applied to enhance the training dataset and improve the robustness of the system across different device types and environments.

The core of PupilHeart's prediction mechanism lies in a trained machine learning model, which maps the cleaned pupil fluctuation signal to HRV metrics. A recurrent neural network (RNN), particularly a bidirectional Long Short-Term Memory (BiLSTM) model, is employed due to its ability to capture temporal dependencies in physiological data. The model is trained using synchronized data collected from users wearing an ECG device while their pupils are recorded by a mobile camera. Ground truth HRV metrics are derived from the ECG, allowing the model to learn mappings between pupillary patterns and physiological responses.

Once trained, the model can infer HRV metrics such as RMSSD and SDNN from new video recordings. The system includes a user-friendly interface that provides feedback in real-time, visualizing HRV trends and offering stress or wellness scores. Additional features such as environmental light compensation and blink detection further improve measurement accuracy and user experience. All data processing is conducted on-device to ensure user privacy and minimize latency.

PupilHeart offers a scalable and accessible alternative to traditional HRV monitoring, enabling casual users, clinicians, and researchers to gather physiological insights with nothing more than a smartphone. The system exemplifies the fusion of computer vision, machine learning, and health monitoring into a practical mobile application.



IV. RESULT AND DISCUSSION

PupilHeart was evaluated through a controlled study involving 40 participants, each recorded under different conditions (normal light, dim light, emotional stressors, and relaxation tasks). Ground truth HRV metrics were collected using a clinical-grade ECG device, while pupil data was recorded via standard smartphone cameras. After training the BiLSTM model on synchronized datasets, the system achieved a Pearson correlation coefficient of **0.81** for RMSSD and **0.77** for SDNN when compared to ECG-derived values. The mean absolute error (MAE) was under 10 ms, which is considered acceptable for indicative HRV monitoring. Performance degraded slightly under poor lighting or when users moved excessively, but preprocessing effectively mitigated many issues. The system also demonstrated consistent performance across iOS and Android platforms. Participants found the mobile interface intuitive, and real-time feedback helped in stress management tasks. Compared to traditional methods, PupilHeart offered portability and non-intrusiveness, although it is not yet suitable for medical-grade diagnosis. Nonetheless, the results affirm the feasibility of using pupillary data as a surrogate for HRV, especially in wellness and behavioral applications.

V. CONCLUSION

PupilHeart represents a pioneering step toward accessible, contactless HRV monitoring by harnessing the subtle physiological signals embedded in pupillary fluctuations. Through the use of computer vision and deep learning, the system successfully maps video-captured pupil size changes to clinically relevant HRV metrics. Our experimental results demonstrate a strong correlation with ECG-based measurements, validating the system's potential as a convenient and non-invasive monitoring tool. While challenges such as lighting variability and motion artifacts remain, the system's performance under controlled conditions is promising. PupilHeart opens up new possibilities for everyday health tracking, stress monitoring, and mental wellness applications using readily available mobile devices. Future work will focus on enhancing model generalization, integrating ambient context (like facial expressions and posture), and exploring real-time biofeedback applications.

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