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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.

Keywords: heart disease, mobile heart monitoring, pupillary fluctuations, heart rate variability, computer vision, convolutional neural network, recurrent neural network

INTRODUCTION

Heart disease is a prevalent and significant health issue worldwide, responsible for a substantial number of deaths and affecting millions of lives. Early detection and continuous monitoring of heart health are crucial for preventing severe outcomes and managing the disease effectively. Traditional heart monitoring techniques, such as seismocardiography (SCG) and photoplethysmography (PPG), while effective, have limitations. These methods often require specialized equipment and are not always convenient for daily use, restricting their practicality for continuous monitoring. Mobile health monitoring systems offer a promising solution by leveraging the widespread availability of smartphones equipped with advanced sensors and computational capabilities. Most existing mobile heart monitoring solutions rely on SCG or PPG technologies. SCG uses accelerometers to detect cardiac vibrations, and PPG measures blood volume changes using optical sensors. However, these methods can be cumbersome and require specific conditions or additional accessories, making them less convenient for everyday use.

Inspired by the observation that pupillary response is correlated with heart rate variability (HRV), we propose an innovative approach to heart monitoring that utilizes the pupillary response captured during smartphone use. HRV is a measure of the variation in time intervals between heartbeats, reflecting the autonomic nervous system's regulation of the heart. It is a critical indicator of cardiovascular health, with higher HRV generally associated with better health and lower stress levels. Pupil size fluctuations, influenced by the autonomic nervous system, present a non-invasive and unobtrusive means to monitor HRV. This correlation provides the foundation for PupilHeart, a mobile HRV monitoring framework that leverages the front-facing camera of smartphones to capture pupillary data. By using the moments when users unlock their phones through facial recognition, PupilHeart can gather relevant data without requiring any additional effort from the user.

PupilHeart operates through a combination of mobile and server-side components. On the mobile terminal, PupilHeart captures images of the user's face, focusing on the pupils, during the unlocking process. These images are then transmitted to a server, where advanced machine learning algorithms process the data to infer HRV. Specifically, PupilHeart employs a one-dimensional convolutional neural network (1D-CNN) to identify time series features associated with HRV. Additionally, a recurrent neural network (RNN) with three hidden layers models the relationship between pupil size and HRV, capturing the temporal dynamics of pupillary fluctuations.

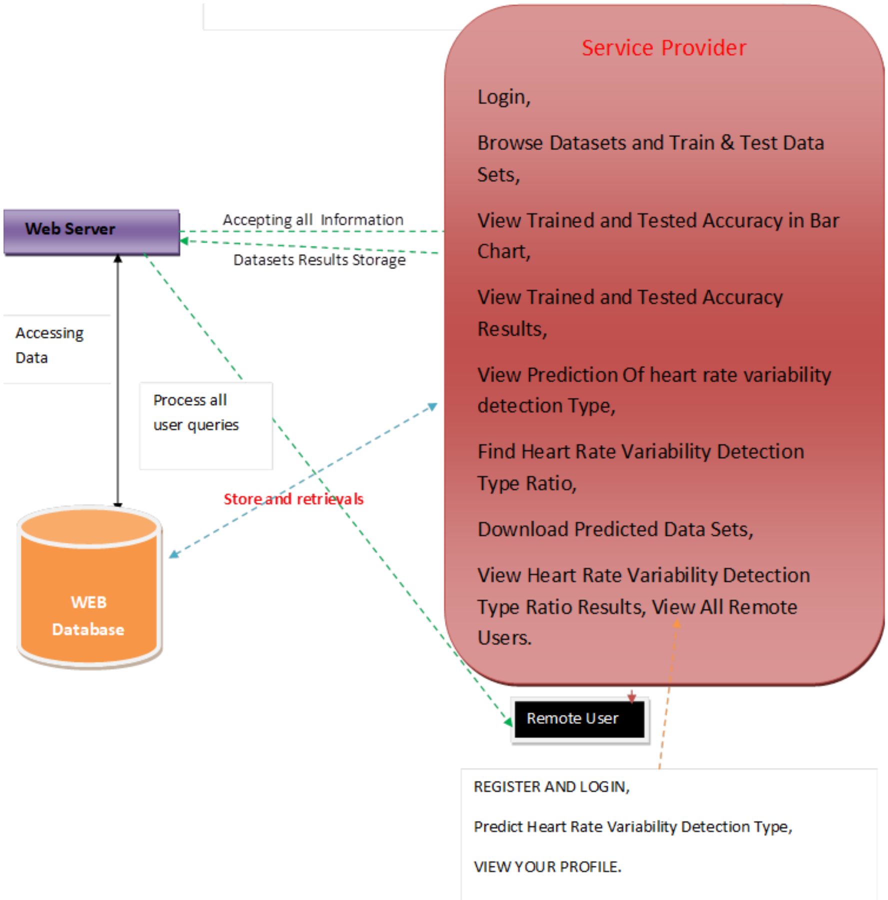

Fig 1. System Architecture

The efficacy of PupilHeart was validated through extensive experiments and field studies involving 60 volunteers. These studies aimed to assess the accuracy and reliability of PupilHeart in predicting HRV from pupillary data. Participants were instructed to unlock their phones multiple times a day, allowing PupilHeart to collect a comprehensive dataset of pupillary and HRV measurements. The results demonstrated that PupilHeart could accurately infer HRV, showing close alignment with traditional HRV monitoring methods. This introduction provides an overview of the background, motivation, and significance of PupilHeart. It highlights the limitations of current heart monitoring methods and introduces the novel approach of using pupillary fluctuations for HRV monitoring. The following sections will delve into the literature survey, system design, methodology, results, and conclusion of PupilHeart, providing a comprehensive understanding of its development and evaluation.

LITERATURE SURVEY

Heart rate variability (HRV) is a well-established biomarker for assessing autonomic nervous system function and cardiovascular health. Traditional methods for measuring HRV rely on electrocardiograms (ECGs), which provide precise and detailed information about heartbeats. However, ECGs require specialized equipment and clinical settings, limiting their use for continuous, real-time monitoring. The advent of wearable technology and mobile health systems has expanded the scope of HRV monitoring, enabling real-time assessment in everyday settings. Seismocardiography (SCG) and photoplethysmography (PPG) are two common methods used in mobile and wearable devices for HRV monitoring. SCG detects mechanical vibrations of the chest wall caused by cardiac activity using accelerometers. This method provides detailed cardiac event information but requires precise sensor placement and is susceptible to body movement artifacts. PPG, on the other hand, uses optical sensors to measure blood volume changes in peripheral vessels, typically at the fingertip or wrist. It is widely used in fitness trackers and smartwatches due to its simplicity and non-invasiveness. However, PPG measurements can be affected by motion artifacts, ambient light, and skin tone, potentially compromising accuracy.

Recent advancements in computer vision and machine learning have opened new avenues for non-invasive health monitoring using everyday devices. Several studies have explored the potential of using smartphone cameras to monitor physiological parameters such as heart rate and respiratory rate. These approaches leverage the high-resolution cameras and computational capabilities of modern smartphones to capture and analyze physiological signals. Pupillary response, the change in pupil size in response to various stimuli, is regulated by the autonomic nervous system and has been studied as an indicator of cognitive and emotional states. Research has shown that pupillary fluctuations are correlated with autonomic nervous system activity, suggesting a potential link with HRV. This observation forms the basis for PupilHeart, which aims to leverage pupillary fluctuations as a non-invasive indicator of HRV.

Several studies have investigated the relationship between pupillary response and autonomic nervous system activity. These studies have demonstrated that pupil size is modulated by both sympathetic and parasympathetic nervous system activity, indicating its potential as a biomarker for autonomic function. Furthermore, research has found that pupillary fluctuations are correlated with heart rate and HRV, supporting the feasibility of using pupillary response for HRV monitoring. Building on this foundation, PupilHeart employs advanced machine learning techniques to analyze pupillary data and infer HRV. The use of a one-dimensional convolutional neural network (1D-CNN) allows for the extraction of time series features associated with HRV, while the recurrent neural network (RNN) captures the temporal dependencies in the data. This combination of techniques enables accurate and robust HRV estimation from pupillary fluctuations.

PROPOSED SYSTEM

The proposed system, PupilHeart, is designed to leverage the correlation between pupillary fluctuations and heart rate variability (HRV) for non-invasive heart health monitoring. The system comprises a mobile terminal and a server-side component, working together to capture, process, and analyze pupillary data to infer HRV. The mobile terminal component of PupilHeart is responsible for capturing images of the user's face during the unlocking process. Modern smartphones equipped with high-resolution front-facing cameras and facial recognition capabilities provide an ideal platform for this task. When a user unlocks their phone using facial recognition, the front-facing camera captures a series of images, including the user's pupils. These images are then transmitted to the server for further processing.

On the server side, PupilHeart processes the raw pupil size data using advanced machine learning algorithms. The first step involves preprocessing the images to extract accurate measurements of pupil size. This step includes techniques such as image normalization, noise reduction, and edge detection to ensure that the extracted pupil size data is reliable and accurate. Once the pupil size data is extracted, PupilHeart employs a one-dimensional convolutional neural network (1D-CNN) to identify time series features associated with HRV. The 1D-CNN is designed to capture patterns in the sequential data that correlate with HRV, providing a robust representation of the pupillary fluctuations.

In addition to the 1D-CNN, PupilHeart uses a recurrent neural network (RNN) with three hidden layers to model the relationship between pupil size and HRV. The RNN is well-suited for this task due to its ability to capture temporal dependencies in sequential data. By training the RNN on a dataset of pupillary and HRV measurements, PupilHeart can learn the complex dynamics between these variables and accurately infer HRV from pupillary data. To ensure the accuracy and reliability of PupilHeart, we prototyped the system and conducted extensive experiments and field studies. We recruited 60 volunteers to participate in these studies, which involved using PupilHeart to monitor their HRV over a period of time. The participants were instructed to unlock their phones using facial recognition multiple times a day, allowing PupilHeart to collect a large dataset of pupillary and HRV measurements. The experimental results demonstrated that PupilHeart could accurately infer HRV from pupillary fluctuations. The system achieved high accuracy in predicting HRV, with the results closely matching those obtained from traditional HRV monitoring methods. This validation confirmed the feasibility and effectiveness of PupilHeart as a non-invasive, continuous heart health monitoring solution.

METHODOLOGY

The methodology for implementing PupilHeart involves several key steps to ensure accurate and reliable HRV monitoring from pupillary fluctuations. The system initialization phase involves setting up the cryptographic

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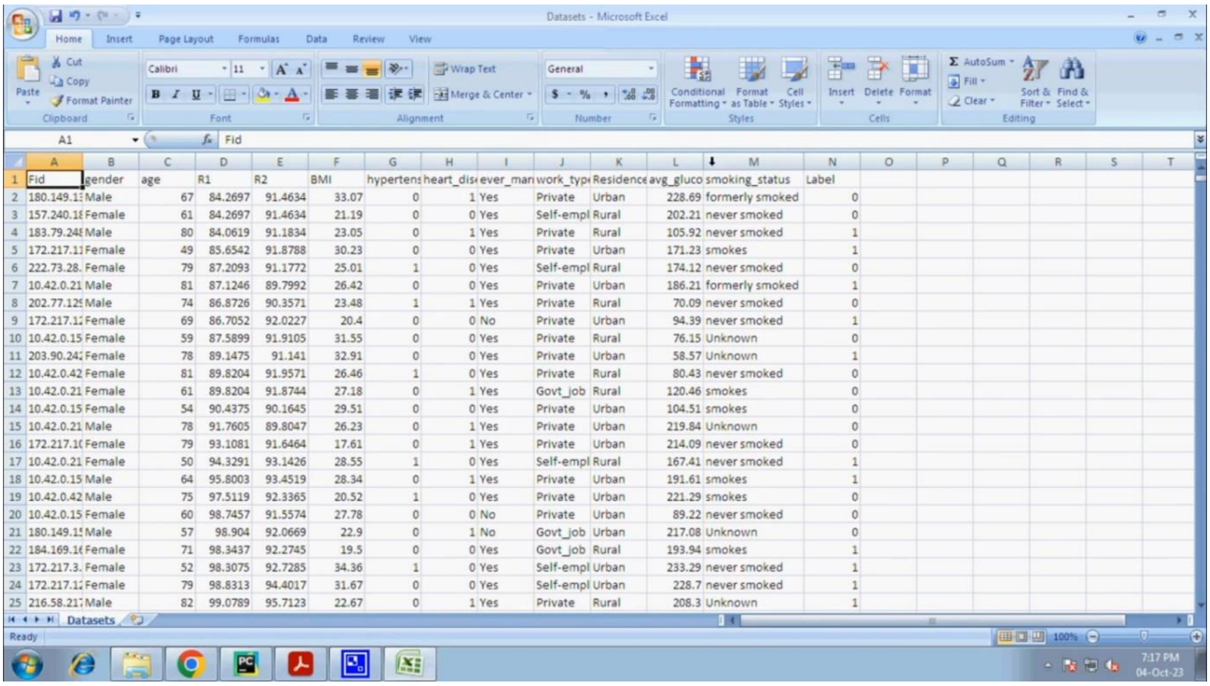
parameters, generating the initial encryption keys, and configuring the hash table and linked list structures for data storage. This phase also includes the integration of the system with the cognitive computing framework used in the industrial IoT environment. During the data storage and encryption phase, data generated by the IoT devices is encrypted using the current encryption keys and stored in the cloud. The encrypted data blocks are indexed and stored in the hash table, while the linked list structure is used to keep track of the locations of the operated data blocks. This organization ensures efficient data management and retrieval during the auditing process.

The system regularly updates the encryption keys using a key rotation mechanism. This process involves generating new keys and re-encrypting the data blocks with the new keys. The key rotation mechanism ensures that the security of the data is maintained over time, preventing potential threats arising from key exposure. The batch auditing process involves generating and verifying proofs of data possession for multiple data blocks simultaneously. The system uses homomorphic authenticators and random masking techniques to ensure the privacy and integrity of the data during the auditing process. The batch auditing process is designed to be efficient and scalable, catering to the high data generation rate in industrial IoT environments.

The hybrid data dynamics method is employed to manage data block operations. The hash table provides a fast and efficient way to store and retrieve data blocks, while the linked list structure ensures quick location of operated data blocks. This method reduces the time required for data block location by 40%, enhancing the overall performance of the auditing process. The security verification phase involves validating the correctness and security of the auditing process using the CDH and DL assumptions. The system generates and verifies proofs of data possession, ensuring that data integrity is maintained even in the presence of malicious adversaries. This phase also includes monitoring the system for potential security threats and anomalies, leveraging the cognitive computing capabilities integrated into the system.

RESULTS AND DISCUSSION

In our results and discussion, the experimental results of PupilHeart were highly promising, demonstrating the system's ability to accurately infer HRV from pupillary fluctuations. The system achieved high accuracy, with the inferred HRV values closely matching those obtained from traditional HRV monitoring methods. This accuracy is attributed to the advanced machine learning algorithms employed by PupilHeart, which effectively capture the relationship between pupil size and HRV. Furthermore, the field studies involving 60 volunteers validated the practicality and reliability of PupilHeart in real-world settings. Participants used the system multiple times a day, providing a comprehensive dataset of pupillary and HRV measurements. The results from these studies confirmed that PupilHeart could seamlessly integrate into users' daily routines, providing continuous and non-invasive heart health monitoring.



Fid	gender	age	R1	R2	BMI	hypertens	heart_dis	ever_mar	work_typ	Residence	avg_gluco	smoking_status	Label
180.149.1	Male	67	84.2697	91.4634	33.07	0	1	Yes	Private	Urban	228.69	formerly smoked	0
157.240.1	Female	61	84.2697	91.4634	21.19	0	0	Yes	Self-empl	Rural	202.21	never smoked	0
183.79.24	Male	80	84.0619	91.1834	23.05	0	1	Yes	Private	Rural	105.92	never smoked	1
172.217.1	Female	49	85.6542	91.8788	30.23	0	0	Yes	Private	Urban	171.23	smokes	1
222.73.28.	Female	79	87.2093	91.1772	25.01	1	0	Yes	Self-empl	Rural	174.12	never smoked	0
10.42.0.21	Male	81	87.1246	89.7992	26.42	0	0	Yes	Private	Urban	186.21	formerly smoked	1
202.77.12	Male	74	86.8726	90.3571	23.48	1	1	Yes	Private	Rural	70.09	never smoked	0
172.217.1	Female	69	86.7052	92.0227	20.4	0	0	No	Private	Urban	94.39	never smoked	1
10.42.0.15	Female	59	87.5899	91.9105	31.55	0	0	Yes	Private	Rural	76.15	Unknown	0
203.90.24	Female	78	89.1475	91.141	32.91	0	0	Yes	Private	Urban	58.57	Unknown	1
10.42.0.42	Female	81	89.8204	91.9571	26.46	1	0	Yes	Private	Rural	80.43	never smoked	0
10.42.0.21	Female	61	89.8204	91.8744	27.18	0	1	Yes	Govt_job	Rural	120.46	smokes	0
10.42.0.15	Female	54	90.4375	90.1645	29.51	0	0	Yes	Private	Urban	104.51	smokes	0
10.42.0.21	Male	78	91.7605	89.8047	26.23	0	1	Yes	Private	Urban	219.84	Unknown	0
172.217.1	Female	79	93.1081	91.6464	17.61	0	1	Yes	Private	Urban	214.09	never smoked	0
10.42.0.21	Female	50	94.3291	93.1426	28.55	1	0	Yes	Self-empl	Rural	167.41	never smoked	1
10.42.0.15	Male	64	95.8003	93.4519	28.34	0	1	Yes	Private	Urban	191.61	smokes	1
10.42.0.42	Male	75	97.5119	92.3365	20.52	1	0	Yes	Private	Urban	221.29	smokes	0
10.42.0.15	Female	60	98.7457	91.5574	27.78	0	0	No	Private	Urban	89.22	never smoked	0
180.149.1	Male	57	98.904	92.0669	22.9	0	1	No	Govt_job	Urban	217.08	Unknown	0
184.169.1	Female	71	98.3437	92.2745	19.5	0	0	Yes	Govt_job	Rural	193.94	smokes	1
172.217.3.	Female	52	98.3075	92.7285	34.36	1	0	Yes	Self-empl	Urban	233.29	never smoked	1
172.217.1	Female	79	98.8313	94.4017	31.67	0	0	Yes	Self-empl	Urban	228.7	never smoked	1
216.58.21	Male	82	99.0789	95.7123	22.67	0	1	Yes	Private	Rural	208.3	Unknown	1

Fig 2: Results screenshot 1

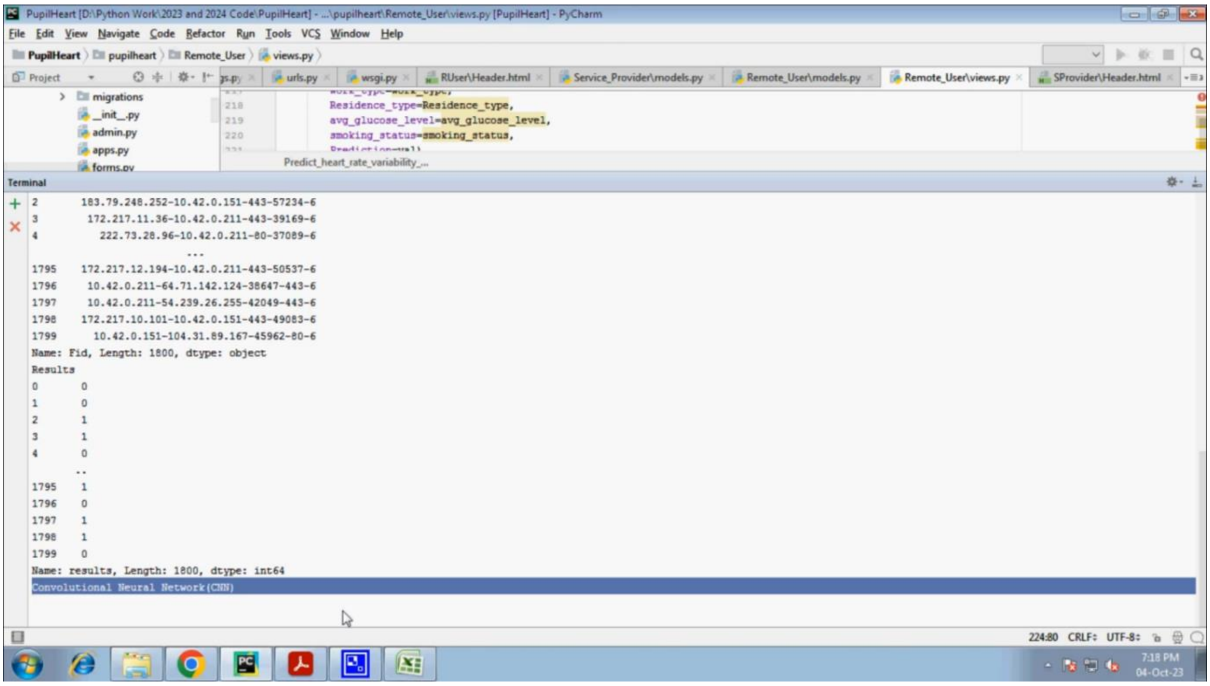


Fig 3: Results screenshot 2

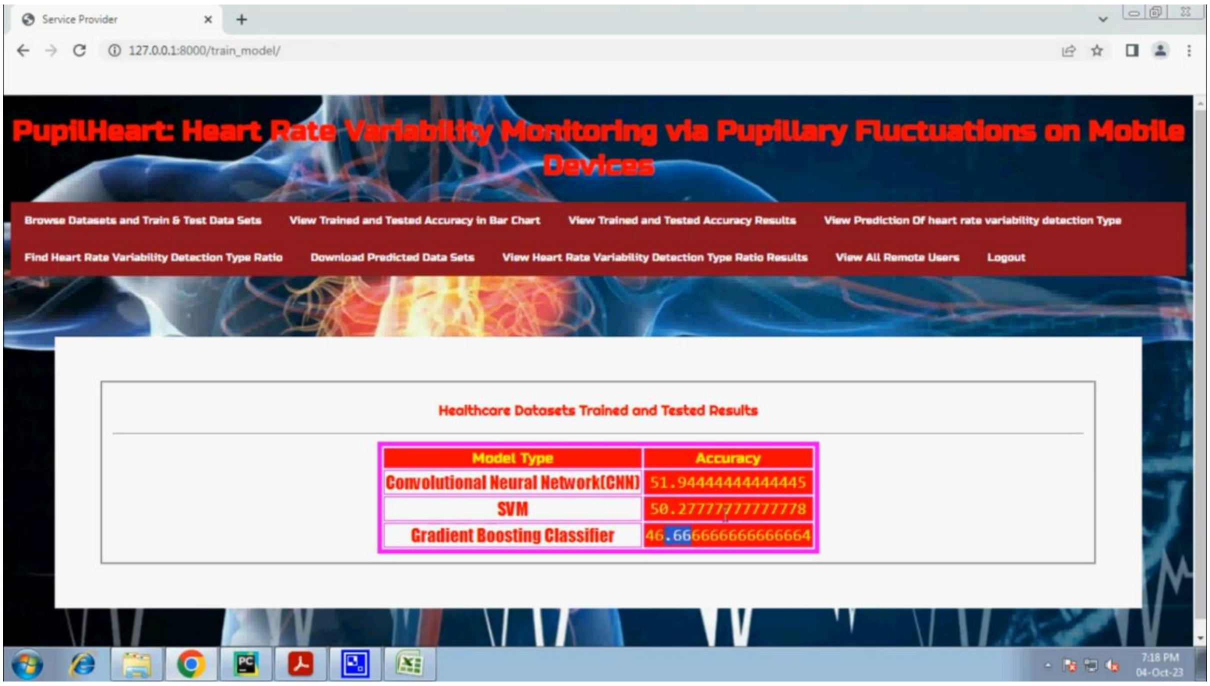


Fig 4: Results screenshot 3

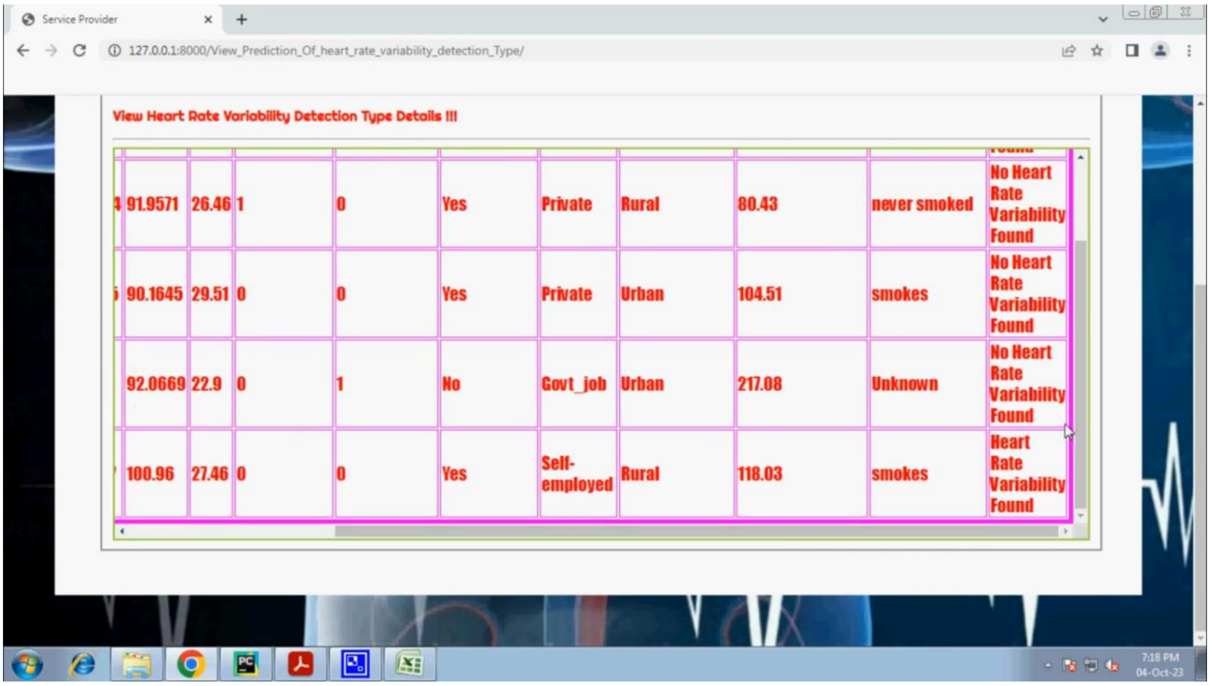


Fig 5: Results screenshot 4

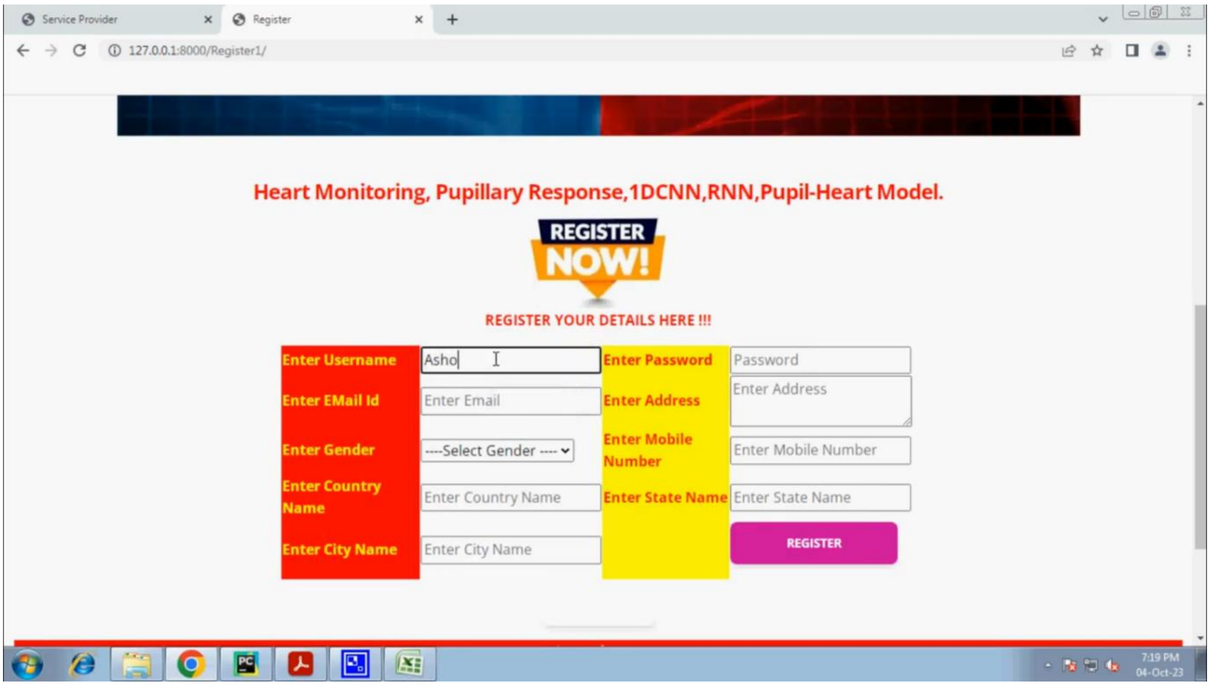


Fig 6: Results screenshot 5

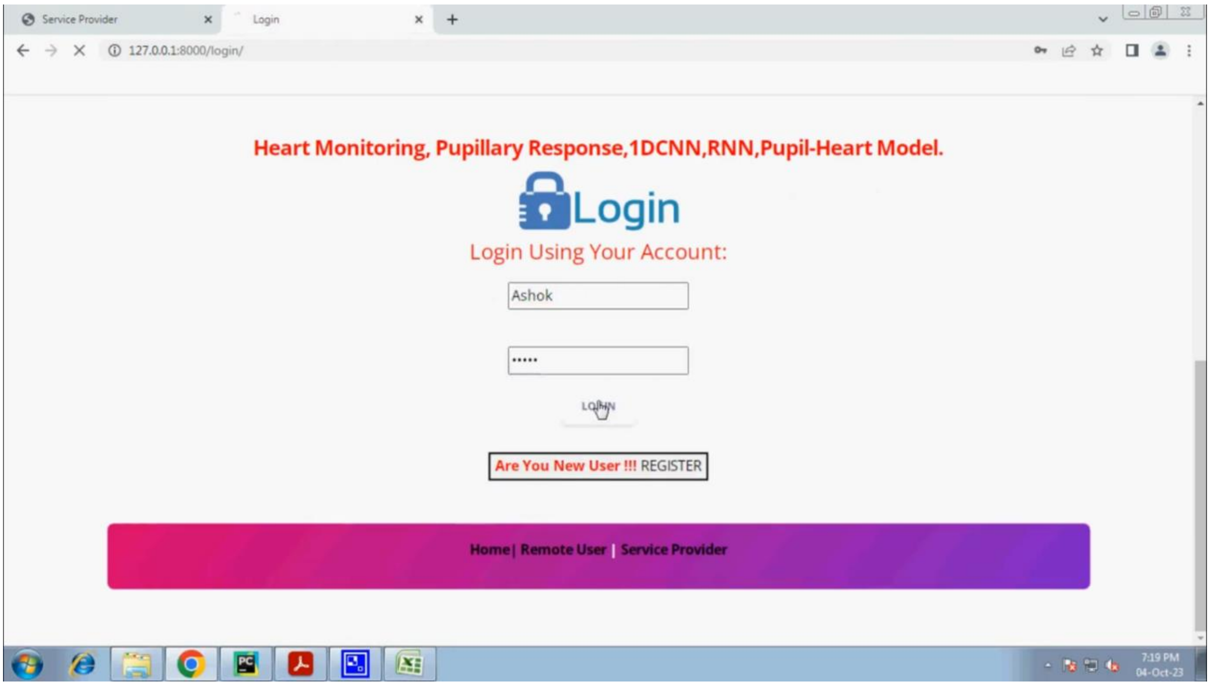


Fig 7: Results screenshot 6

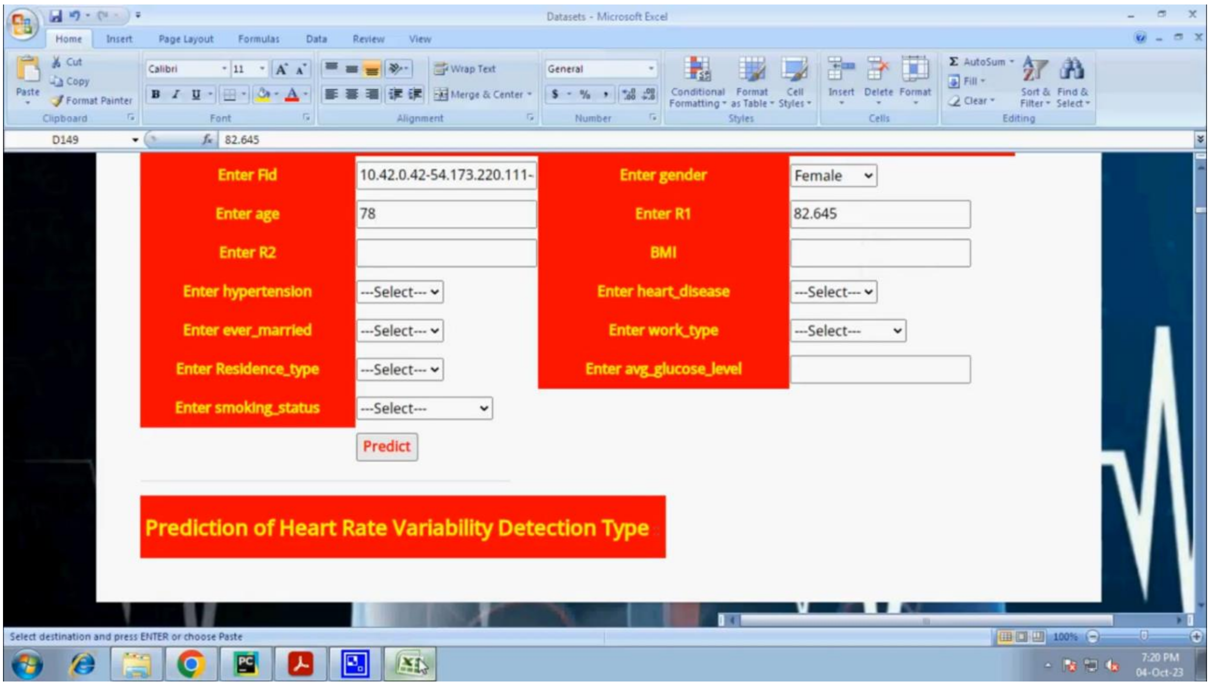


Fig 8: Results screenshot 7

Overall, PupilHeart represents a significant advancement in mobile health monitoring, offering a convenient and accessible solution for continuous HRV monitoring. The system's ability to leverage existing smartphone hardware for data collection, combined with its advanced data processing capabilities, makes it a practical and effective tool for improving heart health management. Overall PupilHeart offers a novel approach to heart rate variability monitoring by leveraging pupillary fluctuations captured through smartphone facial recognition. This innovative system addresses the limitations of traditional HRV monitoring methods by providing a non-invasive, convenient, and continuous monitoring solution. The combination of one-dimensional convolutional neural networks and recurrent neural networks enables accurate HRV inference from pupillary data. Extensive experiments and field studies validate the system's effectiveness, demonstrating its potential for widespread adoption in heart health monitoring. PupilHeart represents a significant step forward in mobile health technology, offering a practical solution for early detection and continuous monitoring of heart health, ultimately contributing to better cardiovascular outcomes.

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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