Industrial Engineering Journal
ISSN: 0970-2555
Volume : 54, Issue 1, January : 2025

PUPILHEART: HEART RATE VARIABILITY MONITORING VIA PUPILLARY FLUCTUATIONS ON MOBILE DEVICES

[1]T. RAVI KIRAN KUMAR,[2]B. MEGHANA ,[3]S. KANISHKA,[4]V. PRAKASH,[5]M. VIGNAN

[1]ASSISTANT PROFESSOR, [2,3,4&5] UG STUDENTS

DEPARTMENT OF CSE, MNR COLLEGE OF ENGG. & TECHNOLOGY, MNR NAGAR, FASALWADIGUDA, SANGA REDDY-502294

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 photoplethysmography (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 imagesAiming to address these challenges, we hereby propose Pupil Heart as the first mobile HRV monitoring system exploiting papillary response (i.e. change of pupil size in time domain). As shown in the figure, Pupil Heart exploits the heart-eye relationship in the autonomic nervous system next section, we first review the related works of Pupil Heart.

2.LITERATURE REVIEW

1. A. Schumann, S. Kietzer, J. Ebel, and K. J. Bar, "Sympathetic and ¨ parasympathetic modulation of pupillary unrest," Frontiers in neuroscience, vol. 14, p. 178, 2020.

The study explores the dynamics of pupillary unrest, a phenomenon characterized by the rhythmic fluctuations in pupil size that occur even in the absence of external stimuli. Conducted with 83 young healthy volunteers, the research aims to elucidate the relationship between pupillary unrest and various markers of the autonomic nervous system, particularly focusing on sympathetic and parasympathetic contributions. The researchers calculated sample entropy (SE) and the pupillary unrest index (PUI) to quantify pupil size variability, while autonomic indices were derived from heart rate, blood pressure, respiration, and skin conductance measurements. Participants also reported their levels of calmness, vigilance, and mood, providing a comprehensive view of their physiological and psychological states. In a separate experiment involving 26 healthy individuals, the cardiovagal system was stimulated through a deep breathing test, revealing a significant relationship between PUI and parasympathetic cardiac indices, as well as sleepiness. The findings indicated that a linear combination of vagal heart rate variability, measured by the root mean square of heart beat interval differences (RMSSD), and skin conductance fluctuations (SCFs) effectively explained the interindividual variance in PUI. Additionally, the complexity of pupil diameter variations was found to correlate with sympathetic skin conductance indices. Notably, spontaneous fluctuations in skin conductance were associated with transient increases in pupil size, suggesting a dynamic interplay between these physiological responses. The independent sample further confirmed the relationship between PUI, RMSSD, and skin conductance, with the slow breathing test enhancing both RMSSD and PUI in a proportional manner, while simultaneously reducing the complexity of pupil diameter dynamics. Overall, the study posits that the slow oscillations in pupil diameter, quantified by PUI, are indicative of parasympathetic modulation, whereas sympathetic arousal, as evidenced by SCFs, is linked to transient increases in pupil size that contribute to non-linear pupillary dynamics. This research provides valuable insights into the autonomic regulation of pupillary unrest and its implications for understanding the underlying mechanisms of emotional and physiological states.

2. K. Hung and Y.-T. Zhang, "Preliminary investigation of pupil size variability: toward non-contact assessment of cardiovascular variability," in 2006 3rd IEEE/EMBS International Summer School on Medical Devices and Biosensors. IEEE, 2006, pp. 137–140.
They present a preliminary investigation into the relationship between pupil size variability and cardiovascular variability, aiming to explore the potential for non-contact assessment methods in monitoring cardiovascular health. The study is motivated by the growing interest in non-invasive techniques for evaluating physiological parameters, particularly in the context of cardiovascular function, where traditional methods often require direct contact and can be cumbersome. The authors hypothesize that pupil size, which is influenced by autonomic nervous system activity, may serve as a viable indicator of cardiovascular variability. To test this hypothesis, they conducted experiments that involved measuring pupil size changes in response to various stimuli while simultaneously recording cardiovascular parameters such as heart rate and blood pressure. The methodology included the use of advanced imaging techniques to capture pupil dynamics without the need for physical contact, thereby enhancing the feasibility of continuous monitoring in real-world settings. The results indicated a significant correlation between pupil size variability and cardiovascular metrics, suggesting that fluctuations in pupil diameter could reflect underlying autonomic nervous system activity related to cardiovascular regulation. The findings support the notion that pupil size variability may serve as a non-invasive biomarker for assessing cardiovascular health, with implications for both clinical practice and research. The authors discuss the potential applications of this approach in various fields, including telemedicine and remote patient monitoring, where non-contact methods could facilitate more accessible and efficient healthcare delivery. They also acknowledge the limitations of their preliminary study, including the need for larger sample sizes and further validation of the results across diverse populations. Overall, Hung and Zhang's investigation lays the groundwork for future research aimed at developing reliable non-contact assessment tools that leverage pupil size variability as a novel indicator of cardiovascular health, ultimately contributing to advancements in medical diagnostics and patient care.

3. C.-A. Wang, T. Baird, J. Huang, J. D. Coutinho, D. C. Brien, and D. P. Munoz, "Arousal effects on pupil size, heart rate, and skin conductance in an emotional face task," Frontiers in neurology, vol. 9, p. 1029, 2018.
Investigates the physiological responses associated with arousal during an emotional face task, focusing on pupil size, heart rate, and skin conductance as indicators of autonomic nervous system activity. The research is grounded in the understanding that emotional stimuli can elicit distinct physiological responses, which are critical for understanding the interplay between emotion and physiological arousal. The study involved participants who were presented with a series of emotional faces while their physiological responses were monitored. Specifically, the researchers measured changes in pupil diameter, heart rate variability, and skin conductance levels to assess the effects of emotional arousal on these parameters. The findings revealed that pupil size increased significantly in response to

emotionally charged faces, indicating heightened arousal levels. Additionally, heart rate showed a corresponding increase, suggesting that emotional stimuli not only affect visual processing but also engage the cardiovascular system. Skin conductance responses further corroborated these findings, as participants exhibited heightened levels of arousal when exposed to faces expressing strong emotions. The study highlights the importance of integrating multiple physiological measures to gain a comprehensive understanding of emotional arousal and its effects on the body. The authors discuss the implications of their findings for the field of affective neuroscience, emphasizing how physiological markers can provide insights into emotional processing and the underlying mechanisms of arousal. They also consider the potential applications of this research in clinical settings, particularly in understanding emotional dysregulation in various psychological disorders. Overall, Wang et al.'s work contributes to the growing body of literature on the physiological correlates of emotion, demonstrating that pupil size, heart rate, and skin conductance are valuable indicators of arousal in response to emotional stimuli, and paving the way for future studies to explore these relationships in greater depth.

4. N. Urrestilla and D. St-Onge, "Measuring cognitive load: Heart-rate variability and pupillometry assessment," in Companion Publication of the 2020 International Conference on Multimodal Interaction, 2020, pp. 405–410.

Explores the relationship between cognitive load and physiological measures, specifically focusing on heart rate variability (HRV) and pupillometry as assessment tools. The study is motivated by the increasing need for effective methods to evaluate cognitive load in various contexts, such as education, human-computer interaction, and cognitive neuroscience. The authors argue that traditional subjective measures of cognitive load, such as self-report questionnaires, can be limited by biases and inaccuracies, thus highlighting the potential of physiological indicators to provide more objective and reliable assessments. To investigate this, the researchers conducted experiments where participants engaged in tasks of varying cognitive demands while their heart rate and pupil size were continuously monitored. The methodology involved analyzing HRV as a marker of autonomic nervous system activity, which reflects the body's response to cognitive challenges, and measuring pupil diameter changes, which are known to correlate with cognitive effort and mental workload. The results demonstrated a significant relationship between increased cognitive load and both reduced HRV and increased pupil size, indicating that as cognitive demands rise, the body exhibits distinct physiological responses. These findings support the hypothesis that HRV and pupillometry can serve as effective indicators of cognitive load, providing valuable insights into the cognitive processes underlying task performance. The authors discuss the implications of their research for the design of adaptive systems and interfaces that can respond to users' cognitive states in real-time, potentially enhancing user experience and performance. They also acknowledge the limitations of their study, including the need for further research to validate these findings across different populations and task types. Overall, Urrestilla and St-Onge's work contributes to the growing field of cognitive load assessment, demonstrating the utility of combining HRV and pupillometry as complementary measures to better understand cognitive processes and improve the design of interactive systems.

5.C. Daluwatte, J. Miles, and G. Yao, "Simultaneously measured pupillary light reflex and heart rate variability in healthy children," Physiological measurement, vol. 33, no. 6, p. 1043, 2012.

Investigates the relationship between pupillary light reflex (PLR) and heart rate variability (HRV) in healthy children, aiming to enhance the understanding of autonomic nervous system function in pediatric populations. The research is grounded in the premise that both PLR and HRV are valuable indicators of autonomic regulation, reflecting the balance between sympathetic and parasympathetic activity. The study involved a cohort of healthy children who underwent simultaneous measurements of PLR and HRV while exposed to controlled light stimuli. The authors employed a standardized protocol to elicit the pupillary light reflex, which involves the constriction of the pupil in response to light, and recorded heart rate data to assess variability through time-domain and frequency-domain analyses. The findings revealed significant correlations between the parameters of PLR and HRV, suggesting that the autonomic responses reflected in these measures are interconnected. Specifically, the results indicated that greater pupillary constriction was associated with higher HRV, implying a robust parasympathetic influence during the light reflex. This relationship underscores the potential of using PLR and HRV as complementary tools for assessing autonomic function in children, providing insights into their physiological responses to environmental stimuli. The authors discuss the implications of their findings for understanding the development of autonomic regulation in children and the potential for using these measures in clinical settings to monitor autonomic function and identify deviations from typical development. They also highlight the importance of considering age-related factors when interpreting the results, as autonomic responses can vary significantly across different developmental stages. Overall, Daluwatte et al.'s research contributes to the growing body of literature on autonomic function in pediatric populations, demonstrating the feasibility and relevance of simultaneously measuring PLR and HRV as a means to gain a deeper understanding of the autonomic nervous system's role in children's physiological responses. This study lays the groundwork for future research exploring the implications of autonomic regulation in various health contexts and developmental conditions.

3.SYSTEM ANALYSIS

3.1 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

- In the existing work, the system did not implement Connecting Pupil with HRV model which leads less effective.
- This system is less performance due to lack of Graph Neural Network and other ml classifiers.

PROPOSED SYSTEM

1) We conduct an in-depth study of the relationship between HRV and pupil size in mobile scenarios. To

Industrial Engineering Journal
ISSN: 0970-2555
Volume : 54, Issue 1, January : 2025

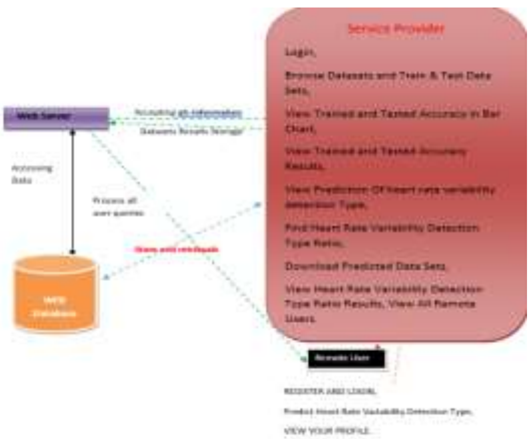
the best of our knowledge, this is the first work to explore the quantitative relationship between people's papillary response and HRV on mobile devices.
2) High-dimensional time-series features associated with user's HRV are identified by using a 1-D CNN to excavate the general physiological processes of papillary responses.
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.IMPLEMENTATION

4.1. SYSTEMARCHITECTURE



4.2. MODULES

Service Provider

In this module, the Service Provider has to login by using valid user name and password. After login successful he can do some operations such as Browse Datasets and Train & Test Data Sets, View Trained and Tested Accuracy in Bar Chart, View Trained and Tested Accuracy Results, View Prediction Of heart rate variability detection Type, Find Heart Rate Variability Detection Type Ratio, Download Predicted Data Sets, View Heart Rate Variability Detection Type Ratio Results, View All Remote Users.

View and Authorize Users

In this module, the admin can view the list of users who all registered. In this, the admin can view the user's details such as, user name, email, address and admin authorizes the users.

Remote User

In this module, there are n numbers of users are present. User should register before doing any operations. Once user registers, their details will be stored to the database. After registration successful, he has to login by using authorized user name and password. Once Login is successful user will do some operations like REGISTER AND LOGIN, Predict Heart Rate Variability Detection Type, VIEW YOUR PROFILE.

4.3. ALGORITHM'S

Decision tree classifiers

Decision tree classifiers are used successfully in many diverse areas. Their most important feature is the capability of capturing descriptive decision making knowledge from the supplied data. Decision tree can be generated from training sets. The procedure for such generation based on the set of objects (S), each belonging to one of the classes C1, C2, …, Ck is as follows:
Step 1. If all the objects in S belong to the same class, for example Ci, the decision tree for S consists of a leaf labeled with this class
Step 2. Otherwise, let T be some test with possible outcomes O1, O2,…, On. Each object in S has one outcome for T so the test partitions S into subsets S1, S2,… Sn where each object in Si has outcome Oi for T. T becomes the root of the decision tree and for each outcome Oi we build a subsidiary decision tree by invoking the same procedure recursively on the set Si.

Gradient boosting

Gradient boosting is a machine learning technique used in regression and classification tasks, among others. It gives a prediction model in the form of an ensemble of weak prediction models, which are typically decision trees.[1][2] When a decision tree is the weak learner, the resulting algorithm is called gradient-boosted trees; it usually outperforms random forest.A gradient-boosted trees model is built in a stage-wise fashion as in other boosting methods, but it generalizes the other methods by allowing optimization of an arbitrary differentiable loss function.

K-Nearest Neighbors (KNN)

- Simple, but a very powerful classification algorithm
- Classifies based on a similarity measure
- Non-parametric
- Lazy learning
- Does not “learn” until the test example is given
- Whenever we have a new data to classify, we find its K-nearest neighbors from the training data

Example

- Training dataset consists of k-closest examples in feature space
- Feature space means, space with categorization variables (non-metric variables)
- Learning based on instances, and thus also works lazily because instance close to the input vector for test or prediction may take time to occur in the training dataset

Logistic regression Classifiers

Logistic regression analysis studies the association between a categorical dependent variable and a set of independent (explanatory) variables. The name *logistic regression* is used when the dependent variable has only two values, such as 0 and 1 or Yes and No. The name *multinomial logistic regression* is usually reserved for the case when the dependent variable has three or more unique values, such as Married, Single, Divorced, or Widowed. Although the type of data used for the dependent variable is different from that of multiple regression, the practical use of the procedure is similar. Logistic regression competes with discriminant analysis as a method for analyzing categorical-response variables. Many statisticians feel that logistic regression is more versatile and better suited for modeling most situations than is discriminant analysis. This is because logistic regression does not assume that the independent variables are normally distributed, as discriminant analysis does. This program computes binary logistic regression and multinomial logistic regression on both numeric and categorical independent variables. It reports on the regression equation as well as the goodness of fit, odds ratios, confidence limits, likelihood, and deviance. It performs a comprehensive residual analysis including diagnostic residual reports and plots. It can perform an independent variable subset selection search, looking for the best regression model with the fewest independent variables. It provides confidence intervals on predicted values and provides ROC curves to help determine the best cutoff point for classification. It allows you to validate your results by automatically classifying rows that are not used during the analysis.

Naïve Bayes

The naive bayes approach is a supervised learning method which is based on a simplistic hypothesis: it assumes that the presence (or absence) of a particular feature of a class is unrelated to the presence (or absence) of any other featureYet, despite this, it appears robust and efficient. Its performance is comparable to other supervised learning techniques. Various reasons have been advanced in the literature. In this tutorial, we highlight an explanation based on the representation bias. The naive bayes classifier is a linear classifier, as well as linear discriminant analysis, logistic regression or linear SVM (support vector machine). The difference lies on the method of estimating the parameters of the classifier (the learning bias). While the Naive Bayes classifier is widely used in the research world, it is not widespread among practitioners which want to obtain usable results. On the one hand, the researchers found especially it is very easy to program and implement it, its parameters are easy to estimate, learning is very fast even on very large databases, its accuracy is reasonably good in comparison to the other approaches. On the other hand, the final users do not obtain a model easy to interpret and deploy, they does not understand the interest of such a technique. Thus, we introduce in a new presentation of the results of the learning process. The classifier is easier to understand, and its deployment is also made easier. In the first part of this tutorial, we present some theoretical aspects of the naive bayes classifier. Then, we implement the approach on a dataset with Tanagra. We compare the obtained results (the parameters of the model) to those obtained with other linear approaches such as the logistic regression, the linear discriminant analysis and the linear SVM. We note that the results are highly consistent. This largely explains the good performance of the method in comparison to others. In the second part, we use various tools on the same dataset (**Weka 3.6.0**, **R 2.9.2**, **Knime 2.1.1**, **Orange 2.0b** and **RapidMiner 4.6.0)**. We try above all to understand the obtained results.

Random Forest Random forests or random decision forests are an ensemble learning method for classification, regression and other tasks that operates by constructing a multitude of decision trees at training time. For classification tasks, the output of the random forest is the class selected by most trees. For regression tasks, the mean or average prediction of the individual trees is returned. Random decision forests correct for decision trees' habit of overfitting to their training set. Random forests generally outperform decision trees, but their accuracy is lower than gradient boosted trees. However, data characteristics can affect their performance. The first algorithm for random decision forests was created in 1995 by Tin Kam Ho[1] using the random subspace method, which, in Ho's formulation, is a way to implement the "stochastic discrimination" approach to classification proposed by Eugene Kleinberg. An extension of the algorithm was developed by Leo Breiman and Adele Cutler, who registered "Random Forests" as a trademark in 2006 (as of 2019, owned by Minitab, Inc.).The extension combines Breiman's "bagging" idea and random selection of features, introduced first by Ho[1] and later independently by Amit and Geman[13] in order to construct a collection of decision trees with controlled variance. Random forests are frequently used as "blackbox" models in businesses, as they generate reasonable predictions across a wide range of data while requiring little configuration.

SVM In classification tasks a discriminant machine learning technique aims at finding, based on an *independent and identically distributed* (*iid*) training dataset, a discriminant function that can correctly predict labels for newly acquired instances. Unlike generative machine learning approaches, which require computations of conditional probability distributions, a discriminant classification function takes a data point *x* and assigns it to one of the different classes that are a part of the classification task. Less powerful than generative approaches, which are mostly used when prediction involves outlier detection, discriminant approaches require fewer computational resources and less training data, especially for a multidimensional feature space and when only posterior probabilities are needed. From a geometric perspective, learning a classifier is equivalent to finding the equation for a multidimensional surface that best separates the different classes in the feature space. SVM is a discriminant technique, and, because it solves the convex optimization problem analytically, it always returns the same optimal hyperplane parameter—in contrast to *genetic algorithms* (*GAs*) or *perceptrons*, both of which are widely used for classification in machine learning. For perceptrons, solutions are highly dependent on the initialization and termination criteria. For a specific kernel that transforms the data from the input space to the feature space, training returns uniquely defined SVM model parameters for a given training set, whereas the perceptron and GA classifier models are different each time training is initialized. The aim of GAs and perceptrons is only to minimize error during training, which will translate into several hyperplanes' meeting this requirement.

5.RESULT

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.

REFERENCES

1. J. I. Hoffman and S. Kaplan, "The incidence of congenital heart disease," Journal of the American college of cardiology, vol. 39, no. 12, pp. 1890– 1900, 2002.
2. G. WHO, "WHO methods and data sources for global burden of disease estimates 2000–2011," Geneva: Department of Health Statistics and Information Systems, 2013.
3. R. Castaldo, P. Melillo, U. Bracale, M. Caserta, M. Triassi, and L. Pecchia, "Acute mental stress assessment via short term HRV analysis in healthy adults: A systematic review with meta-analysis," Biomedical Signal Processing and Control, vol. 18, pp. 370–377, 2015.
4. F. Wang, X. Zeng, C. Wu, B. Wang, and K. R. Liu, "mmhrv: Contactless heart rate variability monitoring using millimeter-wave radio," IEEE Internet of Things Journal, vol. 8, no. 22, pp. 16 623–16 636, 2021.
5. F. Lombardi, "Clinical implications of present physiological understanding of HRV components," Cardiac electrophysiology review, vol. 6, no. 3, pp. 245–249, 2002.
6. E. Kristal-Boneh, M. Raifel, P. Froom, and J. Ribak, "Heart rate variabilityin health

and disease," Scandinavian journal of work, environment & health, pp. 85–95, 1995.

7. M. P. Tarvainen, P. O. Ranta-Aho, and P. A. Karjalainen, "An advanced detrending method with application to HRV analysis," IEEE transactions on biomedical engineering, vol. 49, no. 2, pp. 172–175, 2002.
8. B. Makivi´c, M. Niki´c Djordjevi´c, and M. S. Willis, "Heart Rate Variability (HRV) as a tool for diagnostic and monitoring performance in sport and physical activities." Journal of Exercise Physiology Online, vol. 16, no. 3, 2013.
9. P. J. Zimetbaum and M. E. Josephson, "Use of the electrocardiogram in acute myocardial infarction," New England Journal of Medicine, vol. 348, no. 10, pp. 933–940, 2003.
10. E. C, ic, ekli and E. Emre, "The effect of tension variability for sleep quality in headache patients: A Holter monitoring study," Medicine, vol. 101, no. 30, 2022.
11. Y. Kurt Peker, G. Bello, and A. J. Perez, "On the Security of Bluetooth Low Energy in Two Consumer Wearable Heart Rate Monitors/Sensing Devices," Sensors, vol. 22, no. 3, p. 988, 2022.
12. Y. Gao, V. V. Soman, J. P. Lombardi, P. P. Rajbhandari, T. P. Dhakal, D. G. Wilson, M. D. Poliks, K. Ghose, J. N. Turner, and Z. Jin, "Heart monitor using flexible capacitive ECG electrodes," IEEE Transactions on Instrumentation and Measurement, vol. 69, no. 7, pp. 4314–4323, 2019.
13. J. Parak, A. Tarniceriu, P. Renevey, M. Bertschi, R. Delgado-Gonzalo, and I. Korhonen, "Evaluation of the beat-to-beat detection accuracy of PulseOn wearable optical heart rate monitor," in 2015 37th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC). IEEE, 2015, pp. 8099–8102.
14. W. Huang, W. Tang, H. Jiang, J. Luo, and Y. Zhang, "Stop deceiving! An effective defense scheme against voice impersonation attacks on smart devices," IEEE Internet of Things Journal, vol. 9, no. 7, pp. 5304–5314, 2021.
15. C.-A. Wang, T. Baird, J. Huang, J. D. Coutinho, D. C. Brien, and D. P. Munoz, "Arousal effects on pupil size, heart rate, and skin conductance in an emotional face task," Frontiers in neurology, vol. 9, p. 1029, 2018.