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International Journal of Engineering Research and Science & Technology
ISSN 2319-5991 www.ijerst.com
https://doi.org/10.62643/ijerst.2025.v21.i2.pp952-961
Vol. 21, Issue 2, 2025

# PUPIL-BASED HEART MONITORING: INFERRING HRV FROM SMARTPHONE UNLOCK BEHAVIOR

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## ABSTRACT

Nowadays, heart disease is a fairly prevalent and serious condition that is really preventable with early intervention. As a result, everyday heart health monitoring has grown in significance. The majority of current mobile cardiac monitoring devices rely on either photo plethysmography (PPG) or seismocardiography (SCG). These techniques, however, are inconvenient and require extra equipment, making it impossible for patients to keep an eye on their hearts at any time or location. We explore exploiting the pupillary response when a user unlocks his or her phone using face recognition to infer the user's heart rate variability (HRV) at this period, allowing for heart monitoring, motivated by our finding of the relationship between pupil size and HRV. To do this, we provide PupilHeart, a computer vision-based mobile HRV monitoring platform that has a server side and a mobile terminal. When users unlock their phones using the front-facing camera, PupilHeart gathers information on pupil size changes on the mobile terminal. On the server side, the raw pupil size data is then pre-processed. In particular, PupilHeart finds time series properties linked to HRV using a one-dimensional convolutional neural network (1D-CNN). Furthermore, PupilHeart models the pupil and HRV by training a recurrent neural network (RNN) with three hidden layers. Every time a user unlocks their phone, PupilHeart uses this model to infer their heart rate variability (HRV) and determine their heart status. By enlisting 60 people, we develop PupilHeart and carry out field research and trials to completely assess its efficacy. Overall, the findings demonstrate that PupilHeart is capable of properly predicting the user's HRV.

## I. 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

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https://doi.org/10.62643/ijerst.2025.v21.i2.pp952-961
Vol. 21, Issue 2, 2025

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

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may have a serious impact on the recorded face images.

Aiming 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. Then, we explore the relationship between pupil diameter and user heart rate in Sec. III. We describe the technical details of Pupil Heart in Sec. IV. The performance evaluations of Pupil Heart is presented in Sec. V. Limitations of this work are discussed in Sec. VI, and finally we conclude this work in Sec. VII.

## II. LITERATURE SURVEY

"The prevalence of congenital cardiac conditions,"

S. Kaplan and J. I. Hoffman,

The purpose of this research was to assess the real incidence of congenital heart disease (CHD), identify the factors contributing to its variability, and offer information on the prevalence of the main types of CHD. According to several studies, the incidence of CHD ranges from around 4/1,000 to 50/1,000 live births. Additionally, there are significant differences in the relative frequency of the several main types of CHD across studies. Furthermore, 20 out of every 1,000 live babies have a silent patent ductus arteriosus, isolated aberrant lobar pulmonary veins, or bicuspid aortic valves. We looked at the occurrences reported in 62 papers that were published after 1955. With particular regard to the growing use of echocardiography in the newborn nursery, consideration was given to the methods used in the investigations. The most prevalent form of CHD, ventricular septal defects (VSDs), had a correlation with the overall incidence of CHD. 44 papers were used to calculate the incidences of the several main types of CHD. The amount of tiny VSDs in the series, which is mostly dependent on how early the diagnosis is obtained, determines the incidence of CHD. The amount of trivial lesions included determines the variance in incidence if major types of CHD are divided into trivial, moderate, and severe categories. The prevalence of moderate and severe types of congenital heart disease is around 6/1,000 live births (19/1,000 live births if the potentially dangerous bicuspid aortic valve is included). If small muscular VSDs present at birth and other insignificant lesions are taken into account, the incidence of all kinds of CHD rises to 75/1,000 live births. There is no proof that incidence varies between nations or eras given the reasons of variance.

"A systematic review with meta-analysis of acute mental stress assessment using short-term HRV analysis in healthy adults,"

L. Pecchia, M. Caserta, M. Triassi, U. Bracale, P. Melillo, R. Castaldo, and M. Melillo

In addition to being one of the primary causes of cognitive impairment, cardiovascular problems, and depression, mental stress lowers performance in both the workplace and everyday life. This study thoroughly evaluated the body of research examining the relationships between short-term Heart Rate Variability (HRV) measurements in the temporal, frequency, and non-linear domains and acute mental stress in healthy people. Providing accurate information on the patterns and pivot values of HRV measurements under mental stress was the aim of this research. After conducting a thorough search of electronic repositories and linearly studying the references of works that matched the inclusion criteria, a systematic review and meta-analysis of the evidence were carried out. Journal articles detailing well planned research that thoroughly examined HRV were included after duplicates and irrelevant papers were eliminated, provided that they examined the same population of healthy people both at rest and under mental stress. A total of 758 individuals were included in 12 publications that were selected. These papers examined 22 distinct HRV measures, 9 of which

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were reported by at least two studies and were therefore meta-analyzed in this study. Significant depression was seen under stress in four temporal and non-linear domain measurements that were linked to a normal degree of HRV fluctuations. Acute mental stress may cause sympathetic activation and parasympathetic withdrawal, as seen by the much lower strength of HRV fluctuations at high frequencies and the significantly higher ratio between low and high frequency. Lastly, only two of the fifteen non-linear measures that were extracted were reported by at least two trials, so they were pooled. Of these, only one resulted in a significant decrease in depressive symptoms, indicating a decrease in chaotic behaviour under mental stress. HRV showed less fluctuation and less chaotic behaviour, and it was dramatically lowered by mental stress. During acute mental stress, the pooled frequency domain data showed a considerable change in autonomic balance towards sympathetic activation and parasympathetic withdrawal. For the pooled mean differences of HRV measurements, pivot values are given. It is still need to do further research on HRV non-linear metrics under mental stress. Nonetheless, the suggested approach to meta-analyze and alter the HRV data may be used in other domains where HRV has shown therapeutic significance.

"mmhrv: Millimeter-wave radio-based contactless heart rate variability monitoring,"

Heart rate variability (HRV), which quantifies the variation of heartbeat intervals, has been regarded as a crucial metric for assessing overall health (F. Wang, X. Zeng, C. Wu, B. Wang, and K. R. Liu). Noncontact techniques for HRV monitoring have garnered a lot of interest in an effort to reduce user burden and investigate applicability for long-term health monitoring. In this article, we introduce mmHRV, the first commercial millimeter-wave (mmWave) radio-based contact-free multiuser HRV monitoring system. There are two main parts to the mmHRV design. To determine each user's position, we first create a target detector that doesn't need calibration. Second, a heartbeat signal extractor is developed that can estimate the heartbeat signal by optimising the breakdown of the channel information phase modulated by the chest movement. While the interbeat intervals (IBIs) may be further obtained for measuring the HRV metrics of each target, the precise time of heartbeats is approximated by locating the heartbeat signal's peak. We assess the effectiveness of the system and the effects of various configurations, such as obstruction, accidental angle, user orientation, and distance between the user and the device. With a median IBI estimate error of 28 ms (with regard to 96.16% accuracy), experimental findings demonstrate that mmHRV can measure the HRV correctly. Furthermore, based on trials involving 11 people, the root-mean-square error (RMSE) recorded in the nonline-of-sight (NLOS) situations is 31.71 ms. While the median error of the 3-user case is within 52 ms for all three tested sites, the performance of the multiuser situation is somewhat worse than that of the single-user case.

## III. SYSTEM ANALYSIS & DESIGN

### EXISTING SYSTEM

In the last several years, researchers have focused increasingly on tracking people's heart rate variability in mobile settings. We divide those approaches essentially into two categories. The first group's methods assess HRV by using photoplethysmography (PPG) [19]–[25]. To be more precise, the method described in [19] involves putting a finger on the phone's camera while activating the flash, then using the camera to take pictures to determine the quantity of light absorbed by the finger tissues in order to determine heart rate.

Furthermore, Bolkovsky et al. [20] record RR intervals using both iPhones and Android phones before calculating HRV using a sophisticated algorithm. Additionally, the impact of sample rates on the accuracy of HRV measurements across iPhones and Android phones is

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investigated. Plews et al. [21] also support mobile phone PPG, demonstrating that PPG and ECG had an almost perfect correlation with acceptable technical error in estimate and negligible standard deviation discrepancies. High frame rate CPPG signals may be extracted from a typical built-in low frame rate smartphone's CIS by using the rolling shutter camera mechanism to collect CIS-photoplethysmography (CPPG) data points from CMOS image sensor (CIS) pixel rows [25]. Regarding the particular uses, PPG is used as a measure for estimating heart rate variability (HRV) in individuals suffering from spinal cord damage (SCI) [24].

The second group uses seismocardiography (SCG), a straightforward and non-invasive technique for capturing cardiac activity from the body motions brought on by heart pumping, to quantify HRV. In an initial investigation, J. Ramos-Castro et al. capture this movement and calculate heart rate using a smartphone [26]. To authenticate users on mobile devices, Lei Wang et al. [27] employ heartbeat-induced chest vibrations as a biometric feature. Additionally, M. Scarpetta et al. provide a technique that uses a smartphone to detect respiratory and cardiac intervals simultaneously [28].

In particular, the SCG signal produced by cardiac activity and the acceleration produced by breathing motions are measured using a smartphone's basic accelerometer. Furthermore, Mirella Urzeniczok et al. provide a smartphone app that uses SCG to measure heart rate in real time. A modified version of the Pan-Tompkins method is used to identify heartbeats [29]. All of the aforementioned techniques use PPG or SCG to calculate HRV. In this study, we broke the constraint that measurement from PPG and SCG needs the user to remain in a stable condition all the time or with the use of extra equipment by using a novel technique to measure HRV based on pupillary response characteristics. As far as we are aware, this is the first study to track user HRV using student data on mobile devices.

**Disadvantages**

- The system in the current study was less successful since it did not integrate the Connecting Pupil with HRV model.
- The absence of Graph Neural Networks and other ML classifiers causes this system to perform less well.

**PROPOSED SYSTEM**

1) In mobile settings, we thoroughly investigate the connection between HRV and pupil size. As far as we are aware, this is the first study to investigate the quantitative connection between HRV on mobile devices and people's papillary response.
2) To explore the general physiological mechanisms of papillary responses, a 1-D CNN is used to identify high-dimensional time-series characteristics linked to the user's HRV.
3) In order to simulate the link between pupil and HRV, we use RNN to train the high-dimensional time-series features that were retrieved using 1-D CNN.
4) We enlist 60 participants in order to conduct a comprehensive experiment and confirm PupilHeart's efficacy.One The findings indicate that PupilHeart's accuracy averages up to 91.37%.

**Advantages**

- Convenience. Compared to professional equipment, HRV monitoring on mobile devices is much more portable and doesn't need specialised tools or expert advice.
- Accuracy. Mobile device unlocking-based HRV monitoring takes into account various time periods as well as users' physiological and mental situations, which yields more samples and ensures HRV monitoring accuracy.

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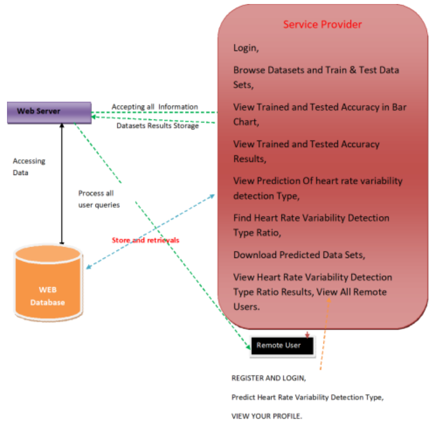
## SYSTEM ARCHITECTURE




## IV. IMPLEMENTATIONS

### Modules

### Service Provider

The Service Provider must use a working user name and password to log in to this module. He can do many tasks after successfully logging in, including browsing datasets and training and testing datasets. See the Bar Chart for Trained and Tested Accuracy, See the Results of Trained and Tested Accuracy, See the Type of Heart Rate Variability Detection Prediction, Find the Type Ratio, Download Predicted Data Sets, View All Remote Users and the Results of the Heart Rate Variability Detection Type Ratio.

### View and Authorize Users

The administrator may see a list of all registered users in this module. Here, the administrator may see the user's information, like name, email, and address, and they can also grant the user permissions.

### Remote User

A total of n users are present in this module. Before beginning any actions, the user needs register. Following registration, the user's information will be entered into the database. Following a successful registration, he must use his password and authorised user name to log in. The user will do many tasks after successfully logging in, including registering and logging in, predicting the kind of heart rate variability detection, Examine your profile.

## ALGORITHMS

### Gradient boosting

One machine learning method for classification and regression problems is gradient boosting. Usually decision trees, it provides a prediction model in the form of an ensemble of weak prediction models. [1] [2] The resultant technique, known as gradient-boosted trees, often performs better than random forest when a decision tree is the weak learner. Like other boosting techniques, a gradient-boosted trees model is constructed step-by-step; however, it goes one step further by allowing optimisation of an arbitrary differentiable loss function.

### K-Nearest Neighbors (KNN)

- A simple but very effective classification technique that uses a similarity metric
- Non-parametric learning that is lazy and doesn't "learn" until the test example is provided
- We use the training data to determine the K-nearest neighbours of any fresh data that has to be classified.

### Example

- Learning is based on instances, which also works sluggishly because instances near the input vector for test or prediction may take time to occur in the training dataset.
- The training dataset comprises the k-closest examples in feature space, which is defined as space with categorisation variables (non-metric variables).

### 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

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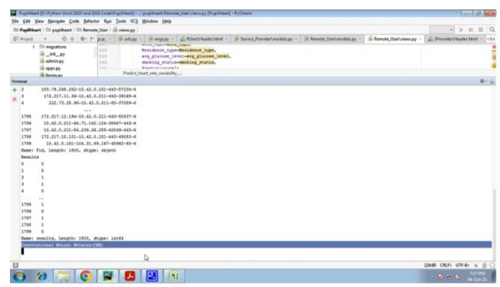
resulting algorithm is called gradient-boosted trees; it usually outperforms random forest.A gradient-boosted trees model is built in a stage-wise fashion as in other boosting methods, but it generalizes the other methods by allowing optimization of an arbitrary differentiable loss function.

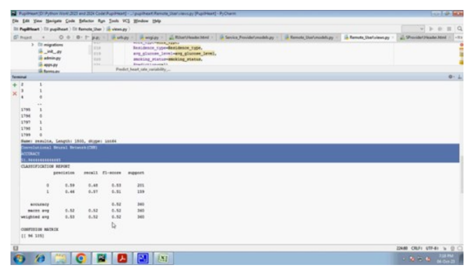
**SVM**

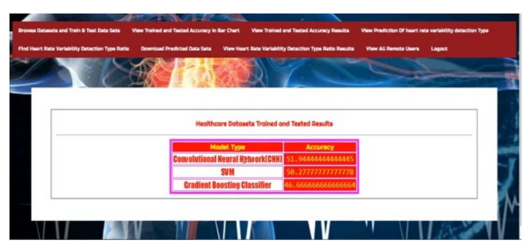
In classification tasks a discriminant machine learning technique aims at finding, based on an *independent and identically distributed* (*iid*) training dataset, a discriminant function that can correctly predict labels for newly acquired instances. Unlike generative machine learning approaches, which 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.

## V. SCREEN SHOTS





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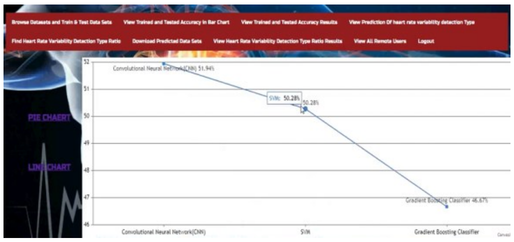
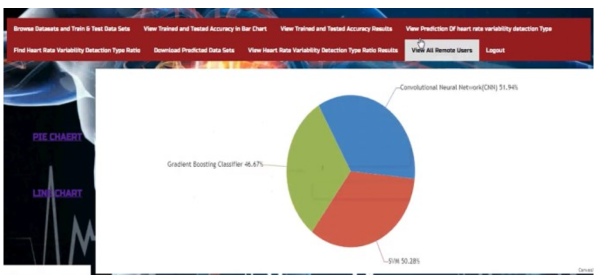
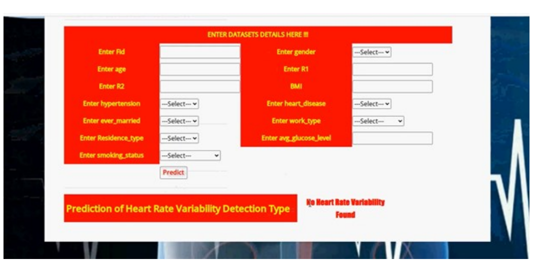
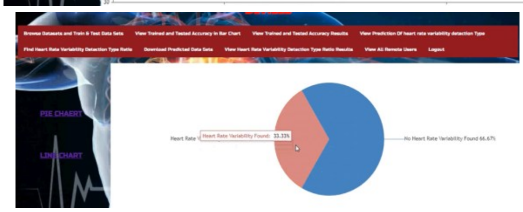
Vol. 21, Issue 2, 2025









## VI. CONCLUSION

In this study, we introduced Pupil Heart, a mobile HRV monitoring system that consists of a server side and a mobile terminal that is based on computer vision. Pupil Heart has used mobile phones' front-facing cameras to gather data on pupil size during face identification on the mobile terminal. Pupil Heart has constructed a pupil-HRV model via RNN on the server side after preprocessing the raw pupil size data and using 1DCNN to extract high-dimension features. Pupil Heart has accomplished daily HRV monitoring as a result. In order to fully assess the effectiveness of Pupil Heart, we recruited 60 participants and carried out experimental and field investigations. Overall, the findings demonstrate that Pupil Heart can correctly estimate a user's heart rate variability (HRV) while using facial recognition to unlock phones. Generally speaking, Pupil-Heart gives us a prototype to investigate pupil size and HRV, illuminating a practical but creative concept for implementing mobile HRV monitoring devices. In order to further enhance our Pupil Heart system, we will broaden the variety of tests in terms of apparatus, participants,

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https://doi.org/10.62643/ijerst.2025.v21.i2.pp952-961
Vol. 21, Issue 2, 2025

and environmental circumstances in subsequent projects.

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ISSN 2319-5991 www.ijerst.com
https://doi.org/10.62643/ijerst.2025.v21.i2.pp952-961
Vol. 21, Issue 2, 2025

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