Assessing the Effect of Long Term Physical Training and Classification of Training Status using HRV and HRR of Female Police Recruits

Remya George
Dept. Electrical and Electronics Engineering
Government Engineering College
Thrissur, Kerala, India.
remyageorge83@gmail.com

Biju Bahuleyan
Department of Physiology
Jubilee Mission Medical College
Thrissur, Kerala, India.
drbijubahuleyan@gmail.com

K. Meenakshy
Department of Applied Electronics and Instrumentation
Government Engineering College
Calicut, Kerala, India.
meenakshymoorthy@gmail.com

***Abstract* - The changes in Heart Rate Variability (HRV) and Heart Rate Recovery (HRR) coincide well with the changes in physical training status in patient populations. But a deep probing in this area reveals that enough attention has not been paid so far to the healthy population, especially those who undergo deliberate training. This study was conducted to quantify the effect of nine months of basic police training in HRV/HRR among a sample of women police recruits of Kerala state. Consequently, the training was found to be effective in altering the parasympathetic and nonlinear control of the cardiovascular system. The statistical analysis using dependent sample t-test showed that there was a significant alteration of linear and nonlinear HRV measures and HRR features prior to post-training. The study also investigated the discriminatory potential of five-minutes each of supine HRV and post-exercise HRR in classifying the recruits into trained and untrained status. The optimal HRV/HRR feature set that could discriminate the training status with the highest accuracy were identified by using Genetic Algorithm-Artificial Neural Network (GA-ANN) and Genetic Algorithm-Support Vector Machine (GA-SVM) based wrapper functions. A reduction in HRV feature set to 50% and HRR feature set to 68.5% was found using the GA optimization. While classifying, the SVM classifier outperformed the ANN with maximum accuracy (89.7%) using the reduced feature set of HRR. The results promise objective selection of well-trained candidates to professions which demand high physical fitness.**

Keywords - Heart rate variability, nonlinear analysis, GA, ANN, SVM classifier, physiological adaptation, physical training status.

I. INTRODUCTION

Police forces in the present global scenario are considered to be the ones with the highest occupational stress and stress- related diseases [1], [2], [3]. Closely related to this is the theory of cross-stressor adaptation which suggests that regular practice of exercise modify the physiological systems and aid in blunting the response to both physical and psychological stressors [4], [5]. Moreover, the available research also emphasizes the fact that increased physical activity or high fitness are likely to facilitate the capacity to handle stress, which ultimately helps in leading a healthy lifestyle [6], [7]. Systematic, cyclic administration of varying loads of training is the key to physiological adaptation [8] to psychological stress. That is why a civil police trainee in India is subjected to rigorous physical and academic training compulsorily for a duration of nine months before starting the official duties. It is to be noted that there will be inter-individual differences among training responses, due to differences in genetic endowment, trainability and health status [9]. In the same camp, there will be responders and non-responders at different levels. Therefore, in a situation like this, the identification of recruits who do not adapt to the training goals and struggle with the physical and psychological demands in the training camp acquires a great significance. This has broad implications for increasing or decreasing the phase durations of training- recovery and thus optimizing the cost of academy training.

Remarkably enough, the scientific studies for objectively assessing the physiological effectiveness of police training and the quantification of training response are still lacking in the field. Majority of the police studies are sociology based, investigating the stress factors and coping styles of the officers. Obviously, last two-decades have witnessed the advent of portable mobile technological devices such as heart rate monitors and other sensing devices, assisting the partnering of information technology with medical and sports science. This has made it possible for monitoring the physiological status of an individual objectively through fast and non-invasive techniques like Heart rate Variability (HRV), Heart Rate Recovery (HRR), blood pressure and Galvanic skin response for decisive computations. Therefore it is of great relevance to apply these technological advancements to assess and evaluate the basic training that a police officer undergoes, and if found necessary, to take remedial measures. Consequently, this approach would certainly result in laying an appropriate foundation for their career.

A. Heart Rate Variability

HRV, the variation in time between adjacent heart beats, is an objective and sensitive bio-marker of integrated physiological functioning. Among the two branches of the autonomic nervous system (ANS), sympathetic branch increases heart rate while parasympathetic branch decreases it and thus creates the variability. Conventionally, the focus of research in exercise physiology was centered in muscle strength and fatigue. But ever since the role of ANS in training adaptation is revealed, much attention is paid to non-invasive methods of assessing physiological correlates of it [10], [11]. Cross-sectional studies have demonstrated an increased HRV in physically conditioned groups and reduced HRV in unconditioned [12], [13] or patient groups [14], [15]. Longitudinal studies have also shown that HRV gets improved after undergoing physical training[16] and individuals adapt better to HRV guided training than conventional one [17]. There is also evidence for the potential of HRV in monitoring the training load among football and soccer players [18], [19]. Undoubtedly, HRV is a reliable mechanism to monitor adaptation and recovery in short and long duration training programs [20], [21]. It is also noticed that, optimized training schedules based on individually determined HRV patterns can prevent over-training [22], [23]. Apparently, literature unanimously claims that cardiac parasympathetic activity measured by HRV is a global marker of homeostasis that reflects adaptation to training.

HRV is usually evaluated in time and frequency domain linear scales to reflect the neural control of the heart via sympathetic and parasympathetic innervation. A number of nonlinear features are also seen calculated, for HRV signal being the representative of a complex interaction of a set of coupled physiological systems. The nonlinear statistics from entropy, correlation dimension, Poincare plot, detrended fluctuation analysis, Lyapunov exponent and recurrence quantification analysis are commonly used in HRV analysis of patient population. Most works on HRV in physically trained subjects use linear methods in time and frequency domain [24], [25]. Few others have used Poincare parameters [26], [27] or their derivatives[28]. Linear measures of HRV often fail to provide relevant information in the presence of rapid and transients changes of the two branches of ANS. They may also fail in conditions of extremely reduced variability and whenever sympatho-vagal co-activation occurs.

B. Heart Rate Recovery

After the cessation of physical exercise, heart rate decreases exponentially towards the resting levels [29], [30] and is designated as the heart rate recovery (HRR). This parameter is often used as an index of vagal modulation and cardio- respiratory fitness along with HRV in the research of exercise physiology. It is worthy of noting that the immediate HRR after exercise is a function of vagal re-activation [31]. Iami et al. [32] and Bosquet et al. [33] have observed that the first 30 seconds and one-minute recovery features are independent of the intensity of exercise. It is clear that exercise training can increase the delta between HR at the end of the exercise and at the beginning of recovery, independent of age and gender [34]. In cross-sectional studies, Darr et al. [29] observed faster recovery (6 beats/min) in trained subjects than their untrained counterparts. Du et al. [35] and Dixon et al. [24] also observed a lower recovery in sedentary subjects than long-distance runners. In longitudinal research, Lambert's study et al. [36] showed an increase in HRR after 4 weeks of high intensity training. Again in a diverse population based study, physical activity was found associated with faster HRR [37]. These findings suggest that HRR has the potential to objectively comment on the fitness and quantify the training level of healthy individuals.

HRR measurements at the thirtieth second, first to fifth minutes are commonly reported for quantification of cardiorespiratory fitness and autonomic system balance. Heffernan et al. [38] and Shetler et al. [39] looked at the difference between the peak HR and post-exercise HR at one to two minutes after the exercise (Number of beats recovered from HRPeak). Some studies have calculated the recovery time constants also by fitting HR decay data to mathematical models such as mono-exponential curves[32], [40]. George et al. [41] have used raw HR and slope from linear regression lines fitted to the recovery trajectory during the first one minute period of cessation of exercise. Further, Bosquet et al. have suggested that raw HR measures being comparatively more reliable than other measures [33].

C. Discrimination of Training Status

At present, in police academies, the physical training follows a pre-scheduled syllabus without an objective focus on the attainment of training goals. There will be the inter-individual differences among training responses, due to differences in genetic endowment, trainability, and health status [9]. In the same camp, there will be responders and non-responders at different levels. As HRV/HRR is a clear bio-marker of training adaptation and current status of physiological systems, the distinct profiles of HRV/HRR may help to filter out those who attained the training goals and those who failed. This has broad implications for increasing or decreasing the phase durations of training-recovery and thus optimizing the cost of academy training.

There are enough reports, pertaining to the discriminatory potential of HRV in classifying patient population from normal counterparts and categorizing the healthy subjects based on selected criteria. Mellio et al. used short-term HRV for the prediction of future vascular risky events such as stroke, months before the event [42]. The linear and nonlinear features were found outperforming the conventional echo graphical predictors of vascular risk with a sensitivity and specificity of 71.4% and 87.8% respectively.

In an attempt to classify 60 healthy subjects into three different age groups, using HRV features computed from linear and non-linear methods, the authors have used SVM, KNN and probabilistic neural network (PNN) classifier modules [43]. In this case, the principal component feature reduction technique accounted for a maximum accuracy of 70% for the PNN. Kampouraki et al. used various time domain statistical features of HRV to discriminate young vs old subjects and healthy vs patients with coronary artery disease. For both cases, they could achieve a classification accuracy of 100% employing a SVM classifier. Moreover, the nonlinear HRV features are proven to be successful in distinguishing the psychological stress states from rest in healthy collegiate students [44].

The quantitative power of HRV and/or HRR in categorizing the healthy study sample based on their physical training status or level is seldom reported in literature. An exception to this is the recent studies by Kublanov et al., who used HRV and stabilographic data [45] for categorizing study sample based on training level and, Ray et al. [46] who used linear measures of HRV, statistical properties of raw ECG and wavelet transformed ECG for discriminating swimmers from non- swimmers. A large body of epidemiological evidence suggests that HRR might be a potential prognostic marker for predicting the cardiovascular dysfunction, risk of all-cause mortality and training adaptation [47], [48]. However, a recent meta-analysis by Qui et al. [49] suggests that the findings regarding the prognostic power is not addressed comprehensively, quantifying the magnitude of the association between HRR and cardiorespiratory fitness.

To the best of our knowledge, this is the first ever study to quantify the predictive utility of HRR in categorizing healthy sample based on their training status. Viewed from this perspective, this is a pioneering longitudinal study for objectively quantifying the effect of physical training in police recruits using the physiological measures such as HRV and HRR.

D. Objectives of the Study

In this work, the changes cardiac autonomic control in a group of female police recruits, from pre-training to post- training are first quantified using measures of ECG derived HRV and post-exercise HRR. The statistical evidence for the effectiveness of police training in altering the autonomic control of cardiovascular system is gathered. The HRV/HRR parameters that have the most discriminating potential for categorizing the recruits into trained or untrained status are then identified using a feature selection wrapper using genetic algorithm. GA optimization is employed to reduce the feature dimension and to optimize the parameters of the classifier. The subset HRV/HRR features are used for discriminating the training status in two classifier models and the performances are compared. The lassifiers selected are Artificial Neural Network (GA-ANN) and Support Vector Machine (GA-SVM) models. The present system could be regarded as a pioneering step in this field, helping the superior officers to discriminate the recruits who have attained the training goals from those who failed to adapt.

II. EXPERIMENTAL DESIGN

A. Sample

One company of the 2016 batch of Recruit Women Po- lice Constable Officers (referred to as RtWPCO popularly) of Kerala Police Academy (KEPA), the largest state police training academy in India is randomly identified as the study sample. They were screened for conditions with established clinical effects on HRV, such as history of heart disease, diabetes mellitus, major depression, respiratory problems, and renal diseases. Finally, 60 recruits provided voluntary written informed consent to participate in the study. None of the recruits were involved in regular physical activity before participating in study. They were then divided into two equal groups, both matched in age and body mass index. Using an Omron hand held BP monitor the blood pressure of the recruits was noted down to ensure they are normotensive. Finally, one of the group is assigned for HRR experiment and other for the HRV experiment. This ensured that the daily routines of the training camp is not disturbed and the recruits did not lose much of the training time. The demographic characteristics of participants are listed in Table I. Numerical data are presented as mean ± standard error (SE).

TABLE I. DEMOGRAPHIC CHARACTERISTICS OF THE PARTICIPANTS

Characteristics	pre-training (Mean ± SE)	post-training (Mean ± SE)	p-value
Age(Yrs)	-	27.925 ± 0.377	-
Weight (kg)	58.4 ± 1.75	56.703 ± 1.29	0.039
Body mass index (kg/m²)	22 ± .65	21.707 ± 0.46	0.139
Systolic BP (mmHg)	108.6 ± 1.17	112.3 ± 2.34	0.884
Diastolic BP (mmHg)	76.7± 1.62	80 ± 2.8	0.673

B. Methodology

Firstly, the nature and purpose of the study were explained to the participants clearly. The participants were guaranteed nominal confidentiality and were also free to withdraw at any stage. Recruits were cautioned not to engage in hardcore physical activities at least 36 hours prior to the start of ECG recording. This was to avoid any residual fatigue which might disturb their resting physiological status. Additionally, they were requested to refrain from drinking coffee, at least for an hour prior to the recording. The recording time and order were kept similar throughout the experiment. The data acquisition time was set from 7.30 am to 10.30 am. The study protocol and procedures were approved by the Institutional Ethics Committee of Jubilee Mission Medical College & Research Institute, Thrissur, Kerala.

1) ECG data collection: Resting ECG was recorded twice, one prior to the start of training, and the other after the completion of training. Pre-training data was recorded during a preparatory week which was free of physical training. The last day of the first week in the camp was chosen to get time for the recruits to be acclimatized with the academy environment. This also ensured homogeneity among recruits in controllable confounding factors such as sleep-wake cycle and psychological stress from social readjustment. Later the post-training data was recorded during the ninth month, after the completion of regular training sessions and before the start of ground practices for passing out ceremony. For HRV measurements, the recruits were visited at their barracks on days after their monthly holiday. They were asked to lie down comfortably for 30 minutes prior to the signal recording. At that stage, Kendall diagnostic tab electrodes were attached to the subjects in lead II configuration and ECG was recorded for five minutes under spontaneous breathing condition in supine rest. The ECG signals were then collected by Vernier EKG sensor unit, connected to a myRIO (National Instrument), programmed to acquire the data at a sampling rate of 500

Hz. The data acquisition protocol was in accordance with the international guidelines [50] for short-term HRV measurement. All the recruits completed the pre-training session and 27 recruits completed the post-training session.

2) HRR data collection: Exercise heart rate dynamics was recorded, twice at time points similar to that of ECG recording. The recruits were given 30-minutes of rest in seated position before the recording. Then the participants had to undergo maximal continuous exercise on a GoFit treadmill. The initial velocity of the treadmill was set at 7.5 km/hr with zero grade. Then the speed was increased by 1 km/hr every minute for a duration of five minutes, until they reach at least 86% of maximum age-adjusted heart rate or more. The recruits were closely monitored by a trained physical instructor during the workout. Target heart rate was calculated as 220 minus age. After the exercise, the recruits continued into a passive recovery phase for five minutes in standing position on the treadmill. Along with the exercise, the heart rate data was acquired with a Polar chest strap exercise heart rate monitor, which in turn communicate with a smart phone via Smart Bluetooth technology. A third party mobile application named Vernier graphical analyzer received the data and locally store it in '.csv' format. A copy of the file was then uploaded to cloud storage, which would be later retrieved into a computer connected to the network. It is noteworthy that all the recording conditions and the instructions to the participants are maintained the same way as that of ECG recording. 29 the recruits completed the pre-training session and 27 recruits completed the post-training session of HRR data collection.

C. Signal Processing and Feature Extraction

TABLE II. SUMMARY OF LINEAR HRV FEATURES

No:	Feature	Description
1	**HRVTRIN**	Integral of NN interval histogram divided by its height
2	**Mean HR**	Mean heart rate (bpm)
3	**Mean RR**	Mean interval between QRS peaks(ms)
4	**NN50**	Number of interval differences of successive NN
5	**Pnn50**	Proportion derived by dividing NN50 by the total number of NN intervals
6	**RMSSD**	Square root of the mean squared differences of successive NN intervals (ms)
7	**SDHR**	Standard deviation of Heart rate (bpm)
8	**SDNN**	Standard deviation of NN interval (ms)
9	**TINN**	Line width of base of NN interval histogram approximated as a triangle
10	**PHF**	Power of high frequncy band (0.15 Hz - 0.4 Hz)
11	**PLF**	Power of low frequncy band (0.04 Hz - 0.15 Hz)
12	**LF/HF**	Sympathovagal ratio
13	**TSP**	Total spectral power

The ECG signal was pre-processed for noise removal and QRS complex detection. The interval between each QRS complex was thoroughly analyzed for rejecting the beats of ectopic and non-physiological origins. All the data recorded were subjected to 20% filtering, in order to ensure that only normal beats are present in the HRV signal. The HRV signal was derived from the normal beat occurrence instances in the pre-processed ECG. The HRV signal was then processed using linear and nonlinear techniques to derive the various features that describe the cardiac control of the ANS. The signal processing was carried out in NI LabVIEW 2015.

TABLE III. SUMMARY OF NONLINEAR HRV FEATURES

No:	Feature	Description
14	**ApEn**	Approximate entropy
15	**d2**	Correlation dimension
16	**dfa1**	Detrended fluctuation short term scaling exponent
17	**dfa2**	Detrended fluctuation long term scaling exponent
18	**SampEn**	Sample entropy
19	**SD1 (ms)**	Poincare plot short term variability dimension
20	**SD2 (ms)**	Poincare plot long term variability dimension

TABLE IV. MEASURES OF HEART RATE RECOVERY (HRR)

Descriptor	HRR measure
Raw heart rate	HRP eak, HR30, HR60, HR2min, HR3min, HR4min, HR5min
Number of beats recovered	HRRec30, HRRec60, HRRec2min, HR3min, HR4min, HR5min
Time constants	{T30, T60}, Td

Features: The linear features included time and frequency domain measures calculated from the RR interval signal as listed in Table II. There were seven time domain features (MeanHR, MeanRR, SDHR, SDNN, RMSSD, NN50, and pNN50), two geometrical features (HRVTRI and TINN) and four frequency domain features (pLF, pHF, LF/HF, and TSP). In order to investigate the HRV in the frequency domain, the RR interval signal was de-trended using smoothness priors algorithm with $\lambda = 300$ to remove the very low frequency trend below 0.015 Hz. Each tachogram was then interpolated with cubic spline method to obtain equally spaced samples, which were then re-sampled at a rate of 4 Hz. This enabled the signal to contain enough sample values to provide a better frequency resolution. Welch's periodogram with a Hamming window (N = 512) and 50% overlap was then used for the estimation of power spectral density in various bands of the HRV spectrum, as listed in Table II. The nonlinear measures used in this study are listed in Table III and Table IV shows the various measures of HRR used in this study.

D. Statistical Analysis

The test for normality, examining skewness and the Shapiro- Wilks test was carried out. All HRV/HRR features were normally distributed except frequency domain HRV measures. The frequency domain parameters were hence transformed to the natural log scale. Paired sample t-test was used for the analysis of paired mean difference in HRR and HRV features across the training period. All the statistical analysis were carried out in IBM SPSS V. 22.0, with a p value of.05.

E. Classification of Trainees based on Training Level

The physical exercise is reported to be effective in modifying the physiological integrity of an individual, especially the para-sympathetic means of cardiac control. We hence investigated whether the five-minute supine HRV or HRR data was sufficient in recognizing the training level of the recruits. The first step in classification was the selection of an optimal set of HRV/HRR features which had the highest potential of maximizing the distance between the two classes of recruits.

E1. Feature Selection:

There are a number of machine learning approaches by which feature selection problems can be addressed with high accuracy and speed. The genetic algorithm (GA) based feature search and optimization algorithms have consistently shown desirable performance in many bio- medical problems [51]. In the present study, GA based wrapper algorithms were used to generate the best set of features. The GA would select a subset of HRV/HRR features with Roulette wheel method. An artificial neural network (ANN) and a support vector machine (SVM with linear kernel) would evaluate the goodness of the selected subset in each iteration of the GA. The fitness value was calculated based on the sum of square error (SSE) of the test set and individual with high fitness had a high probability of being reserved.

The parameters of GA were set as follows: Coding scheme was binary, the number of individual was 20 and 16 respectively for HRV and HRR; the population size was 7; and the maximum generation was 25. The crossover percentage was equal to 70 and mutation percentage was set at 30. Further, the mutation rate was 0.1 and the selection pressure was 8. Roulette wheel selection was applied to select parent solutions.

Offspring were produced using single point crossover, and these offspring were mutated by single point mutation for offering variation. With each iteration of GA, the average fitness and the best fitness gradually improved, and a set of promising HRR/HRV features were filtered by the GA optimization algorithm. After the last iteration, the GA output the most promising feature subset which can discriminate the training status with the highest accuracy.

Thus at the twenty fifth iteration, an optimal set of features were produced, which were automatically used for discrimination of the training status. The topology of the feature selection and classification algorithm is as shown in Figure 1, next page.

E2. Classification:

In this work, the classification of training status is treated as a two-class discrimination problem, and the two classes were referred to as" trained" and" untrained". Two classifiers were modeled and tested with the filtered features in order to compare the effectiveness of classification.

The ANN adopted in the present work was a feed forward neural network. The network was trained using Levenberg Marquards back propagation algorithm. The input nodes were assigned to one of the features selected by the GA. The number of hidden layer neurons was set at ten and there were one output layer neurons for the training status in binary form. During the training phase of the network, each node is assigned with a determined bias or threshold. For each interconnection between two nodes, a weight is also assigned to represent the link-strength between the neurons.

In order to reduce the bias caused by the over-fitting of the model to the HRV/HRR data, the predictive ability of the model must be tested on a different set of data, not seen by the algorithm during training. On the basis of the results calculated by GA optimization, the filtered features containing the training and testing data from the original data set were extracted to re-establish the ANN and SVM models for testing. We used tenfold cross-validation, where data is partitioned into ten sets, one subset is used as the holdout set. Ten models were built and tried, each using a different subset to test against. To evaluate the performance of the classifiers, the following statistical measures were used:

- True Positive (TP): The subject is a physically trained one and the classifier correctly recognizes her.
- False Positive (FP): The subject is untrained but the classifier misinterprets her as trained.
- True Negative (TN): The subject is not trained and the classifier correctly interprets that she is untrained.
- False Negative (FN): The subject is untrained but the classifier misinterprets the subject as physically trained.
- Sensitivity: It refers to the ability of the classifier to identify the physically trained subjects correctly.
- Specificity: It refers to the ability of the classifier to recognize untrained subjects correctly.
- Accuracy: This refers to the ratio of the total number of correct assessments to the total number of assessments.
- The area under the ROC: A classifier with area under the ROC equals to one is considered as a perfect classifier.

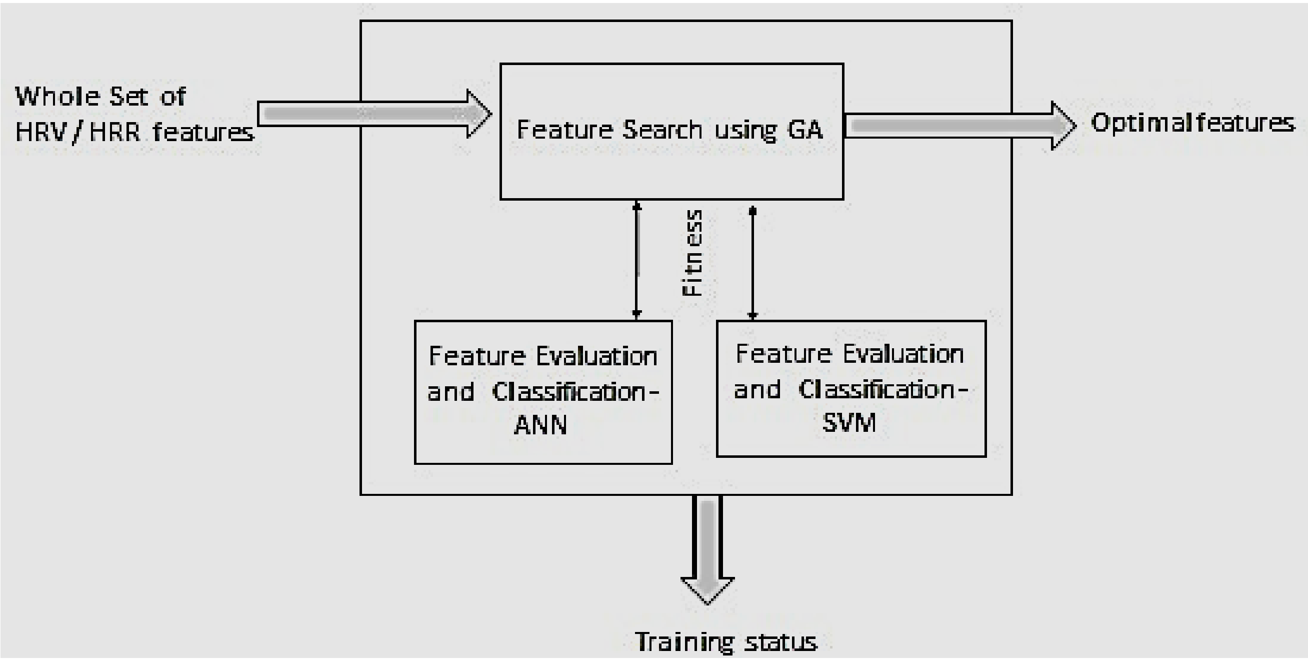


Fig. 1. Topology of HRV / HRR feature selection and classification.

III. RESULTS AND DISCUSSION

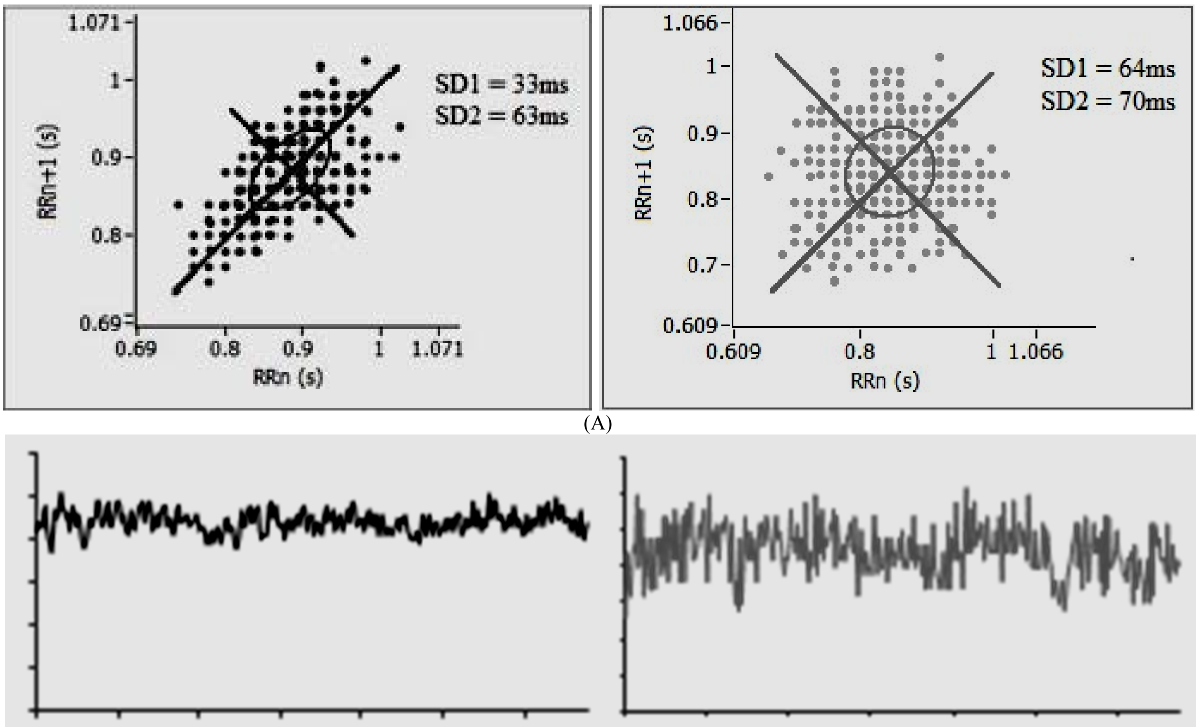
A. Effect of Training on HRV

The results revealed that there is significant effect of training on HRV as a whole. The t- test shows that 16 HRV features differ significantly across the training period (Table 5). There is a significant ($p < .05$) increment of parasympathetic and nonlinear measures of HRV from pre to post-training. This is in accordance with the available research that repeated physical exercise will lead to physiological adaptations of the ANS [52]. Except MeanHR and SDHR, all the time domain features are significantly affected by the training status. As expected, MeanHR gets reduced and SDHR seems to improve from the pre-training value. This is in agreement with other studies [53], [54]. The reduction in resting heart rate is attributed to the increased ventricular muscle capacity and stroke volume. RMSSD, which reflects the contribution of variations specifically related to vagal modulation gets significantly improved after training ($p \leq .001$). SDNN is one of the most representative parameter of HRV. A very significant improvement of this parameter ($p = .007$) is linked with the better ability of ANS to keep homeostasis against various internal and external challenges [11], [13].

TABLE V. HRV PARAMETERS BEFORE AND AFTER THE 9 MONTHS TRAINING

	Pre-training HRV	Post-training HRV	t	p-value	Effect size
meanRR	823.552 ± 21.798	883.659 ± 24.123	2.01	0.055	0.386
meanHR	74.721 ± 1.685	69.659 ± 1.684	-2.333	.028*	0.449
SDNN	53.818 ± 5.155	69.637 ± 3.310	2.95	0.007**	0.567
SDHR	5.204 ± 0.335	6.064 ± 0.271	10.749	0.092	0.336
RMSSD	64.581 ± 6.031	97.168 ± 4.778	5.252	.000**	1.01
NN50	127.8 ± 14.742	196.703 ± 6.022	3.729	.001**	0.717
pNN50	36.568 ± 4.389	58.557 ± 1.735	4.676	.000**	0.897
HRVTRIN	12.262 ± 1.003	15.73 ± 0.75	30.455	.002**	0.664
TINN	283.833 ± 24.797	355.74 ± 14.408	2.72	.011*	0.523
Ln pLF	6.64 ± 0.213	6.89 ± 0.166	-0.498	0.622	0.095
Ln pHF	6.62 ± 0.22	7.74 ± 0.133	2.776	0.01**	0.534
Ln TSP	7.49 ± 0.185	7.99 ± 135	0.637	0.53	0.122
LF/HF	1.335 ± 0.185	0.662 ± 0.071	-3.419	.002**	0.657
SD1	45.732 ± 4.272	68.814 ± 3.385	5.253	.000**	1.01
SD2	60.016 ± 6.152	69.558 ± 3.755	1.38	0.202	0.251
ApEn	1.1582 ± 0.011	1.148 ± 0.012	-0.629	0.535	0.127
SampEn	1.749 ± 0.037	2.013 ± 0.03	4.672	.000**	0.898
D2	2.192 ± 0.256	1.27 ± 0.244	-2.563	.017*	0.497
α1	0.844 ± 0.039	0.676 ± 0.033	-3.704	0.001	0.712
α2	0.345± 0.018	0.285 ± 0.018	-2.258	.033*	0.431

*. Significant at the 0.05 level (2-tailed).
**. Significant at the 0.01 level (2-tailed).



(A)

(B)

Fig. 2. Poincare plots (A) and inter-beat interval signals, (B) of a subject, pre (left) and post (right) training status.

While focusing on frequency domain, log transformed pLF, which is a measure of the power of the combined sympatho-vagal oscillation, shows a statistically non-significant increment. On the other hand, there is a remarkable increase in log transformed TSP and log transformed pHF. pLF is highly associated with the sympathetic activity, which enables the energy supply in psycho-physiological demands. Increased power in this band clearly reveals the better coping ability of the recruits [10], [16] in emotional and physical stressors. Further, pHF indicates the strength of the relaxation mechanism of ANS [23], [21], a sole determinant of recovery and rest. It is noteworthy that the improvement in pHF is critical in aiding the recruits to recover quickly from a sym- pathetic excitation. The variable TSP reflects the contribution of rhythmic components from both branches of the ANS. The increased TSP also indicates the higher adaptability of the ANS after training. Sympatho-vagal balance as measured by LF/HF shows a significant reduction (p = .003), shifting the autonomic balance to parasympathtic dominance after training. All nonlinear HRV features significantly changed from pre to post-training except ApEn (p = .535) and SD2 (p = .202), showing an overall increased complexity of ANS in its effort to encompass complex demands of the body.

Moving on to the Cohen's d effect size listed in Table V, moderate to large effect sizes are observed in most features. Large effect size is observed in RMSSD, pNN50, SD1, all of which are measures of parasympathetic modulation of HRV. SampEn from nonlinear features also exhibited a large effect size. Figure 2 shows the RR intervals and Poincare plots of a recruit trainee during pre and post-training.

TABLE VI. MEASURES OF HEART RATE RECOVERY (HRR)ACROSS THE TRAINING PERIOD

	Pre-training HRR	Improvement	t	p-value
HRPeak	171.08 ± 1.16	-5.96 ± 1.13	-3.907	.001**
HR5min	101.85 ± 1.46	-18.85 ± 1.85	-7.346	.000**
HR30	157.93 ± 1.58	-7.45 ± 2.06	-2.944	.007**
HR60	140.93 ± 2.09	-20.63 ± 2.7	-5.872	.000**
HRRec30	14.14 ± 2.13	1.4 ± 1.52	0.919	0.367
HRRec60	30.14 ± 1.81	14.59 ± 2.24	5.535	.000**
HRRec2min	53.5 ± 1.44	19.87 ± 1.82	9.657	.000**
HRRec3min	62.43 ± 1.22	16.08 ± 1.71	8.345	.000**
HRRec4min	68.29 ± 1.21	11.98 ± 1.96	6.122	.000**
HRRec5min	69.23 ± 1.33	13.25 ± 1.67	6.712	.000**
T30	0.49 ± 0.04	0.02 ±0.05	0.317	0.754
T60	0.58 ± 0.03	0.22 ±0.05	4.879	.000**
T d	88.36 ± 2.81	-17.29 ± 3.3	-5.236	.000**

*. Significant at the 0.05 level (2-tailed).

**. Significant at the 0.01 level (2-tailed).

B. Effect of Training on HRR

Table VI shows the pre-training recovery measures and their mean difference from post-training values along with the t value, statistical significance and effect size d. The results of t-test show that there is an overall significant improvement in almost all measures of HRR pre to post-training. The beats recovered in the initial 30-sec (HRRec30) and exponential decay constant (T d) do not reach to a level of statistical significance (p = .367, .754 respectively) even though improved from pre-training values. However, vagal re-entry velocity as obtained from T30, and T60 showed significantly faster recovery after training. Moderate to large effect sizes are observed for all measures except the initial 30 sec HRR values T30 and HRRec30.

Figure 3 illustrate the dynamics of exercise heart rate of a single recruit during pre and post-training. It can be seen that physical training has increased the rate of decline of heart rate after exercise. Further, the baseline heart rate after training is at a much lower level than the corresponding values before training. The time constants Td and T60 as obtained from mono-exponential curve and linear regression lines, fitted in the least square error criterion, also demonstrate the effectiveness of the physical training.

The results are in agreement with the available findings that, practice of repeated exercise conditions the ANS control on heart and improves the vagal tone [47], [48]. During exercise, the heart rate increases with the activation in sympathetic system and depression in parasympathetic system [28], [55]. After exercise, the reactivation of the parasympathetic system plays the major role of accelerating the recovery dynamics [39], [56].

The significant enhancement of parasympathetic activity of ANS after physical training is evident from the results obtained for HRV study (Table V). Significant modification of time and frequency domain HRV measures clearly indicate the functional enhancement of ANS. The reduction in LF/HF ratio and increment in total spectral power (TSP) also suggest, a proportionately high influence of the parasympathetic system after the training.

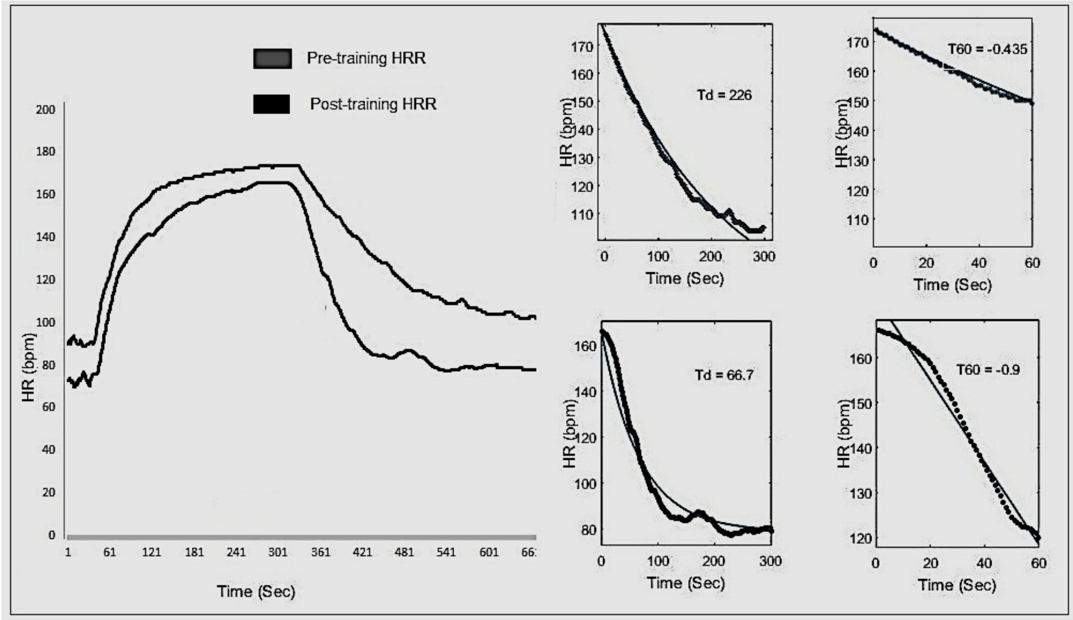


Fig. 3. HR dynamics during treadmill test and time constants of recovery phase of a recruit.

TABLE VII. PERFORMANCE COMPARISON OF CLASSIFIERS - USING HRV

	Performance of ANN		Performance of SVM	
	Without GA	With GA	Without GA	With GA
Accuracy	72 %	76.6%	77.9%	80.2%
Sensitivity	78.3%	87.0%	82.6%	89.1%
Specificity	65%	65%	72.5%	70.1%
Precision	72.2%	74.1%	78.4%	84.8%
ROC	0.823	0.829	0.82	0.811

TABLE VIII. PERFORMANCE COMPARISON OF CLASSIFIERS - USING HRR

	Performance of ANN		Performance of SVM	
	Without GA	With GA	Without GA	With GA
Accuracy	82.8%	84.5%	84.5%	89.7%
Sensitivity	86.2%	82.6%	86.2%	96.6%
Specificity	79.3%	86.2%	82.8%	82.8%
Precision	80.6%	85.7%	83.3%	84%
ROC	0.835	0.844	0.92	0.921

C. Discriminatory Potential of Five-Minute Supine HRV

The GA hybrid feature selection algorithm reduced the potential feature size to 50%. The selected features include MeanRR, NN50, pNN50, RMSSD, pLF, TSP, D2, SampEn, SD1 and α2. The maximum accuracy obtained is for SVM-Linear kernel model (80.2%) after optimization. The performance of all the three classifiers with the reduced feature set and with the whole features is tabulated in Table VII. The use of GA in optimizing the feature set has improved the accuracy of SVM by 2.1% and ANN by 4.4%.

In the physical training level discrimination problem [45], Kublanov et al. used pNN50, mean RR and TSP and achieved 77.7% classification accuracy. Further, they could also increase the accuracy up to 84.4% using stabilio-graphic data in combination with the HRV features. In the problem of classifying swimmers from sedentary group, Ray et al. [46] observed different combinations of HRV feature giving different performance metric when used with various classification algorithms.

Summarizing their results, SD2, LF/HF and PLF contributed an accuracy of 86% and 94% each when used with neural networks employing multilayer perceptron and radial basis function (RBF) kernels respectively. For the same problem, the RBF neural network contributed 100% classification accuracy with pNN50, HRVTRIN and TINN features. It can be seen that in our classification problem, features of both linear and non-linear measures together contributed to 80.2%. A direct comparison of classification accuracy is meaningless here, due to the differences in the groups involved and the design of the study.

The above mentioned studies [45] and [46] are cross-sectional in nature and at this time we do not have a longitudinal case report to refer to. But the results suggest that HRV analyzed in multiple domains is capable in classifying healthy subjects based on the training level.

D. Discriminatory Potential of HRR

From the original thirteen HRR features, GA selected four potential ones. The selected features are T30, exercise, governed solely by vagal tone and other recovery measures could classify the training level with a maximum accuracy of 89.7% when used with SVM and 84.5% with ANN (Table VIII). Taking into consideration all the HRR features, the performance of the same model dropped down to 84.5% and 82.8% for SVM and ANN respectively. The percentage improvement in classification accuracy with GA is 1.7 % for ANN and 5.2% for SVM.

With the exception of fatigue or overreaching, HRR is reported to improve with a better training status, decrease with decrement in training status and remain unchanged with no change in training status [57]. Further, both the cross-sectional [35] and longitudinal studies [36], [40] support the capacity of HRR to quantify differences in training status between trained and untrained healthy individuals. A general observation in HRR studies is that, the feasibility of the recovery measures in categorizing the study sample based on training status is not addressed. The above furnished results culminate in the fact that HRR can practically quantify the training level and distinguish training status of recruits with at least 89.2% accuracy.

IV. CONCLUSION

The police training based on a nine-month schedule of physical exercise is found effective in altering the parasympathetic and complex control of cardiovascular system of the female recruits. Considering the HRV features, it is evident that both linear and nonlinear measures are modified in response to the training in a beneficial manner. Similarly, all HRR measures are significantly improved (p = .000). An exception to this is only HRR30 and Td, whose improvement do not reach a level of statistical significance. The classification attempts demonstrated that, both HRV/HRR features have the potential to categorize trainees based on their level of training. Additionally, the HRR features outperformed the HRV features in both the classifiers with and without feature optimization.

The highest accuracy obtained is 89.7%, with the reduced features set of HRR in SVM classifier. Other performance measures such as specificity and sensitivity are also high for classifiers using the HRR measures. Hence, HRR measures can be considered as a better predictor of training status compared to that of the supine HRV measures. Further the classification accuracy of SVM is found to be better than that of ANN. With SVM, 89.2% and 80.2% of the recruits could be correctly classified as trained or untrained using HRR and HRV, respectively.

The use of GA evolutionary search algorithm reduces the HRV feature set from twenty to ten and HRR features from thirteen to four. This has implications for improved speed and efficiency of the classification algorithms. Obviously, the subject selection bias in this study is addressed with a longitudinal design. The significant factors such as age, sex and BMI of the trainees are hence automatically corrected.

Other confounding factors such as psychological stress, poor recovery and physical fatigue are reported to adversely affect HRV and HRR. Under these circumstances, enough attention is paid to the subjects to get relieved from training related physical fatigue during data acquisition program and also, recruits are monitored on holidays, in a very familiar experimental setup. Nevertheless, it cannot be assumed that all the recruits have adapted to the training in a similar manner. It will be ideal if large inter-individual variation among the recruits in possible confounding factors are taken into consideration in future studies.

Therefore, studies on homogeneous clusters of recruits, with similar characteristics traits such as pre-training physiology, personality and stress coping ability should be carried out to improve the already attained results. The quantitative results in the study highlight the potential of HRV/HRR to certainly aid the conventional training methodology adopted in police academies. Early identification of the trainees who do not adapt to the training can help the trainers in adjusting the training load and duration, accordingly. This will certainly contribute towards helping the trainers in preventing a sort of over-training which might culminate in the adverse health outcomes of the trainees.

ACKNOWLEDGEMENT

The authors would like to thank the officials of Kerala Police Academy, Thrissur, Sri. Suresh Rajpurohit IPS, (former IGP-Training), Sri. Ramachandran C.K., (Superintendent of Police, Director-Training), for granting permissions, Dr. Jayesh K. Joseph (Criminologist, KEPA), for supervising the conduct of the study, Sri. Rajesh P. (Asst. Professor, Dept. Economics, Govt. Engg. College, Thrissur) for supporting the statistical analysis of data and Dr. Suseela V.D. (Adjunct Faculty in English, Govt. Engg. College, Thrissur) for proofreading the manuscript.

REFERENCES

[1] M. J. Hickman, J. Fricas, K. J. Strom, and M. W. Pope, "Mapping police stress," Police Quarterly, vol. 14, no. 3, pp. 227–250, 2011.

[2] S. Tharkar, S. Kumpatla, P. Muthukumaran, and V. Viswanathan, "High prevalence of metabolic syndrome and cardiovascular risk among police personnel compared to general population in india," JAPI, vol. 56, pp. 845–849, 2008.

[3] K. S. Me´nard and M. L. Arter, "Stress, coping, alcohol use, and posttraumatic stress disorder among an international sample of police officers: Does gender matter?," Police Quarterly, vol. 17, no. 4, pp. 307– 327, 2014.

[4] K. Forcier, L. R. Stroud, G. D. Papandonatos, B. Hitsman, M. Reiches, J. Krishnamoorthy, and R. Niaura, "Links between physical fitness and cardiovascular reactivity and recovery to psychological stressors: A meta-analysis.," Health Psychology, vol. 25, no. 6, p. 723, 2006.

[5] S. Rosenbaum, B. Stubbs, F. Schuch, and D. Vancampfort, "Exercise and posttraumatic stress disorder," Handbuch Stress regulation und Sport, pp. 1–13, 2017.

[6] D. Scully, J. Kremer, M. M. Meade, R. Graham, and K. Dudgeon, "Physical exercise and psychological well being: a critical review," British Journal of Sports Medicine, vol. 32, no. 2, pp. 111–120, 1998.

[7] D. A. Boullosa, A. J. Hautala, and A. S. Leicht, "Introduction to the research topic: The role of physical fitness on cardiovascular responses to stress," Frontiers in Physiology, vol. 5, 2014.

[8] D. J. Smith, "A framework for understanding the training process leading to elite performance," Sports medicine, vol. 33, no. 15, pp. 1103–1126, 2003.

[9] J. D. MacDougall, H. A. Wenger, and H. J. Green, "Physiological testing of the high-performance athlete," 1991.

[10] P. D. Loprinzi, S. M. Herod, B. J. Cardinal, and T. D. Noakes, "Physical activity and the brain: a review of this dynamic, bi-directional relationship," Brain Research, vol. 1539, pp. 95–104, 2013.

[11] A. H. Okano, E. B. Fontes, R. A. Montenegro, P. d. T. V. Farinatti, E. S. Cyrino, L. M. Li, M. Bikson, and T. D. Noakes, "Brain stimulation modulates the autonomic nervous system, rating of perceived exertion and performance during maximal exercise," Br J Sports Med, pp. bjsports–2012, 2013.

[12] T. Teisala, S. Mutikainen, A. Tolvanen, M. Rottensteiner, T. Leskinen, J. Kaprio, M. Kolehmainen, H. Rusko, and U. M. Kujala, "Associations of physical activity, fitness, and body composition with heart rate variability–based indicators of stress and recovery on workdays: a cross- sectional study," Journal of Occupational Medicine and Toxicology, vol. 9, no. 1, p. 16, 2014.

[13] R. McCraty and M. A. Zayas, "Cardiac coherence, self-regulation, autonomic stability, and psychosocial well-being," Frontiers in Psychology, vol. 5, p. 1090, 2014.

[14] C. RenuMadhavi and A. Ananth, "Spectral entropy estimation of hrv data of thyroid & healthy subjects," International Journal of Computer Applications, vol. 30, no. 1, 2011.

[15] R. K. Sunkaria, V. Kumar, S. C. Saxena, and A. M. Singhal, "An ANN based hrv classifier for cardiac health prognosis," International journal of electronic healthcare, vol. 7, no. 4, pp. 315–330, 2014.

[16] M. Almeida and G. Claudio, "Effects of aerobic training on heart rate," Revista Brasileira de Medicina do Esporte, vol. 9, no. 2, pp. 113–120, 2003.

[17] I. Heikura, "Individual adaptation to endurance training guided by heart rate variability," 2015.

[18] A. A. Flatt, M. R. Esco, and F. Y. Nakamura, "Individual heart rate variability responses to preseason training in high level female soccer players," Journal of Strength and Conditioning Research, vol. 31, no. 2, pp. 531–538, 2017.

[19] A. E. Schaafsma, Heart rate variability and wellness monitoring in collegiate athletes. PhD thesis, University of Illinois at Urbana-Champaign, 2015.

[20] D. J. Plews, P. B. Laursen, J. Stanley, A. E. Kilding, and M. Buchheit, "Training adaptation and heart rate variability in elite endurance athletes: opening the door to effective monitoring," Sports medicine, vol. 43, no. 9, pp. 773–781, 2013.

[21] J. Stanley, J. M. Peake, and M. Buchheit, "Cardiac parasympathetic reactivation following exercise: implications for training prescription," Sports medicine, vol. 43, no. 12, pp. 1259–1277, 2013.

[22] A. M. Kiviniemi, A. J. Hautala, H. Kinnunen, and M. P. Tulppo, "Endurance training guided individually by daily heart rate variability measurements," European Journal of Applied Physiology, vol. 101, no. 6, pp. 743–751, 2007.

[23] E. Hynynen, A. Uusitalo, N. Konttinen, and H. Rusko, "Heart rate vari- ability during night sleep and after awakening in overtrained athletes," Medicine and Science in Sports, Exercise, vol. 38, no. 2, p. 313, 2006.

[24] E. M. Dixon, M. V. Kamath, N. McCartney, and E. L. Fallen, "Neural regulation of heart rate variability in endurance athletes and sedentary controls," Cardiovascular research, vol. 26, no. 7, pp. 713–719, 1992.

[25] A. J. Hautala, T. Rankinen, A. M. Kiviniemi, T. H. Makikallio, H. V. Huikuri, C. Bouchard, and M. P. Tulppo, "Heart rate recovery after maximal exercise is associated with acetylcholine receptor m2 (chrm2) gene polymorphism," American Physiological Society, vol. 291, no. 1, p. H459, 2006.

[26] M. Buchheit, S. Voss, L. Nybo, M. Mohr, and S. Racinais, "Physiological and performance adaptations to an in-season soccer camp in the heat: Associations with heart rate and heart rate variability," Scandinavian Journal of Medicine and Science in Sports, vol. 21, no. 6, pp. e477– e485, 2011.

[27] M. Javorka, I. Zˇ ila, T. Balha´rek, and K. Javorka, "On-and off-responses of heart rate to exercise–relations to heart rate variability," Clinical Physiology and Functional Imaging, vol. 23, no. 1, pp. 1–8, 2003.

[28] M. Buchheit, S. Racinais, J. Bilsborough, P. Bourdon, S. Voss, J. Hock- ing, J. Cordy, A. Mendez-Villanueva, and A. Coutts, "Monitoring fitness, fatigue and running performance during a pre-season training camp in elite football players," Journal of Science and Medicine in Sport, vol. 16, no. 6, pp. 550–555, 2013.

[29] K. C. Darr, D. R. Bassett, B. J. Morgan, and D. P. Thomas, "Effects of age and training status on heart rate recovery after peak exercise," American Journal of Physiology - Heart and Circulatory Physiology, vol. 254, no. 2, pp. H340–H343, 1988.

[30] G. F. Fletcher, V. F. Froelicher, L. H. Hartley, W. L. Haskell, and M. L. Pollock, "Exercise standards. a statement for health professionals from the american heart association.," Circulation, vol. 82, no. 6, pp. 2286–2322, 1990.

[31] M. B. Almeida and C. G. S. Arau´jo, "Effects of aerobic training on heart rate," Revista Brasileira de Medicina do Esporte, vol. 9, no. 2, pp. 113–120, 2003.

[32] K. Imai, H. Sato, M. Hori, H. Kusuoka, H. Ozaki, H. Yokoyama, H. Takeda, M. Inoue, and T. Kamada, "Vagally mediated heart rate recovery after exercise is accelerated in athletes but blunted in patients with chronic heart failure," Journal of the American College of Cardi- ology, vol. 24, no. 6, pp. 1529–1535, 1994.

[33] L. Bosquet, F.-X. Gamelin, and S. Berthoin, "Reliability of postexercise heart rate recovery," International journal of sports medicine, vol. 29, no. 03, pp. 238–243, 2008.

[34] S. C. Hao, A. Chai, and P. Kligfield, "Heart rate recovery response to symptom-limited treadmill exercise after cardiac rehabilitation in patients with coronary artery disease with and without recent events," The American journal of cardiology, vol. 90, no. 7, pp. 763–765, 2002.

[35] N. Du, S. Bai, K. Oguri, Y. Kato, I. Matsumoto, H. Kawase, and T. Matsuoka, "Heart rate recovery after exercise and neural regulation of heart rate variability in 30-40 year old female marathon runners," Journal of sports science & medicine, vol. 4, no. 1, p. 9, 2005.

[36] R. P. Lamberts, J. Swart, T. D. Noakes, and M. I. Lambert, "Changes in heart rate recovery after high-intensity training in well-trained cyclists," European journal of applied physiology, vol. 105, no. 5, pp. 705–713, 2009.

[37] M. R. Carnethon, D. R. Jacobs Jr, S. Sidney, B. Sternfeld, S. S. Gidding, C. Shoushtari, and K. Liu, "A longitudinal study of physical activity and heart rate recovery: Cardia, 1987-1993.," Medicine and science in sports and exercise, vol. 37, no. 4, pp. 606–612, 2005.

[38]K. S. Heffernan, E. E. Kelly, S. R. Collier, and B. Fernhall, "Cardiac autonomic modulation during recovery from acute endurance versus resistance exercise," European Journal of Cardiovascular Prevention & Rehabilitation, vol. 13, no. 1, pp. 80–86, 2006.

[39] K. Shetler, R. Marcus, V. F. Froelicher, S. Vora, D. Kalisetti, M. Prakash, D. Do, and J. Myers, "Heart rate recovery: validation and methodologic issues," Journal of the American College of Cardiology, vol. 38, no. 7, pp. 1980–1987, 2001.

[40] R. P. Lamberts, K. A. Lemmink, J. J. Durandt, and M. I. Lambert, "Variation in heart rate during submaximal exercise: implications for monitoring training.," The Journal of Strength & Conditioning Research, vol. 18, no. 3, pp. 641–645, 2004.

[41] R. George and K. Meenakshy, "Stress-recovery correlates of cardiac vagal modulation in women recruit undergoing basic combat police training," in India Conference (INDICON), 2016 IEEE Annual, pp. 1–5, IEEE, 2016.

[42] P. Melillo, R. Izzo, A. Orrico, P. Scala, M. Attanasio, M. Mirra, N. De Luca, and L. Pecchia, "Automatic prediction of cardiovascular

and cerebrovascular events using heart rate variability analysis," PloS one, vol. 10, no. 3, p. e0118504, 2015.

[43] M. Poddar, V. Kumar, and Y. P. Sharma, "Heart rate variability: Analysis and classification of healthy subjects for different age groups," in Computing for Sustainable Global Development (INDIACom), 2015 2nd International Conference on, pp. 1908–1913, IEEE, 2015.

[44] P. Melillo, M. Bracale, and L. Pecchia, "Nonlinear heart rate variability features for real-life stress detection. case study: students under stress due to university examination," Biomedical engineering online, vol. 10, no. 1, p. 96, 2011.

[45] V. Kublanov, D. Yamaliev, A. Dolganov, and G. E.A., "Classification of the physical training level by heart rate variability and stabilography data," in Siberian Symposium on Data Science and Engineering (SSDSE), pp. 49–54, IEEE, 2017.

[46] A. Ray, S. K. Nayak, B. Champaty, D. Tibarewala, and K. Pal, "Non-linear analysis of heart rate variability and ECG signal features of swimmers from NIT-Rourkela: A case study," pp. 56–75, 2016.

[47] H. A. Daanen, R. P. Lamberts, V. L. Kallen, A. Jin, and N. L. Van Meeteren, "A systematic review on heart rate recovery to monitor changes in training status in athletes," International journal of sports physiology and performance, vol. 7, no. 3, pp. 251–260, 2012.

[48] C. R. Bellenger, J. T. Fuller, R. L. Thomson, K. Davison, E. Y. Robertson, and J. D. Buckley, "Monitoring athletic training status through autonomic heart rate regulation: a systematic review and meta- analysis," Sports Medicine, vol. 46, no. 10, pp. 1461–1486, 2016.

[49] S. Qiu, X. Cai, Z. Sun, L. Li, M. Zuegel, J. M. Steinacker, and U. Schumann, "Heart rate recovery and risk of cardiovascular events and all-cause mortality: A meta-analysis of prospective cohort studies," Journal of the American Heart Association, vol. 6, no. 5, p. e005505, 2017.

[50] M. Malik, "Heart rate variability," Annals of Noninvasive Electrocardiology, vol. 1, no. 2, pp. 151–181, 1996.

[51] M. Sansone, R. Fusco, A. Pepino, and C. Sansone, "Electrocardiogram pattern recognition and analysis based on artificial neural networks and support vector machines: a review," Journal of healthcare engineering, vol. 4, no. 4, pp. 465–504, 2013.

[52] M. P. Tulppo, A. J. Hautala, T. H. Ma¨kikallio, R. T. Laukkanen, S. Nissila¨, R. L. Hughson, and H. V. Huikuri, "Effects of aerobic training on heart rate dynamics in sedentary subjects," Journal of Apploed Physiology, vol. 95, no. 1, pp. 364–372, 2003.

[53] R. S. Oliveira, A. R. Barker, K. M. Wilkinson, R. A. Abbott, and C. A. Williams, "Is cardiac autonomic function associated with cardiorespiratory fitness and physical activity in children and adolescents? a systematic review of cross-sectional studies," International Journal of Cardiology, vol. 236, pp. 113–122, 2017.

[54] Chemical coagulation efficiency in removal of water turbidity", (2018) International Journal of Pharmaceutical Research, 10 (3), pp. 188-194.

[55] E. Tulumen, I. Khalilayeva, K. Aytemir, O. Sinan Deveci, H. Aksoy, U. Kocabas, S. Okutucu, L. Tokgozoglu, G. Kabakci, H. Ozkutlu, et al., "The reproducibility of heart rate recovery after treadmill exercise test," Annals of Noninvasive Electrocardiology, vol. 16, no. 4, pp. 365–372, 2011.

[56] D. Simhaee, N. Corriveau, R. Gurm, Z. Geiger, E. Kline-Rogers, C. Goldberg, K. A. Eagle, and E. A. Jackson, "Recovery heart rate: an indicator of cardiovascular risk among middle school children," Pediatric cardiology, vol. 34, no. 6, pp. 1431–1437, 2013.

[57] J. Borresen and M. I. Lambert, "Changes in heart rate recovery in response to acute changes in training load," European journal of applied physiology, vol. 101, no. 4, pp. 503–511, 2007.

.