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Data-Driven Statistical Analysis of Heart Rate Variability in Meditation: Feature Extraction and Classification

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ABSTRACT: This paper investigates the utility of heart rate variability (HRV) analysis in differentiating physiological responses to meditative practices, offering insights into their distinct effects on autonomic nervous system function. In this work HRV features among five distinct subject groups—Chi meditation, Kundalini Yoga meditation, spontaneous breathing, metronomic breathing, and elite athletes—has been analysed. The collected data is subjected to statistical, dimensionality reduction, and classification techniques. ANOVA technique highlighted the statistically significant differences in several HRV features and Principal Component Analysis (PCA) and K-means clustering highlighted natural group separability, and an SVM classifier achieved 64.71% accuracy. The results obtained show statistically significant differences in HRV features among the meditation groups, and provides a high accuracy in the classification of the groups using machine learning algorithms.

KEYWORDS: Heart Rate Variability, Meditation, Statistical Analysis, SVM, PCA .

I. INTRODUCTION

Heart Rate Variability (HRV) analysis has emerged as a pivotal tool in assessing the intricate interplay between the autonomic nervous system and various physiological and psychological states. Its non-invasive nature and capacity to reflect the heart's response to regulatory impulses make it suitable for diagnostics purpose [1]. HRV allows us to see how the autonomic nervous system regulates heart rate dynamically, reflecting the balance of sympathetic and parasympathetic activity [2]. The nonlinear dynamics and physics-based method can predict myocardial infarction mortality, sleep apnea, autonomic nervous system activity, and circadian rhythms [3]. Heart rate variability is utilized in stress detection, autonomic nerve activity, geriatric medicine, medical diagnostics, and human psychology as a non-invasive, non-contact method [4].

Heart Rate Variability

The science of HRV has led to the development of analytical methods, that provide a way into the underlying physiological processes, and these techniques are offering different domains, like time domain, frequency domain, entropy domain, and scale-invariant domain [3]. Time-domain analysis, the most straightforward approach, quantifies the intervals between successive heartbeats, offering metrics like the standard deviation of normal-to-normal intervals and the root mean square of successive differences [5]. Frequency-domain analysis decomposes HRV into its constituent oscillatory components, revealing the power distribution across different frequency bands, such as low frequency and high frequency, which are associated with sympathetic and parasympathetic activity, respectively. Nonlinear methods, encompassing entropy measures and fractal dimensions, capture the intricate and unpredictable nature of heart rate dynamics, offering insights into the system's complexity and adaptability.

HRV arises from the continuous modulation of the sympathetic and parasympathetic branches of the autonomic nervous system, representing the variations between consecutive heartbeats. Reduced HRV has been associated with an increased risk of cardiovascular events. Conversely, elevated HRV often correlates with improved cardiovascular function and a greater capacity for stress management. This balance reflects the ability of the autonomic nervous

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system to adapt to changing environmental conditions, with higher HRV indicating greater parasympathetic vagal innervation [6]. The low-frequency spectral power, typically between 0.04 Hz and 0.15 Hz, mirrors both sympathetic and parasympathetic activities, while the high-frequency spectral power, between 0.15 Hz and 0.4 Hz, primarily reflects parasympathetic activity [7]. The ratio between low-frequency and high-frequency power provides a measure of sympathovagal balance, reflecting the interplay between the two branches of the autonomic nervous system. This ratio is indicative of the body's readiness for action versus its inclination toward rest and recovery. Analysis of HRV, offering valuable insights into cardiovascular health, stress management, and overall well-being [8].

The practice of meditation, recognized for its capacity to foster mental and emotional equilibrium, has been demonstrated to induce significant changes in HRV [9]. Meditation practices such as mindfulness and focused attention, have been shown to increase HRV, suggesting an enhancement of parasympathetic activity and autonomic flexibility [10]. Meditation's effects on HRV are thought to be mediated by its influence on the autonomic nervous system, reducing sympathetic tone and promoting parasympathetic activity [11]. This modulation results in a more balanced autonomic state, characterized by enhanced adaptability to stress and improved physiological resilience. The impact of meditation on HRV underscores its potential as a therapeutic intervention for stress-related disorders and cardiovascular health.

II. LITERATURE REVIEW

Studies have highlighted the real-time responsiveness of cardiovascular markers of parasympathetic activity to stressful classroom scenarios, such as tests and oral presentations, underscoring the utility of HRV as an immediate marker of stress responses in students [12]. Such findings suggest that HRV can serve as an objective measure of stress levels in educational settings, providing insights into the impact of different teaching methods and assessment strategies on students' physiological states. Furthermore, the investigation into wearable sensing systems provides a promising avenue for continuous mental health monitoring by tracking cardiac, respiratory, and perspiration activities [13]. The unobtrusive nature of wearable sensors allows for the collection of physiological data in real-world settings, providing a more comprehensive understanding of mental health fluctuations over time. The insights gained from these analyses could facilitate timely interventions and personalized treatment plans for individuals at risk of mental health disorders.
Emotional reactivity, characterized by peripheral physiological responses mediated by the autonomic nervous system, is closely linked to HRV. Individuals exhibiting higher HRV demonstrate enhanced emotional regulation capabilities, enabling them to effectively manage and modulate their emotional responses in challenging situations [14]. Conversely, reduced heart rate variability has been associated with heightened emotional reactivity and increased susceptibility to stress-related disorders. Interventions aimed at enhancing HRV, such as meditation, have shown good results. Mental stressors, such as mental math, are commonly employed to induce physiological stress in laboratory settings, producing similar physiological responses to other stress-inducing tasks [15]. These mental tasks offer a controlled and standardized method for investigating the effects of stress on physiological parameters. The utilization of electrophysiological multiparametric models offers comprehensive insights into an individual's current mental health state, facilitating objective evaluations of the efficacy of stress-reduction interventions.

The World Health Organization recognizes stress as a major health epidemic of the 21st century, exacerbated by traumatic experiences, family issues, workplace challenges, economic concerns, and global events like the COVID-19 pandemic [16]. Wearable devices, capable of monitoring physiological and behavioral data, offer a promising avenue for early detection of mental disorders [17]. Variations in parameters such as movement, sleep duration, heart rate, and skin temperature are often associated with psychiatric disorders [18]. Analysis at the micro level provides precise information about the biochemical, psychophysiological, and neurological processes underlying behaviour [19]. Foetal phono-cardio-graphy (PCG) compression [20] with typical signal processing approaches, while ECG compression [21] uses optimization-based methods to make the process more supple and operative. The relationship between fetal cardiac activity, gestational age, and maternal conditions has been analysed and evaluated in [22]. A comparable statistical analysis was performed on biomedical signals, including EHG and EEG to predict normal and emergency situations by acquiring these signals through non-invasive methods [23-24].

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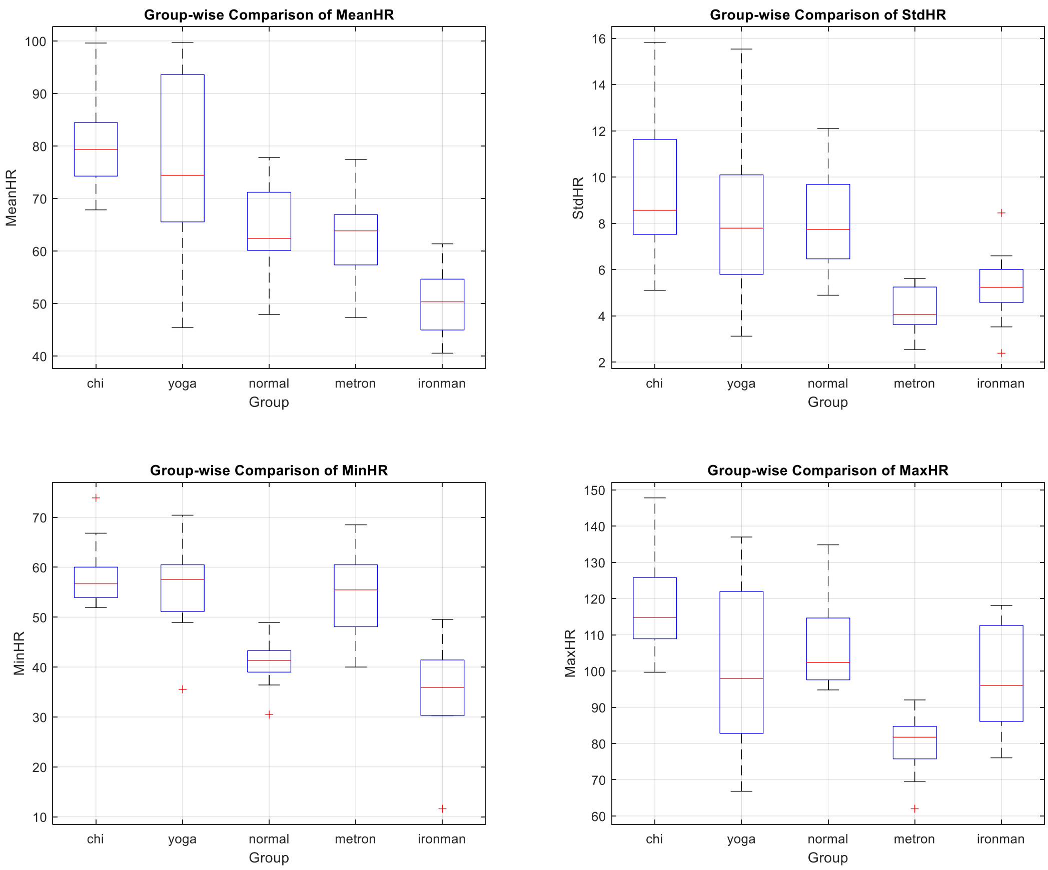
III. METHODOLOGY

Data is collected [25] for 58 subjects for five separate categories under different physical states as follows: Chi meditation (C1-C8) and Kundalini Yoga (Y1-Y4) for pre and during meditation, normal participants (N1-N11): spontaneous breathing during sleep; metronomic (M1-M14): controlled breathing at 0.25 Hz; and Ironman Athletes (I1-I9): trained athlete's sleep state. Then Nine time-domain and statistical features were calculated for each subject: MeanHR, StdHR, MinHR, MaxHR, RMSSD, SDNN, pNN50, Skewness, Kurtosis, followed by ANOVA statistical Analysis to test if HRV features vary significantly across subject group. PCA was used for Dimensionality Reduction and K- mean Clustering was used for group clustering. Finally, SVM classifier was implemented using the extracted features.

IV. RESULTS AND DISCUSSION

Figure 1 (a-i) shows the groupwise comparison of all extracted features. The results show clear HRV differences across the five groups, particularly for **MeanHR**, **StdHR**, and higher-order statistical features like **Skewness** and **Kurtosis**. These indicate that meditative practices (Chi, Yoga) and physical conditioning (Ironman) affect the HRV notably.



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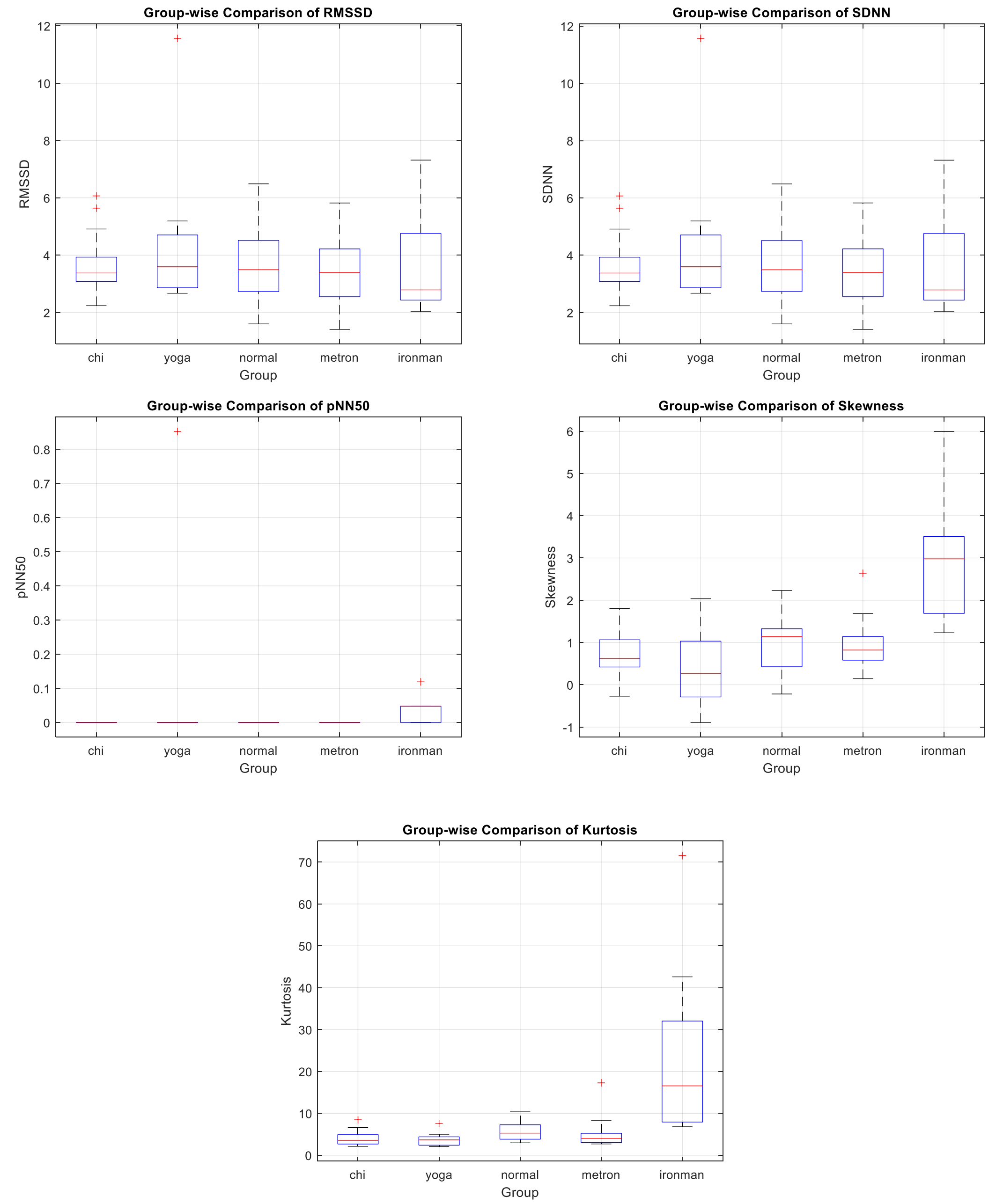

Figure 1 (a-i) Groupwise comparison of features

Figure 2 shows the PCA which revealed two primary components capturing significant variance in the dataset. The PCA visualization showed overlapping but somewhat distinct clusters, especially separating athletes and spontaneous breathing subjects from meditators.

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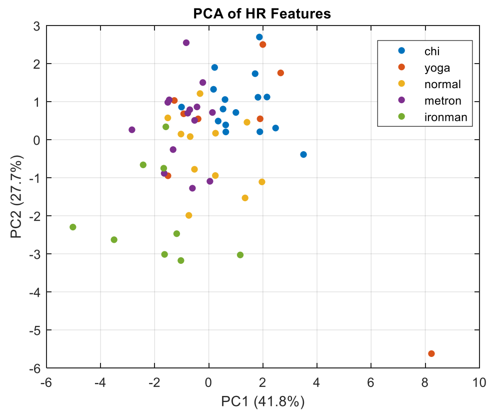

Figure 2: PCA of HR features

However, the clustering was not entirely separable, suggesting that some HRV characteristics are shared across states. Figure 3 shows the SVM matrix. This classifier achieved moderate performance, indicating that HRV alone, while informative, might not be sufficient for high-accuracy classification of meditative states. Additionally, RMSSD, SDNN, and pNN50 were not statistically significant, possibly due to short recording durations or intrinsic variability in meditation practices.

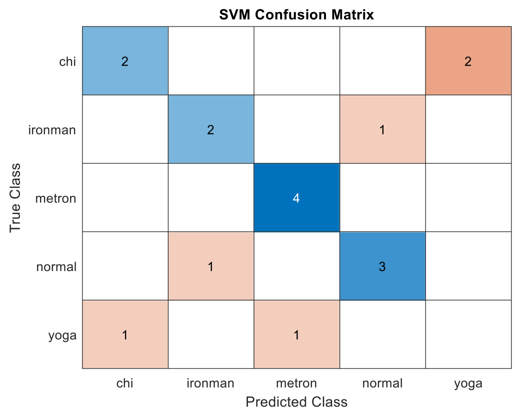

Figure 3: SVM matrix of different category groups

V. CONCLUSION

The observations highlight both the potential and the challenges of using HRV to classify meditative states and physiological conditions. Even clear group differences exist for features like MeanHR and Skewness, full separability remains challenging using basic HRV metrics alone. With the integration of more sophisticated features and models, future systems could support health monitoring, stress management, and personalized meditation training.

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