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Wearable-Enabled Screening of RBD Through HRV-Based Machine Learning

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***Abstract*—Rapid Eye Movement Sleep Behavior Disorder (RBD) is one of the strongest prodromal markers of neurodegenerative diseases such as Parkinson's disease. However, its current diagnosis relies on overnight video-polysomnography, which is costly, intrusive, and unsuitable for population-level screening. Heart Rate Variability (HRV), which reflects autonomic regulation, offers a promising non-invasive alternative based on wearable ECG sensing, enabling scalable detection in pervasive healthcare environments.**

This PhD research investigates the feasibility of HRV-based automatic RBD screening through Machine Learning (ML). Four polysomnography datasets (184 subjects) were analyzed to evaluate the robustness of HRV features under realistic conditions. A comprehensive set of 528 time, frequency, and nonlinear-domain attributes was extracted from FullNight and SleepOnly ECG segments, and multiple ML pipelines were trained and optimized for two binary tasks: healthy vs. RBD, and non-RBD (healthy+OSAS) vs. RBD.

Results show that HRV biomarkers enable accurate discrimination, achieving F1-scores above 90% in healthy-RBD classification and above 80% even when confounding sleep disorders are included. Moreover, stage-agnostic FullNight extraction improved generalization across heterogeneous datasets, supporting wearable deployment without expert scoring.

These findings highlight the potential of autonomic-based pervasive screening for prodromal neurodegeneration and motivate further validation on real-world wearable data toward home-based early diagnosis.

***Index Terms*—Supervised Machine Learning, Heart Rate Variability, REM Sleep Behavior Disorder, Diagnostic Support System**

I. Introduction

Neurodegenerative diseases (ND), such as Parkinson's Disease (PD) and Dementia with Lewy Bodies (DLB), represent a major global healthcare challenge, both in terms of associated costs, which are expected to rise significantly in the coming years, and from a clinical point of view, as there is currently only symptomatic treatment available [1]. That's why early detection is crucial for maximizing the effectiveness of emerging disease-modifying therapies. In this scenario, Rapid Eye Movement (REM) Sleep Behavior Disorder (RBD) is acknowledged as one of the strongest prodromal markers of α-synucleinopathies. Longitudinal studies confirm high phenoconversion rates (over 80% to 96.6%), positioning RBD as a key target for early screening programs [2].

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However, the current gold standard for RBD diagnosis is overnight video-polysomnography (v-PSG) [3], which is resource-intensive, invasive, costly ($500–$3,000 per study), and time-consuming due to reliance on manual scoring, thus making population-level screening impractical [4]. To overcome these limitations, there is growing interest in developing automated, scalable diagnostic approaches based on physiological signals.

Heart Rate Variability (HRV), which reflects autonomic regulation, has emerged as a promising, non-intrusive biomarker for early detection [5]. HRV-derived features offer key advantages for scalable screening, including reliability and compatibility with wearable ECG technology, making this research highly relevant to the pervasive computing community. While Machine Learning (ML) and Deep Learning have been applied using other biosignals, HRV has received limited attention, and a key research gap is the lack of consensus on optimal feature sets or robust evaluation under real-world conditions [6].

This doctoral research aims to advance scalable, minimally invasive, ML-based diagnostic tools. The chosen approach consists of two steps:

- **RQ1**: HRV features discriminatory power assessment in terms of RBD classification [7];
- **RQ2**: Automatic classification feasibility evaluation using ML pipelines [8].

For each step, the influence of methodological choices (i.e., epoch duration, exclusion of wakefulness phases), generalizability across datasets, and robustness to the inclusion of confounding factors (patients with sleep disorders other than RBD) were evaluated in detail.

II. Methods & Technical Contributions

In order to best evaluate the aspects described above, four polysomnography (PSG) datasets were used, including healthy controls (HC), iRBD patients and Obstructive Sleep Apnea Syndrome (OSAS) patients, for a total of 184 subjects.

To extract HRV features, the ECG signals recorded during the PSG examination underwent preprocessing. They were uniformed by resampling them to 512 Hz and standardizing the measurement unit. A zero-phase Chebyshev band-pass filter (10–30 Hz) was applied to facilitate the detection of R peaks. This was achieved by applying maximal-overlap discrete wavelet transform algorithm, thus finding the RR-intervals required to compute HRV features.

To ensure applicability in wearable and real-world pervasive scenarios, HRV features were extracted without relying on sleep stage labels, which are not available outside clinical settings. That's why two setups were considered: *FullNight*, including all recorded R-peaks, and *SleepOnly*, excluding wake epochs from manual hypnograms. For each subject, 528 features were extracted, obtained by combining 22 classic HRV metrics, calculated on windows of four lengths (30 s, 1 min, 2 min, 4 min), with 6 statistical indices.

To answer RQ1, the feature importance was quantified through a robust importance analysis. Since most metrics exhibited non-normal distributions, feature relevance was computed as the normalized average of three distribution-independent methods. RQ2 was investigated through a systematic evaluation of 24 supervised ML pipelines, combining four feature-selection strategies and six classifiers. Each model was trained and validated through stratified train–test splits to preserve demographic balance. The F1-score served as the primary metric to reduce false negatives in screening scenarios. All analysis were carried out for two binary tasks: HC vs. RBD, and non-RBD (HC+OSAS) vs. RBD, enabling assessment of generalizability, wake-inclusion effects, and resilience to confounding disorders.

III. Experimental Findings and Research Insights

The conducted experiments provide a first comprehensive assessment of HRV-based automatic RBD screening under realistic and pervasive computing conditions. Results obtained from four heterogeneous PSG datasets demonstrate that autonomic alterations can be reliably identified through machine learning on HRV-derived features. In the HC vs. RBD classification task, multiple pipelines achieved F1-scores above 90%, confirming the strong discriminative power of autonomic markers linked to RBD pathophysiology. These outcomes validate the technical feasibility of HRV as a scalable screening biomarker.

Performance remained high even when datasets differed in collection protocols and demographic distributions, indicating generalization capability, an essential requirement for deployment beyond controlled sleep-lab environments. Classifiers such as Gaussian Naive Bayes and Random Forests showed the most consistent performance across dataset combinations, suggesting that relatively lightweight models are sufficient for effective detection, which is beneficial for embedded or wearable implementations.

When OSAS subjects were included as non-RBD cases, performance understandably decreased, reflecting the similarity of autonomic alterations across sleep disorders. Nonetheless, several configurations still exceeded 80% F1-score, demonstrating resilience to clinical confounders that are frequently present in real-world populations. This confirms that the proposed approach can move beyond narrow laboratory validation toward population-level applicability.

A second relevant insight concerns data segmentation and feature design. Models using FullNight recordings generally outperformed those relying exclusively on sleep epochs, especially in heterogeneous settings. This suggests that autonomic imbalance associated with RBD is not confined to REM phases alone and that stage-agnostic HRV monitoring is a viable direction for pervasive systems where sleep staging is unavailable. Moreover, while longer windows (2–4 minutes) yielded the most robust HRV descriptors, shorter segments contributed complementary nonlinear information, improving ML performance without rigid constraints on recording continuity.

Together, these findings highlight the practical value of HRV-enabled wearable screening, revealing a promising trade-off between accuracy, scalability, and clinical relevance. They also show that traditional assumptions in sleep analysis (strict stage dependency, PSG-only monitoring) may be relaxed in favor of low-cost, continuous, home-based tools.

IV. Limitations and Future Directions

Current findings are based on ECG from clinical PSG systems, which do not fully reflect home-use conditions. To address this, wearable ECG acquisitions are currently ongoing to evaluate robustness under real-world noise. Future work will explore temporal deep learning, which can learn autonomic dynamics directly from ECG and capture inter-individual variability better than handcrafted features. These steps aim to transition from feasibility demonstration to real-world pervasive screening of prodromal neurodegenerative disorders.

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