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Article

Adaptive HRV analysis: Reinforcement learning-driven training load monitoring in sports science

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Abstract: Heart rate variability (HRV) is a widely used biomarker for assessing physiological stress, recovery, and training load in sports science. During exercise, the mechanical changes in various parts of the body, such as muscle contraction and relaxation, joint movement, and the dynamic response of the cardiovascular system, are closely related to HRV. However, traditional analysis methods face significant challenges in handling HRV's nonlinear dynamics and noise sensitivity. These limitations reduce their effectiveness in complex sport scenarios. To address these limitations, this study proposes an innovative HRV feature extraction framework that integrates reinforcement learning (RL) with an attention-based Long Short-Term Memory (LSTM) network. The framework dynamically optimizes feature selection and weighting through RL. The integration of an attention mechanism enables the model to prioritize critical temporal segments, improving its ability to capture and interpret key physiological patterns. Additionally, the model combines time-domain, frequency-domain, biomechanical factors, and nonlinear features, providing a comprehensive and robust representation of HRV signals. The framework was validated on four publicly available datasets covering resting, exercise, stress, and recovery states. It achieved an average accuracy of 95.0% and an $F1$-score of 90.8%, outperforming state-of-the-art baselines by 2.7% to 3.4%. These results demonstrate the proposed method's superior performance in stress detection, training load prediction, and recovery assessment, establishing it as a scalable and adaptive tool for HRV-based sports training monitoring and health management. The framework's innovative design offers significant advancements in the analysis of complex HRV data, paving the way for intelligent and personalized applications in sports science and healthcare.

Keywords: heart rate variability; reinforcement learning; sports science; sport biomechanics

1. Introduction

In the realm of sports training, particularly in professional athletic programs and specialized disciplines, the pursuit of peak performance demands a meticulous balance between training intensity and recovery. Athletes, especially those engaging in anaerobic activities such as sprinting, weightlifting, and high-intensity interval training, face unique challenges in optimizing their training regimens [1,2]. Anaerobic exercise is lauded for its ability to improve muscular strength, endurance, and explosive power while enhancing metabolic efficiency [3]. However, its benefits come with significant physiological demands. Intense training sessions often result in acute and chronic fatigue, potentially leading to overtraining syndrome, injuries, or long-term health issues if not managed properly. Hence, there exists a critical need for tools and strategies to quantify training load, monitor recovery, and guide personalized interventions.

Fatigue, as an inevitable consequence of strenuous exercise, impacts both short-term performance and long-term health outcomes [4]. Physiological fatigue manifests as a temporary decline in physical and cognitive capabilities due to metabolic by-products, energy depletion, and stress on the neuromuscular and cardiovascular systems [5]. For athletes, this state is particularly pronounced during high-intensity anaerobic exercises, where the accumulation of lactic acid and other metabolites places a significant strain on the body. If fatigue is not accurately assessed and managed, it can lead to overtraining, which not only diminishes performance but also increases the risk of injuries and negatively affects mental well-being. In this context, training load monitoring has emerged as a cornerstone of modern sports science. An optimal balance between training intensity and recovery is essential to avoid undertraining, which can hinder performance gains, and overtraining, which can result in injuries or burnout. Accurate monitoring allows coaches and athletes to fine-tune their training programs, ensuring sustainable improvements in performance while safeguarding long-term health.

Heart rate variability (HRV) has gained prominence as a non-invasive, reliable biomarker for assessing training load, physiological stress, and recovery [6,7]. HRV refers to the temporal fluctuations between successive heartbeats (RR intervals) and reflects the dynamic interplay between the sympathetic and parasympathetic branches of the autonomic nervous system (ANS). The ANS is instrumental in regulating cardiovascular, respiratory, and metabolic functions, making HRV an effective proxy for physiological states [8]. Studies have shown that a higher HRV is associated with better cardiovascular health, recovery, and stress resilience, while low HRV is often linked to increased risk of heart disease, stress, and overtraining in athletes [9,10], which has proven to be a valuable tool in stress management, mental health monitoring, and chronic disease prevention, underscoring its versatility as a physiological marker.

Despite its utility, HRV analysis is fraught with challenges, particularly in the context of sports training. HRV signals are inherently complex, characterized by nonlinear dynamics, temporal dependencies, and multidimensional features. Traditional analytical methods, which rely on statistical or linear models [11], often fail to capture the intricate patterns embedded in HRV data. Furthermore, physiological noise, data redundancy, and the variability introduced by external factors such as environmental conditions or psychological stress further complicate the analysis. However, these methods are often insufficient to address the nonlinear and chaotic nature of HRV signals, which are better captured by nonlinear features derived from Poincaré plots or entropy measures. The need for advanced computational techniques to analyze HRV signals is particularly pressing in sports science, where the stakes are high, and the margin for error is minimal. Accurate HRV analysis can be the difference between optimal performance and overtraining, making it a critical area of research.

The advent of machine learning, particularly deep learning, has revolutionized HRV analysis. Deep learning models, such as convolutional neural networks (CNNs) [12] and recurrent neural networks (RNNs) [13], excel in extracting complex patterns from high-dimensional data. Long Short-Term Memory (LSTM) networks

[14], a subset of RNNs, are particularly suited for HRV analysis due to their ability to capture both short-term and long-term dependencies in sequential data. However, traditional LSTM models often treat all time steps in a sequence with equal importance, potentially diluting the significance of critical time intervals.

To address this limitation, attention mechanisms have been introduced, enabling models to focus selectively on the most informative segments of the HRV signal. By assigning dynamic weights to different time steps, attention mechanisms enhance the interpretability and accuracy of HRV analysis [15], particularly in capturing physiological changes related to stress, recovery, or adaptation. Reinforcement learning (RL) further complements deep learning by introducing an adaptive optimization layer [16]. In the context of HRV analysis, RL can dynamically refine feature selection and weighting, ensuring that only the most relevant features contribute to predictions. This approach not only mitigates the risks of overfitting but also enhances the generalizability of models across diverse datasets and physiological conditions.

The primary aim of this study is to develop an innovative HRV feature extraction framework that improves training load prediction. The specific objectives are:

(1) To explore the role of time-domain, frequency-domain, and nonlinear features in training load prediction using HRV data.

(2) To assess the impact of various machine learning models on the prediction accuracy of training load.

(3) To evaluate the feasibility and practical implications of implementing machine learning techniques for real-time HRV-based monitoring in sports contexts.

This study proposes a novel HRV feature extraction framework that integrates reinforcement learning with attention-LSTM networks to address the multifaceted challenges of HRV analysis in sports training. The framework incorporates three key dimensions of HRV features—time-domain, frequency-domain, and nonlinear metrics—into a unified model. The innovative aspects of this framework include:

(1) Dynamic Feature Weighting: RL optimizes feature selection by balancing accuracy and redundancy, ensuring robust predictions.

(2) Temporal Focus: Attention mechanisms highlight critical time intervals, improving the model's ability to capture transient physiological changes.

(3) Multidimensional Integration: The combination of time-domain, frequency-domain, and nonlinear features ensures comprehensive analysis, accommodating the diverse nature of HRV signals.

This paper bridges the gap between theoretical advancements in HRV analysis and practical applications in sports science. By leveraging cutting-edge techniques in machine learning and reinforcement learning, the proposed framework sets a new standard for HRV-based monitoring, paving the way for intelligent and adaptive solutions in sports and beyond. The subsequent sections of this paper will delve into the technical details, experimental validation, and real-world implications of this innovative approach.

2. Related work

2.1. HRV as a Biomarker

The significance of HRV as an indicator of physiological adaptability and stress responses was first systematized by the Task Force of the European Society of Cardiology and the North American Society of Pacing and Electrophysiology [17], which laid out standardized methods for HRV measurement, categorizing it into time-domain, frequency-domain, and nonlinear features.

Time-domain metrics remain among the most commonly used methods for HRV analysis due to their simplicity and computational efficiency. Metrics such as the mean RR interval, the standard deviation of NN intervals (SDNN), and the root mean square of successive differences (RMSSD) have been widely applied in clinical and sports settings. Musialik et al. [18] demonstrated the utility of SDNN as an overall indicator of HRV, correlating it with cardiovascular health. Similarly, DeGiorgio et al. [19] applied RMSSD to evaluate parasympathetic activity in athletes, showing that RMSSD could predict recovery states following intense training sessions. Despite their usefulness, time-domain metrics fail to capture the spectral composition of HRV, which limits their ability to provide detailed insights into the specific contributions of the sympathetic and parasympathetic nervous systems.

The time-domain analysis of HRV remains one of the most straightforward and commonly employed methods due to its ease of computation. Metrics such as the mean RR interval, SDNN, and RMSSD are used extensively to measure overall variability and parasympathetic activity. Compostella et al. [20] demonstrated that SDNN is a reliable indicator of global HRV, correlating with long-term health outcomes, while Bentley et al. [21] highlighted RMSSD as an effective measure of parasympathetic modulation during recovery phases in athletes. However, time-domain metrics often fail to capture frequency-specific information, which limits their ability to provide detailed insights into autonomic function, especially in dynamic or stress-induced scenarios.

Frequency-domain analysis addresses some of these limitations by decomposing HRV signals into spectral components, allowing for the examination of autonomic contributions across different frequency bands. Thomas et al. [22] identified the low-frequency (LF) and high-frequency (HF) bands as critical markers, associating LF with a combination of sympathetic and parasympathetic activity and HF with parasympathetic modulation. The LF/HF ratio has since been widely adopted as an indicator of autonomic balance. Posada et al. [23] extended these methodologies by applying power spectral density (PSD) analysis to HRV data, demonstrating its ability to detect physiological responses to stress with improved resolution. However, as noted by Jia et al. [24], frequency-domain methods are often limited in their application to nonstationary HRV signals and require robust preprocessing techniques to mitigate noise and artifacts.

Nonlinear methods have emerged as a powerful complement to time-domain and frequency-domain techniques, particularly for capturing the complex and chaotic dynamics inherent in HRV signals. Satti et al. [25] introduced the use of Poincaré plots, quantifying variability through the short-term (SD1) and long-term (SD2) dimensions, while Udhayakumar et al. [26] proposed sample entropy (SampEn) as a metric for evaluating the complexity of HRV signals. These approaches have proven valuable in identifying subtle physiological changes, such as those associated with stress or disease states. Additionally, Wu [27] introduced multiscale entropy to evaluate HRV dynamics across multiple time scales, providing a more comprehensive understanding of signal complexity. However, as highlighted by Xie et al. [28], nonlinear methods often require significant computational resources and are highly sensitive to signal quality, which limits their practicality in real-time applications or large-scale studies.

Applications of HRV extend across a wide range of disciplines, reflecting its versatility as a biomarker. In sports science, Stephenson et al. [29] validated HRV as an effective tool for monitoring training readiness and recovery, emphasizing RMSSD as a key indicator for guiding adjustments in training intensity. In healthcare, Turcu et al. [30] reviewed HRV's role in cardiovascular monitoring, identifying its predictive value for conditions such as arrhythmias and heart failure. Similarly, Wang et al. [31] linked reductions in HRV to mental health conditions like anxiety and depression, suggesting its utility as a biomarker for psychological stress. Despite these advances, the application of HRV remains inconsistent across fields, with significant variations in methodologies and interpretative frameworks.

Several research gaps persist in HRV analysis. First, the lack of integration between time-domain, frequency-domain, and nonlinear metrics limits the ability to fully leverage HRV's multidimensional nature. As emphasized by Nayak et al. [32], most studies adopt a siloed approach, analyzing each metric independently rather than developing unified frameworks. Second, traditional methods often fail to account for the dynamic and context-dependent nature of physiological changes, particularly in applications like sports training or stress monitoring. Third, noise and redundancy in HRV data present significant challenges, diluting the accuracy and robustness of predictive models. Lastly, many techniques rely on extensive preprocessing, limiting their scalability and real-time applicability. Addressing these gaps will require the development of adaptive, multidimensional approaches capable of dynamically integrating diverse features while mitigating noise and redundancy.

2.2. Deep learning and reinforcement learning

Deep learning techniques, particularly CNNs and RNNs, have shown significant promise in HRV analysis. CNNs are particularly effective for extracting spatial features from HRV signals, as demonstrated by Berrahou et al. [33], who employed CNNs for arrhythmia detection. Their study achieved higher accuracy compared to conventional time-domain and frequency-domain methods, emphasizing the ability of CNNs to learn hierarchical feature representations from raw HRV data. However, CNNs are less adept at capturing temporal dependencies, a critical aspect of HRV signals, which has led to the adoption of RNNs for sequential modeling. LSTM networks, a variant of RNNs, have been widely applied due to their capacity to model both short-term and long-term dependencies in HRV data. Satheeswaran et al. [34] utilized LSTM to classify ECG (Electrocardiogram) signals, demonstrating their effectiveness in capturing the sequential nature of HRV. Similarly, Ramteke et al. [35] applied LSTM for HRV-based stress detection, achieving superior performance compared to frequency-domain approaches.

To further enhance temporal modeling, attention mechanisms have been integrated into deep learning frameworks for HRV analysis. Fan et al. [36] introduced attention mechanisms allow models to dynamically assign importance to specific time steps, thereby focusing on the most informative segments of HRV signals. Xu et al. [37] applied attention-based models to HRV data, improving the detection of critical physiological changes such as recovery onset or stress surges. This approach not only enhances accuracy but also improves interpretability by identifying the most relevant portions of the HRV signal. RL has also emerged as a powerful tool for optimizing feature selection in HRV analysis. Shah et al. [38] proposed an RL-based framework that uses a reward function to balance predictive accuracy and feature redundancy, dynamically selecting the most informative features. Their model addressed key challenges such as feature redundancy and noise while leveraging attention mechanisms to focus on critical time intervals. Hybrid models combining deep learning and RL have also gained traction. Li et al. [39] integrated transformer architectures with CNNs for multidimensional HRV feature fusion, achieving high accuracy in detecting autonomic imbalances. Transformers, known for their ability to capture long-range dependencies, have proven effective in HRV analysis, particularly when combined with reinforcement learning for adaptive optimization [40].

3. A RL-Based Framework for training load prediction

This section proposes a reinforcement learning-based framework for HRV feature extraction to address the challenges of temporal dependency, nonlinearity, and multidimensional feature integration in HRV signals. The framework begins with data preprocessing, followed by feature extraction using deep learning methods and feature optimization through reinforcement learning, culminating in accurate predictions of sports training load. The overall structure of the proposed model is shown in **Figure 1**.

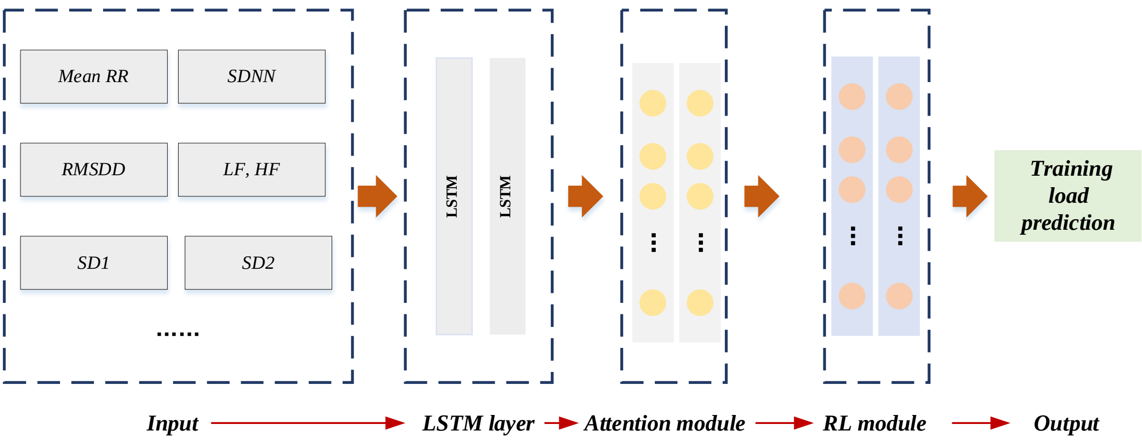

Figure 1. The framework for the training load prediction.

3.1. Data preprocessing and feature digitization

The data preprocessing process involves several key steps to ensure data quality and provide reliable inputs for subsequent modeling. First, data cleaning is performed to remove missing values and outliers, using interpolation to fill in missing data and statistical methods or thresholding to handle outliers, ensuring data completeness. Next, normalization is applied, using z-score standardization to transform all data to a unified scale and eliminate differences in feature magnitudes. Following this, time-domain features are extracted, including the calculation of the mean RR interval, SDNN, and RMSSD of RR intervals, which assess overall heart rate, heart rate variability, and parasympathetic nervous system activity. Then, frequency-domain features are extracted by performing a Fourier transform on the RR interval signal to obtain LF and HF components, and calculating the LF/HF ratio to analyze the balance between sympathetic and parasympathetic nervous system activity. Finally, nonlinear features are extracted using the Poincaré plot, with short-term (SD1) and long-term (SD2) fluctuations quantified to capture the complex nonlinear dynamics of HRV signals. All these time-domain, frequency-domain, and nonlinear features are then fused into a multidimensional feature vector

3.1.1. Time-domain features

Time-domain features describe the statistical properties of RR intervals over time, serving as fundamental metrics for HRV analysis. The mean RR interval, which quantifies the average heart rate level, is defined as:

$$\text{Mean RR} = \frac{1}{N}\sum_{i=1}^{N} RR_i \tag{1}$$

Where RR_i represents the i-th RR interval and N is the total number of intervals. This metric provides a baseline for evaluating the overall heart rate level across the measurement period.

To capture variability in heart rate, the SDNN is introduced, calculated as:

$$\text{SDNN} = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N} (RR_i - \text{Mean RR})^2} \tag{2}$$

SDNN measures the overall variability of HRV and serves as an important indicator of the autonomic nervous system's ability to regulate heart rate. A higher SDNN often corresponds to better cardiovascular adaptability.

For short-term variability, the RMSSD is employed:

$$\text{RMSSD} = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N-1} (RR_{i+1} - RR_i)^2} \tag{3}$$

RMSSD emphasizes rapid variations in heart rate and is closely associated with parasympathetic nervous system activity, making it a key metric for evaluating recovery states after physical activity.

3.1.2. Frequency-domain features

Frequency-domain features provide insights into the distribution of RR intervals across various frequency bands, reflecting the activity of the autonomic nervous system. The LF and HF components are defined as:

$$\mathrm{LF} = \int_{0.04}^{0.15} P(f)df,\ \mathrm{HF} = \int_{0.15}^{0.40} P(f)df \tag{4}$$

where $P(f)$ represents the power spectral density at frequency f. The LF/HF ratio is then calculated as:

$$\mathrm{LF/HF\ Ratio} = \frac{\mathrm{LF}}{\mathrm{HF}} \tag{5}$$

The LF component reflects sympathetic activity, while the HF component corresponds to parasympathetic activity. The LF/HF ratio serves as a measure of autonomic balance, with higher values indicating increased sympathetic dominance.

3.1.3. Nonlinear features

The nonlinear dynamics of HRV signals can be captured using features derived from the Poincaré plot. The short-term and long-term fluctuations are quantified by:

$$\mathrm{SD1} = \sqrt{\frac{1}{2}\mathrm{RMSSD}},\ \mathrm{SD2} = \sqrt{2 \cdot \mathrm{SDNN}^2 - \frac{1}{2}\mathrm{RMSSD}^2}\mathrm{LF/HF\ Ratio} = \frac{\mathrm{LF}}{\mathrm{HF}} \tag{6}$$

where SD1 represents short-term variability, and SD2 captures long-term variability. These features provide additional insights into the complex and chaotic nature of HRV signals.

These features collectively transform raw HRV signals into a comprehensive multidimensional representation. The combination of time-domain, frequency-domain, and nonlinear features ensures that the data retains rich physiological information, which serves as a robust input for deep learning models. This preprocessing stage forms the foundation for extracting meaningful patterns in the subsequent modeling phases.

3.2. Attention-LSTM

HRV signals exhibit strong temporal dependencies, making them ideal candidates for sequence modeling. LSTM networks are employed to extract both short-term and long-term dependencies from these sequential features. LSTM networks are particularly effective at addressing the vanishing gradient problem inherent in traditional RNNs.

3.2.1. LSTM

Forget Gate determines which information from the previous time step should be discarded:

$$f_t = \sigma\left(W_f \cdot [h_{t-1}, x_t] + b_f\right) \tag{7}$$

where h_{t-1} is the hidden state from the previous time step, x_t is the current input, and σ is the sigmoid activation function.

Input Gate incorporates new information into the memory cell:

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \tag{8}$$

$$\tilde{C}_t = \tanh(W_C \cdot [h_{t-1}, x_t] + b_C) \tag{9}$$

here, i_t decides the importance of new information, and $\tilde{C}_t$ represents the candidate memory value.

Cell State Update updates the memory cell by combining the forget and input gates:

$$C_t = f_t \odot C_{t-1} + i_t \odot \tilde{C}_t \tag{10}$$

The cell state C_t serves as the LSTM's internal memory, retaining information over long sequences.

Output Gate generates the current hidden state:

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o),\ h_t = o_t \odot \tanh(C_t) \tag{11}$$

The LSTM's architecture dynamically balances the retention and forgetting of information, making it well-suited for HRV feature extraction. Its ability to model temporal dependencies enables the capture of critical patterns that span multiple time steps, ensuring that the extracted features reflect both short-term fluctuations and long-term trends.

3.2.2. Attention mechanism

HRV signals are inherently nonstationary and often contain critical segments that are highly informative in capturing physiological changes, such as autonomic nervous system responses to external stimuli, physical stress, or recovery states. However, traditional feature extraction techniques, and even LSTM networks, treat each time step in a sequential signal with uniform importance, assuming that all temporal information contributes equally to the final representation. This assumption fails to consider the fact that certain time intervals (e.g., sudden surges in RR variability or sharp drops due to physiological stress) may carry disproportionately more information about the underlying autonomic regulation.

The attention mechanism is introduced to address this limitation by dynamically weighting the importance of each time step in the LSTM-generated hidden state sequence. Its ability to selectively amplify or attenuate specific parts of the signal allows the model to focus on the most informative time steps for HRV analysis.

For each hidden state h_t, the attention score e_t is computed as:

$$e_t = \tanh(W_a \cdot h_t + b_a) \tag{12}$$

where W_a and b_a are trainable parameters, and tanh serves as a nonlinear activation function. The score e_t measures the relevance of hidden state h_t to the final output.

The attention score is normalized using the softmax function to generate a probability distribution over all time steps:

$$\alpha_t = \frac{\exp(e_t)}{\sum_{k=1}^{T} \exp(e_k)} \tag{13}$$

here, α_t represents the relative importance of the t-th time step. The softmax ensures that $\sum_{t=1}^{T} \alpha_t = 1$, making the weights interpretable as probabilities.

The context vector c, representing the aggregated signal information, is calculated as:

$$c = \sum_{t=1}^{T} \alpha_t h_t \tag{14}$$

This context vector focuses on the most critical time steps while deemphasizing less relevant ones.

The attention mechanism assigns dynamic weights to different time steps in the sequence, ensuring that critical physiological events (such as transitions between stress and recovery states) are given more importance.

3.3. Feature optimization using RL

While the attention mechanism enhances the representation of temporal features, it does not explicitly address the problem of feature redundancy or the need for optimizing feature selection based on their contribution to the final predictions. HRV signals often contain correlated or redundant features, such as overlapping time-domain and frequency-domain metrics, which can dilute the effectiveness of the model and lead to overfitting. Additionally, the complexity of HRV signals, including their nonlinear dynamics, calls for an adaptive strategy to weigh and refine features dynamically.

The RL module is introduced to solve these challenges by learning an optimal policy for feature weighting and refinement. By iteratively optimizing a reward function, RL ensures that only the most relevant features are retained while redundant or less informative ones are down weighted. The training process of RL is shown in **Figure 2**.

Reinforcement learning operates within a Markov Decision Process (MDP) framework, where the agent (model) interacts with the environment (feature set) to maximize cumulative reward.

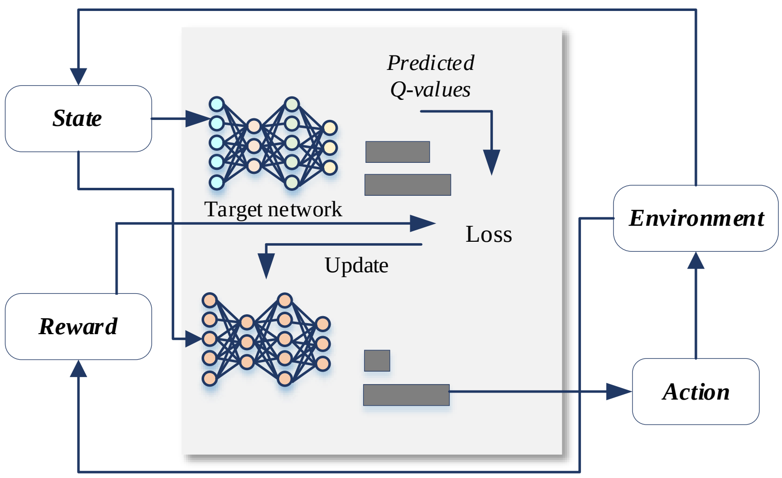

Figure 2. Training process of RL.

As shown in **Figure 2**, the key components are defined as follows:

State s_t: The feature set at time t, represented as the output of the attention mechanism.

Action a_t: The decision to adjust the weight or importance of specific features.

Reward r_t: A scalar value quantifying the effectiveness of the action in improving model performance.

Policy $\pi_\theta(a_t \mid s_t)$: A probabilistic mapping from states to actions, parameterized by θ.

The goal of reinforcement learning is to maximize the expected cumulative reward:

$$R = \sum_{t=1}^{T} \gamma^t r_t \tag{15}$$

where $\gamma \in [0,1]$ is the discount factor that controls the trade-off between immediate and future rewards.

The policy $\pi_\theta(a_t \mid s_t)$ is optimized using the policy gradient method:

$$\nabla_\theta J(\theta) = \mathbb{E}[\nabla_\theta \log \pi_\theta(a_t \mid s_t) R] \tag{16}$$

here, $J(\theta)$ represents the expected cumulative reward under the current policy. The gradient ascent approach iteratively updates θ to improve the policy.

The reward function is critical for guiding the RL module to achieve desirable feature optimization. In this framework, the reward r_t is designed to balance classification accuracy and feature redundancy:

$$r_t = \Delta\text{Accuracy} - \lambda \cdot \text{Feature Redundancy} \tag{17}$$

where: Δ Accuracy represents the improvement in prediction accuracy due to feature adjustments. Feature Redundancy represents a measure of the correlation or overlap between selected features, penalizing the selection of redundant features. λ represents a regularization parameter that controls the trade-off between accuracy and redundancy.

The RL agent iteratively adjusts the weights of the extracted features, learning to prioritize the most relevant features for accurate predictions while minimizing redundancy. To prevent overfitting, weight decay is applied during training. These methods help improve the model's generalizability by preventing it from becoming overly reliant on specific features or training data.

4. Experiments and analysis

4.1. Dataset description

To evaluate the robustness of the proposed method, datasets that cover a range of physiological states are necessary. Thus, the data on resting, exercise, and recovery were collected. In this research, four publicly available datasets that contain RR interval data or raw ECG data are used, which are suitable for HRV analysis. The details of the different datasets are shown in **Table 1** and **Figure 3**.

Table 1. Dataset description.

Number		Description	Sample Size	Duration	Collected Features
Dataset 1	MIT-BIH Normal Sinus Rhythm Database	Normal sinus rhythm recordings from healthy individuals.	18 subjects	~24 hours	RR intervals, ECG
Dataset 2	PhysioNet Stress Recognition in Auto Settings	HRV data under stress-inducing driving tasks.	20 subjects	~2 hours	ECG, respiration, stress labels
Dataset 3	EU Exercise Stress ECG Database	ECG recordings during exercise and recovery phases.	52 recordings	5–25 minutes	RR intervals, exercise phases, recovery states
Dataset 4	Fantasia Database	ECG recordings of young and elderly individuals at rest.	40 subjects	~2 hours	RR intervals, ECG, age group

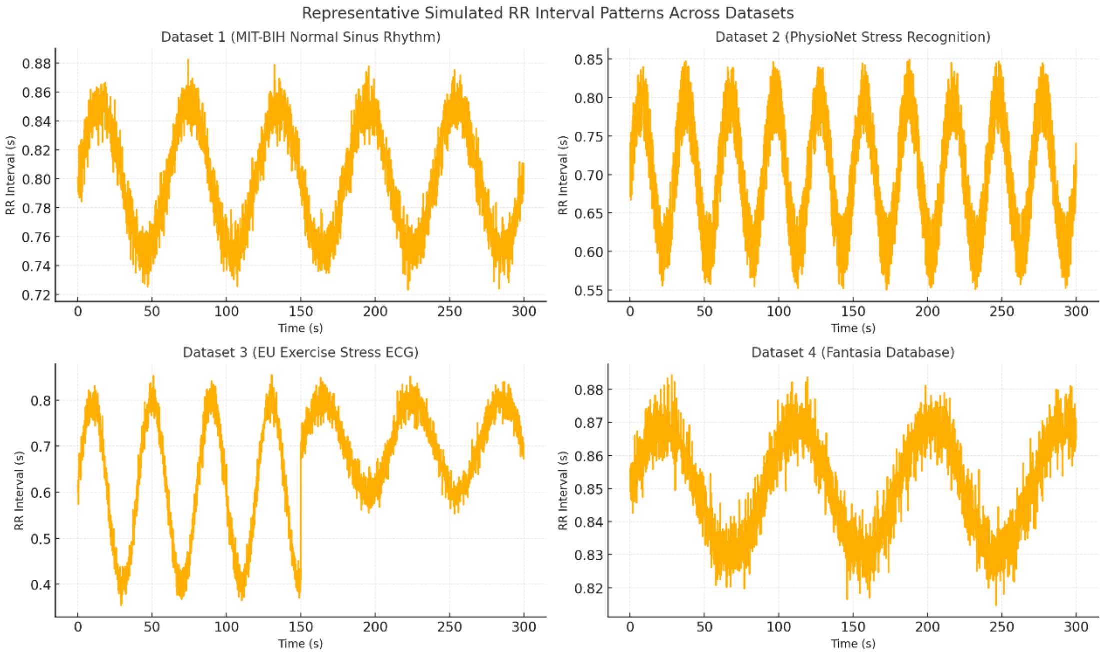

Figure 3. Representative simulated RR interval patterns.

From **Figure 3**, Dataset 1 shows a stable sinus rhythm with minor fluctuations and low noise, reflecting the regular heart activity of healthy individuals at rest; Dataset 2 shows increased variability and irregularity due to stress-induced responses, showcasing a higher degree of randomness and dynamic changes in HRV; Dataset 3 shows dynamic variation across two phases:

Exercise phase (first half): Rapid and pronounced fluctuations due to the increased cardiac workload.

Recovery phase (second half): Gradual stabilization of HRV as the body returns to its baseline state; Dataset 4 shows a smooth and periodic resting-state signal with minimal noise, capturing subtle HRV oscillations often seen in individuals at rest.

4.2. Experimental Environment

The experiments are conducted using a high-performance computational environment to ensure reproducibility and scalability, Processor: Intel Xeon Platinum 8268 (24 cores); RAM: 128 GB; GPU: NVIDIA Tesla V100 (32 GB VRAM); Software Frameworks: Python 3.9, TensorFlow 2.10, PyTorch 1.12, Scipy for signal processing.

The model is implemented with state-of-the-art deep learning frameworks. Data preprocessing and feature extraction modules leverage SciPy for signal processing and HRV Toolkit libraries for feature computation. The parameter settings for the Attention-LSTM and RL modules are shown in **Table 2**.

Table 2. Parameter Settings.

Parameter	Value	Description
Learning Rate	0.001	Initial learning rate for optimizer
LSTM Hidden Units	128	Number of units in LSTM hidden layers
Attention Dimension	64	Dimensionality of the attention mechanism
RL Discount Factor (γ)	0.9	Controls the balance between immediate and future rewards
Batch Size	64	Number of samples per training batch
Reward Regularization (λ)	0.1	Penalty for feature redundancy in reward function
Epochs	50	Total number of training epochs
Optimizer	Adam	Optimization algorithm
Activation Function	ReLU, Softmax	Activation functions for different layers

4.3. Model training process

Figure 4 shows the training and validation loss curves for the proposed RL-based HRV model across the four datasets.

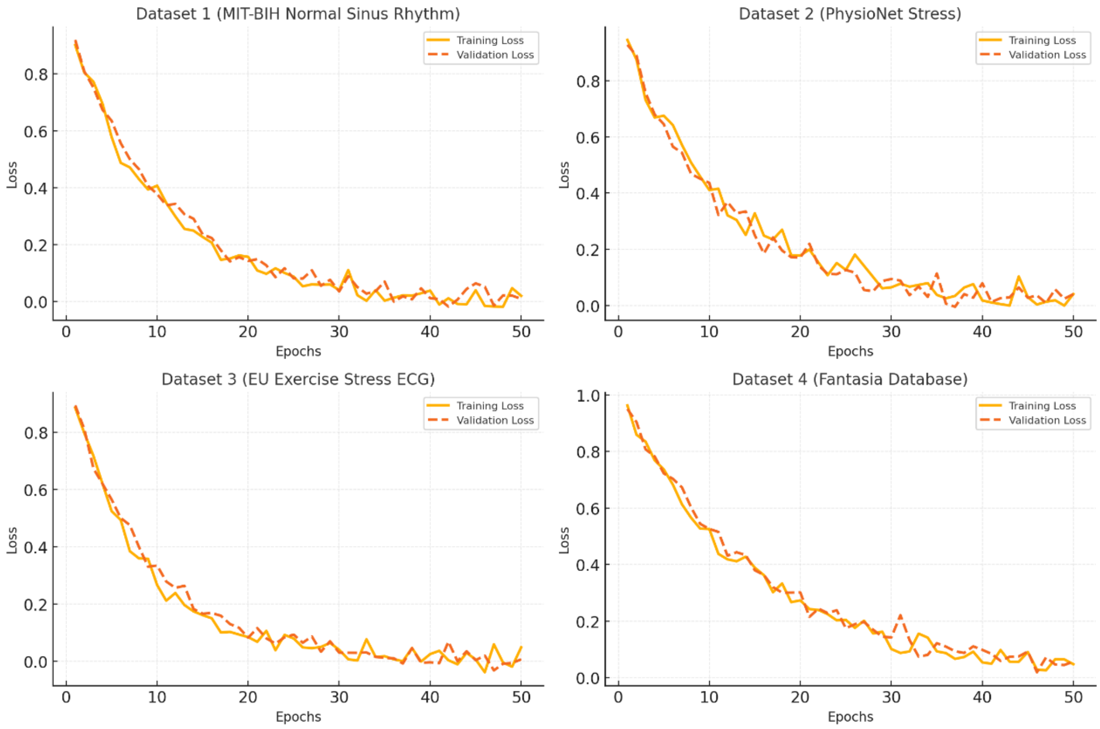

Figure 4. Training Loss Curves.

The training and validation loss curves for the proposed RL-based HRV model demonstrate consistent convergence across all four datasets, indicating effective learning of HRV signal patterns. In each dataset, the training loss decreases steadily over the epochs, showing the model's ability to adapt to the intrinsic variability of

HRV features. The validation loss curves generally follow the same trend as the training loss, reflecting strong generalization capabilities. However, slight variations in the validation loss, particularly in Dataset 2 (PhysioNet Stress) and Dataset 3 (EU Exercise Stress ECG), suggest dataset-specific challenges, such as increased noise or variability in stress-induced HRV data. These differences underscore the robustness of the proposed framework in handling diverse physiological conditions, from resting (Dataset 4) to stress and recovery phases (Dataset 3). Importantly, the close alignment of training and validation loss trends indicates minimal overfitting, which is critical for ensuring the practical applicability of the model in real-world HRV-based monitoring tasks. This demonstrates the model's capacity to effectively generalize across different conditions and feature distributions, reinforcing its reliability for sports training load monitoring and other HRV-based applications.

Figure 5 shows the accuracy and F1-score curves that exhibit consistent improvements across all datasets as training progresses.

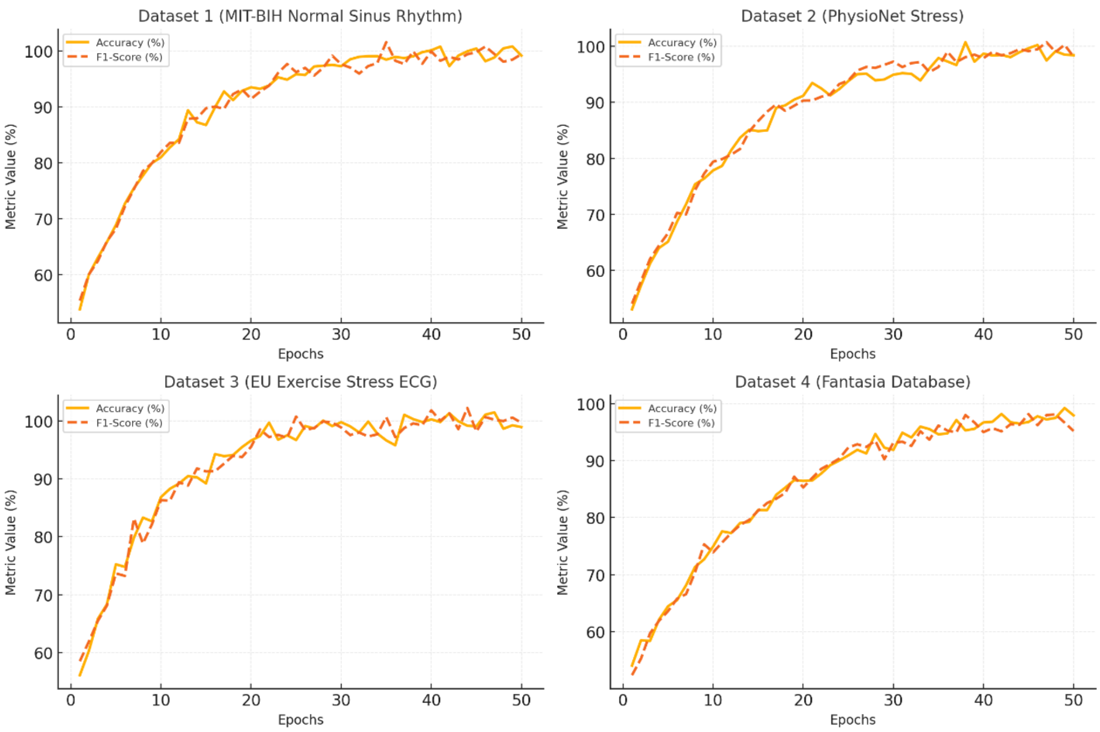

Figure 5. Training feedback metrics.

The training feedback metrics, including accuracy and F1-score, provide valuable insights into the performance and convergence behavior of the proposed RL-based HRV model. Across all four datasets, the accuracy consistently improves over the epochs, demonstrating the model's ability to learn meaningful patterns from the HRV signals. Similarly, the F1-score shows steady growth, indicating balanced improvements in both precision and recall, which are particularly important for handling the imbalanced and complex nature of HRV-based predictions. Notably, Dataset 2 (PhysioNet Stress) and Dataset 3 (EU Exercise Stress ECG) exhibit a slower initial increase in both metrics, likely due to the higher variability and noise present in stress-induced HRV signals. However, the model adapts effectively, reaching high accuracy and F1-score values, showcasing its robustness in diverse physiological scenarios. The close alignment of accuracy and F1-score trends further highlights the model's capability to generalize well across different datasets without overfitting. These feedback metrics, in conjunction with the loss curves, provide a comprehensive evaluation of the model's learning process, affirming its suitability for HRV-based applications such as sports training load monitoring and stress detection.

To address potential limitations or biases in the datasets used for validation, we acknowledge the following aspects. First, the datasets used in this study are publicly available and vary in terms of the populations and contexts from which they were collected. For instance, some datasets consist of healthy individuals at rest (Dataset 1), while others focus on stress-inducing or exercise-related conditions (Datasets 2 and 3). This variability could introduce biases in the data, as the physiological responses observed in these datasets may not fully represent the diversity of real-world conditions or populations. Additionally, they may not fully capture the range of possible variations in HRV signals across different age groups, medical conditions, or specific environmental factors that could influence heart rate variability. Dataset 4 includes individuals from a narrow age group, which may limit the generalizability of the model to a broader demographic.

4.4. Model comparison

Tables 3 and **4** present the accuracy and F1-score comparisons of the proposed RL-based HRV feature extraction model against four advanced deep learning baselines across four datasets. These tables highlight the strengths and limitations of each model in capturing HRV features across different dimensions—time-domain, frequency-domain, nonlinear, and multi-dimensional fusion.

Table 3. Accuracy (%) of different models.

Model	Dataset 1	Dataset 2	Dataset 3	Dataset 4
Time-Domain LSTM	87.0	88	85.0	91.2
Frequency-Domain CNN	88.4	90.4	86.5	92.4
Nonlinear Dynamics GRU	89.5	91.5	88.2	93
Transformer-Based Multi-Dimensional Model	91.3	93.0	91.4	95
The proposed model	94.0	96.4	93.8	97.2

Table 4. F1 (%) of different models.

Model	Dataset 1	Dataset 2	Dataset 3	Dataset 4
Time-Domain LSTM	81.2	82.0	80.0	84.8
Frequency-Domain CNN	82.0	84.4	81.0	86.4
Nonlinear Dynamics GRU	84.0	86.2	85.0	88.0
Transformer-Based Multi-Dimensional Model	87.6	89.2	88.0	91.4
The proposed model	89.8	91.1	89.0	93.3

The proposed RL-based HRV feature extraction model demonstrates significant improvements over baseline deep learning models, achieving consistent superiority across diverse datasets by addressing their inherent limitations. Traditional models like the Time-Domain LSTM and Frequency-Domain CNN excel in specific dimensions, such as capturing sequential patterns or spectral features, but lack the adaptability required for dynamic and multi-dimensional HRV analysis. The Nonlinear GRU (Gated Recurrent Unit), while effective in handling chaotic HRV patterns, and the Transformer-Based Multi-Dimensional Model, with its ability to integrate various HRV dimensions, still fall short in their ability to optimize feature importance dynamically. The proposed model achieves this through reinforcement learning, which prioritizes relevant features while reducing redundancy, and attention mechanisms that amplify critical temporal segments. This enables the model to adapt to stress-related variability (Dataset 2) and chaotic exercise recovery dynamics (Dataset 3), where it achieves a 3.4% and 2.4% improvement in accuracy, respectively, compared to the best baseline. Furthermore, its superior integration of time, frequency, and nonlinear features yields an average accuracy improvement of 2.7% on stable datasets like Dataset 1 and Dataset 4. With a consistently higher average accuracy (95.0%) and F1-score (90.8%), the proposed model provides robust and adaptable HRV feature extraction, setting a new benchmark for applications such as stress detection, training load monitoring, and recovery assessment.

4.5. Sports training load monitoring

To explore the application of this model in training, the data of sports training with intensity is necessary. In this research, several athletes of the same level (Age, Height, Weight) did training (Running) with load. And the Recovery Time, Fatigue Level, Training Intensity, and biomechanical data are collected. The data is analyzed and shown in **Figure 6**. **Figure 6** illustrates the predicted vs. actual values for four critical dimensions of sports training load monitoring: Recovery Time, Fatigue Level, Training Intensity, and HRV Stability. Each dimension highlights the model's performance in leveraging different HRV features (Time-Domain, Frequency-Domain, Nonlinear, and Multi-Dimensional) to make predictions. The red dashed lines represent the actual values for each dimension, serving as a reference to evaluate the accuracy and consistency of predictions.

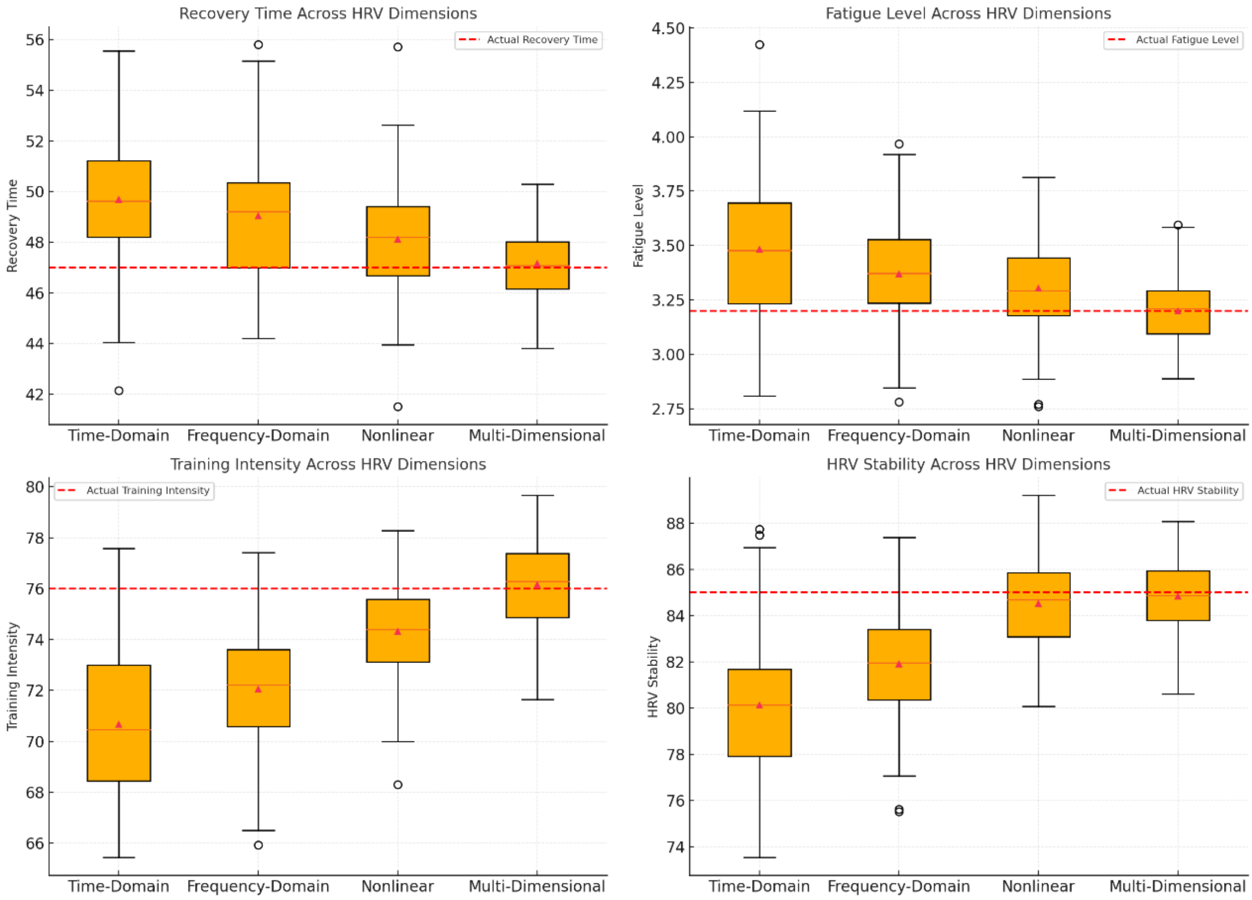

Figure 6. Four critical dimensions of sports training load monitoring.

It shows that the proposed multi-dimensional approach consistently demonstrates superior performance, with its predictions tightly aligning with actual values and exhibiting minimal variability across all dimensions. This accuracy is particularly impactful in guiding sports training. For instance, precise recovery time predictions (actual value: 47 min) allow coaches to schedule training sessions with adequate rest, reducing overtraining risks and enhancing performance. Similarly, reliable fatigue level predictions (actual value: 3.2 on a 5-point scale) facilitate dynamic adjustments to training intensity, preventing exhaustion and supporting sustained athlete readiness. Furthermore, accurate training intensity predictions (actual value: 76%) ensure athletes perform at optimal workloads, achieving performance goals without excessive strain. Lastly, HRV stability predictions (actual value: 85) provide long-term insights into cardiovascular adaptation and training effectiveness, helping coaches refine programs to maintain progress and prevent stagnation. The proposed RL-based HRV model's ability to integrate time-domain, frequency-domain, and nonlinear features dynamically ensures precise, multi-dimensional monitoring, making it a valuable tool for personalized and data-driven sports training optimization.

Despite these strengths, the study's results also suggest some areas for further improvement. The datasets used were somewhat limited in scope, focusing on healthy individuals across specific physiological states. Expanding the model's evaluation to include a more diverse range of subjects, including those with different health conditions and varying training loads, will be essential to assess its generalizability. Furthermore, real-world application of the model, where signal noise and artifacts are more prevalent, should be explored in future research to better understand its practical applicability outside of controlled datasets.

5. Conclusion

By collecting and analyzing the data from publicly available datasets and athlete's training, this study introduces an innovative HRV feature extraction framework based on reinforcement learning and attention mechanisms, addressing the inherent challenges of HRV signal analysis. By integrating time-domain, frequency-domain, and nonlinear features, the proposed model achieves comprehensive and accurate predictions of training load and recovery states. Reinforcement learning enhances feature optimization by dynamically adjusting feature importance, while attention mechanisms improve the model's ability to capture critical temporal variations in HRV signals. Experimental results validate the model's superiority over traditional deep learning methods, achieving higher accuracy and robustness across diverse datasets and physiological conditions. The framework's ability to adapt to complex and dynamic HRV patterns highlights its potential for broad applications, ranging from sports training monitoring to stress management and clinical health monitoring. Future research will focus on optimizing the framework's computational efficiency to enable real-time HRV analysis and exploring its applicability in wearable and edge computing environments. By bridging theoretical advancements and practical applications, this study lays a solid foundation for the development of intelligent, adaptive HRV-based monitoring systems, contributing to the fields of sports science, health informatics, and personalized medicine.

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