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A Critical Review of Hybrid AI Architectures for Analysis and Forecasting of Cardio Time Series

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***Abstract*— The analysis of cardio time series, including signals derived from the electrocardiogram, photoplethysmogram and heart rate variability, play a central role in the assessment of cardiac function and autonomic regulation. These signals are characterized by strong nonlinearity, nonstationarity and susceptibility to noise and artifacts. Such properties impose fundamental constraints on both signal analysis and forecasting and challenge the applicability of modern artificial intelligence methods.**

Recent advances in artificial intelligence have led to the widespread use of neural network architectures for cardio time series analysis. Recurrent neural networks, convolutional neural networks and attention-based models have demonstrated promising performance in various tasks, yet their effectiveness is often limited by data scarcity, inter-subject variability, noise sensitivity and limited physiological interpretability. Consequently, reported improvements in predictive accuracy frequently lack robustness and generalizability across datasets and acquisition conditions.

This paper presents a comprehensive and critical review of contemporary artificial intelligence architectures for short-term cardio time series analysis. Classical statistical, fractal and entropy-based methods are examined alongside modern neural approaches, emphasizing their complementary roles. Furthermore, a structured taxonomy of hybrid artificial intelligence models is introduced, combining data-driven learning with established signal analysis techniques to enhance robustness and interpretability. Rather than focusing solely on predictive performance, this review adopts a dynamics-oriented perspective, explicitly addressing the limits of short-term forecasting and outlining future research directions for hybrid and physiology-informed cardio data modeling.

***Keywords*— Artificial intelligence, cardio—signals, electrocardiogram, heart rate variability, hybrid models, photoplethysmogram, short-term forecasting, time series analysis.**

I. Introduction

Cardio time series derived from the electrocardiogram (ECG), photoplethysmogram (PPG) and heart rate variability (HRV) are widely used for the assessment of cardiac electrophysiology, hemodynamic activity and autonomic nervous system regulation. These signals play a key role in both clinical diagnostics and continuous monitoring applications, including wearable and ambulatory systems. However, cardio signals are inherently nonlinear, nonstationary and strongly affected by noise and artifacts, such as motion interference, baseline wander, ectopic beats and sensor-dependent distortions, which significantly complicates their analysis and interpretation [1], [2].

In many practical scenarios, cardio signals are available only over short observation windows, often ranging from a few seconds to one minute. Such short-term recordings impose fundamental limitations on both signal analysis and forecasting, as physiological variability and stochastic influences restrict the degree of temporal predictability [3]. Traditional approaches to cardio time series analysis have relied on statistical models, spectral methods and nonlinear dynamics descriptors. Autoregressive and state-space models have been used to capture short-term temporal dependencies, while entropy-based and fractal measures have provided valuable insights into signal complexity and autonomic regulation [4], [5]. Although these methods offer physiological interpretability and robustness in low-data regimes, they are limited in their ability to model complex temporal interactions and morphological patterns present in raw ECG and PPG signals.

Recent advances in artificial intelligence have led to the widespread adoption of deep learning architectures for time series analysis. Recurrent neural networks, including long short-term memory and gated recurrent unit models, have demonstrated strong capabilities in modeling temporal dependencies [17]–[19]. Convolutional neural networks have been successfully applied to morphological analysis of cardio signals and large-scale arrhythmia detection [21], [22], while attention-based and Transformer architectures have been proposed to capture global temporal context [23]–[25]. Despite promising results, the application of such models to short-term cardio signals remains challenging due to limited data availability, inter-subject variability, noise sensitivity and reduced physiological interpretability. Moreover, reported improvements in predictive accuracy often lack robustness and generalizability across datasets and acquisition conditions [22], [35].

To address these challenges, recent research has increasingly focused on hybrid modeling approaches that combine deep learning architectures with classical statistical, fractal and entropy-based methods. These hybrid models aim to leverage the representation learning capabilities of neural networks while preserving robustness, interpretability and physiological grounding. However, the existing literature lacks a unified and critical overview that relates modern artificial intelligence architectures and hybrid designs to the intrinsic dynamics of cardio time series, particularly in the context of short-term analysis and forecasting.

This paper presents a comprehensive and critical review of contemporary artificial intelligence architectures for cardio time series analysis, with a focus on short-term ECG, PPG and HRV signals. Rather than emphasizing predictive accuracy alone, the review adopts a dynamics-oriented perspective, highlighting the limits of short-term forecasting and the complementary roles of classical and data-driven methods. A structured taxonomy of hybrid artificial intelligence models is introduced and open challenges and future research directions are discussed.

II. CHARACTERISTICS OF CARDIO TIME SERIES

Cardio time series exhibit a set of intrinsic properties that fundamentally distinguish them from many other classes of temporal data. These properties arise from the underlying physiological mechanisms governing cardiac activity and autonomic regulation, as well as from the conditions under which signals are acquired. Understanding these characteristics is essential for selecting appropriate analysis and modeling approaches, particularly in short-term observation scenarios.

A. Signal Types and Physiological Origin

Electrocardiogram signals represent the electrical activity of the heart and are characterized by well-defined morphological components associated with cardiac depolarization and repolarization. Photoplethysmogram signals are optical measurements reflecting blood volume changes in peripheral tissue and are therefore indirectly related to cardiac activity, making them more sensitive to motion artifacts and sensor placement. Heart rate variability time series are derived signals, typically obtained from beat-to-beat intervals and primarily reflect autonomic nervous system modulation rather than direct cardiac morphology [1], [2].

The heterogeneous physiological origin of these signals leads to significant differences in sampling rates, noise sensitivity and information content. While electrocardiogram signals preserve detailed morphological structure, heart rate variability reflects temporal dynamics and regulatory mechanisms. Photoplethysmographic signals contain morphological information, but with increased sensitivity to external disturbances [3].

B. Nonlinearity, Nonstationarity and Multiscale Dynamics

A defining feature of cardio time series is their pronounced nonlinearity and nonstationarity. Cardiac dynamics are governed by complex feedback mechanisms involving the heart, autonomic nervous system and respiratory processes, resulting in temporal variations that cannot be adequately described by linear or stationary models [4]. Moreover, cardio signals exhibit multiscale behavior, with fast beat-to-beat fluctuations superimposed on slower regulatory trends related to autonomic modulation and circadian rhythms.

In short observation windows, typically below one minute, these multiscale characteristics become particularly challenging to capture. The limited number of samples restricts reliable estimation of long-range correlations and complicates the separation of deterministic structure from stochastic variability. As a result, many conventional assumptions underlying time series modeling, such as stationarity or ergodicity, are violated in practical cardio monitoring scenarios [5].

C. Noise, Artifacts and Data Limitations

Cardio time series are strongly affected by noise and artifacts arising from both physiological and technical sources. Motion artifacts, baseline wander, electrode displacement and sensor-dependent distortions are common in ambulatory and wearable recordings, particularly for photoplethysmogram signals. Errors in peak detection and ectopic beats can significantly distort derived time series and bias subsequent HRV analysis [6], [7].

Another critical limitation is the frequent availability of only short-duration recordings. Short time series constrain the applicability of data-intensive modeling approaches and reduce the statistical reliability of many nonlinear descriptors. These limitations highlight the importance of robustness, interpretability and data efficiency in cardio time series analysis and motivate the use of hybrid modeling strategies that combine classical signal analysis with modern artificial intelligence techniques [8].

III. CLASSICAL STATISTICAL, FRACTAL AND ENTROPY-BASED METHODS

Classical methods for cardio time series analysis have been extensively studied and remain fundamental for understanding cardiac dynamics, particularly in short-term and low-data scenarios. These approaches are grounded in statistical signal processing and nonlinear dynamics theory and often provide physiologically interpretable descriptors that complement modern data-driven models.

A. Statistical and Linear Modeling Approaches

Statistical models have traditionally been employed to characterize temporal dependencies in cardio signals. Autoregressive and autoregressive moving average models have been applied to electrocardiogram-derived and heart rate variability time series to capture short-term linear correlations and rhythmic patterns [9]. State-space formulations further extend this framework by allowing time-varying parameters and explicit modeling of hidden physiological states [10].

While such models are computationally efficient and interpretable, their applicability is limited by assumptions of linearity and stationarity, which are frequently violated in cardio signals. In short observation windows, parameter estimation becomes unreliable and model performance is highly sensitive to noise and artifacts. As a result, purely statistical models often serve as baselines or components within more complex hybrid frameworks rather than standalone solutions [11].

B. Fractal and Scaling Analysis

Fractal analysis has played a central role in the study of cardio dynamics, particularly in the analysis of heart rate variability. Methods such as detrended fluctuation analysis and scaling exponent estimation have been used to quantify long-range correlations and self-similar behavior in cardiac time series [12]. These approaches provide insight into the underlying regulatory mechanisms and have demonstrated sensitivity to pathological conditions and aging.

However, the reliability of fractal measures depends strongly on signal length and quality. In short-term recordings, the estimation of scaling exponents is often unstable and the distinction between deterministic structure and stochastic variability becomes blurred. Consequently, fractal analysis is most informative when used as a descriptive or comparative tool rather than as a basis for direct forecasting [13].

C. Entropy-Based Complexity Measures

Entropy-based methods are widely used to quantify the irregularity and complexity of cardio time series. Approximate entropy, sample entropy, permutation entropy and multiscale entropy have been applied to electrocardiogram and heart rate variability signals to assess autonomic regulation and system complexity [14], [15]. These measures are particularly attractive in short-term analysis due to their relative robustness to noise and minimal assumptions about signal structure.

Despite their advantages, entropy measures are sensitive to parameter selection and may yield biased estimates in the presence of artifacts or missing data. Moreover, entropy-based descriptors capture complexity rather than explicit temporal dynamics and therefore provide limited predictive capability when used in isolation. In recent studies, entropy measures have increasingly been incorporated as features within hybrid modeling frameworks, where they enhance interpretability and robustness while deep learning components handle representation learning and temporal modeling [16].

IV. AI ARCHITECTURES FOR TIME SERIES ANALYSIS

Recent advances in artificial intelligence have significantly expanded the set of tools available for cardio time series analysis. Deep learning architectures enable automatic representation learning from raw signals and have demonstrated strong performance across a variety of tasks. Nevertheless, their applicability to short-term cardio ~~data~~ is constrained by data availability, noise sensitivity and physiological interpretability. This section reviews the main classes of neural architectures used in cardio time series analysis, emphasizing their strengths and limitations.

A. Recurrent Neural Networks, Long Short-Term Memory and Gated Recurrent Units

Recurrent neural networks (RNNs) were among the first deep learning architectures applied to sequential biomedical data due to their ability to model temporal dependencies. Standard RNNs, however, suffer from vanishing and exploding gradient problems, which limit their capacity to capture long-range dependencies [17]. To address these issues, gated architectures such as long short-term memory (LSTM) networks and gated recurrent units (GRUs) introduce memory cells and gating mechanisms that regulate information flow over time [18], [19].

In cardio applications, LSTM and GRU models have been widely used for heart rate variability modeling, arrhythmia detection and short-term signal prediction. These architectures are particularly effective in capturing local temporal patterns and rhythm-related dynamics. However, their performance is strongly influenced by signal quality and window length. In short observation windows, recurrent models may overfit noise or device-specific artifacts and their hidden states often lack clear physiological interpretation. Moreover, training recurrent models can be computationally demanding and sensitive to hyperparameter selection [20].

B. Convolutional Neural Network-Based Models

Convolutional neural networks (CNNs) have become a dominant architecture for cardio signal analysis, particularly for electrocardiogram and photoplethysmogram data. One-dimensional convolutional layers are well suited for capturing local temporal patterns and morphological features, such as waveform shape and amplitude variations [21]. Multi-scale and dilated convolutional designs further enhance the ability of CNNs to model patterns across different temporal resolutions.

CNN-based models have demonstrated strong performance in tasks such as arrhythmia classification and signal quality assessment. Their feedforward structure allows for efficient training and parallelization, making them attractive for real-time and embedded applications. Nevertheless, CNNs inherently focus on local receptive fields and lack explicit mechanisms for modeling long-range temporal dependencies. As a result, CNNs alone may be insufficient for capturing global dynamics in cardio time series, particularly in tasks involving temporal evolution rather than static morphology [22].

C. Transformer and Attention-Based Architectures

Attention mechanisms and Transformer architectures have recently been introduced to time series analysis to address the limitations of recurrent models in capturing long-range dependencies. By computing pairwise attention weights across time steps, Transformers can model global temporal relationships without relying on sequential processing [23]. This property has motivated their application to cardio signals, including electrocardiogram classification and multivariate physiological monitoring [24].

Despite their theoretical advantages, Transformer-based models present several challenges in cardio applications. These architectures are typically data-intensive and may require large training datasets to generalize effectively. In short-term cardio recordings, the available temporal context is often insufficient to fully exploit global attention mechanisms. Furthermore, attention weights may capture spurious correlations related to noise or subject-specific patterns rather than meaningful physiological dynamics. Consequently, Transformers are often more effective as representation learners or components within hybrid architectures than as standalone models for short-term cardio forecasting [25].

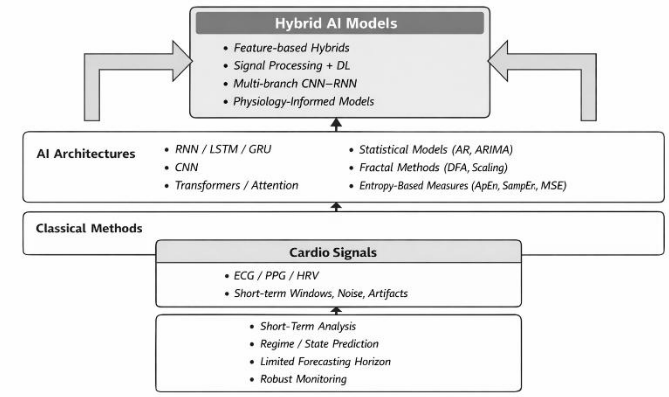

Fig. 1. *Conceptual taxonomy of classical, artificial intelligence, and hybrid modelling approaches for short-term analysis and forecasting of cardio time series.*

Figure 1 summarizes the relationships between classical methods, modern AI architectures and hybrid modeling approaches for short-term cardio time series analysis.

V. HYBRID AI MODELS FOR DYNAMIC ANALYSIS AND FORECASTING OF CARDIO SIGNALS

As illustrated in Fig. 1, hybrid AI models integrate classical signal analysis with neural architectures to address the limitations of short-term cardio data. Hybrid artificial intelligence models have emerged as a promising direction for cardio time series analysis, particularly in short-term and low-data regimes. These approaches aim to combine the representation learning capabilities of deep neural networks with the robustness, interpretability and physiological grounding of classical statistical, fractal and entropy-based methods.

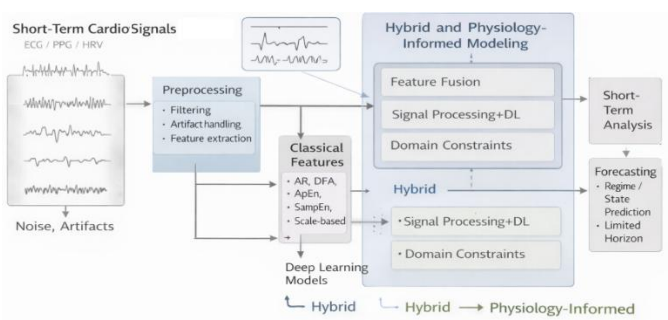

Fig. 2. *Conceptual pipeline of hybrid artificial intelligence models for short-term cardio signal analysis*

To clarify the integration of classical signal analysis and modern artificial intelligence techniques, Fig. 2 presents an end-to-end conceptual pipeline for short-term cardio time series analysis and forecasting. The diagram illustrates how preprocessing, handcrafted feature extraction, deep learning architectures and physiology-informed constraints are combined within hybrid modeling frameworks to address the limitations of short-term data and enhance robustness and interpretability. By integrating complementary modeling paradigms, hybrid architectures address key limitations of standalone data-driven or analytical approaches.

A. *Taxonomy and Design Principles*

Hybrid models for cardio signals can be broadly categorized according to the nature of integration between classical methods and neural architectures. A first category combines signal processing techniques, such as filtering, wavelet decomposition, or empirical mode decomposition, with deep learning models. In this design, classical preprocessing enhances signal quality and stabilizes subsequent neural representation learning, particularly for noisy electrocardiogram and photoplethysmogram data [26].

A second category consists of feature-based hybrid models, where handcrafted statistical, fractal and entropy-derived features are used as inputs to neural networks. This approach preserves physiological interpretability and reduces data requirements, while neural models capture nonlinear interactions among features [27]. Such designs are particularly effective for heart rate variability analysis, where derived features carry well-established clinical meaning.

Multi-branch hybrid architectures represent a third category, explicitly separating morphological and dynamical modeling. In these systems, convolutional neural networks are typically employed to extract morphological features from raw signals, while recurrent or attention-based modules capture temporal dependencies and regulatory dynamics [28]. This separation mirrors the physiological distinction between waveform morphology and autonomic modulation and has shown improved robustness in heterogeneous datasets.

Finally, physiology-informed hybrid models incorporate explicit constraints, priors, or regularization terms derived from cardio physiology. These constraints may encode heart rate limits, rhythm regularity, or known relationships between signal components. By embedding domain knowledge into the learning process, such models improve generalization and reduce the risk of learning spurious correlations [29].

B. *Comparison with Classical Approaches*

Compared to purely classical methods, hybrid AI models offer enhanced expressive power and adaptability to complex signal patterns. While statistical, fractal and entropy-based techniques provide stable and interpretable descriptors, they lack the capacity to automatically learn hierarchical representations from raw data. Hybrid approaches bridge this gap by augmenting classical descriptors with learned representations, resulting in improved robustness under noise and inter-subject variability [30].

At the same time, hybrid models mitigate several weaknesses of deep learning architectures. By incorporating classical features or constraints, they reduce data requirements and enhance interpretability, addressing key concerns in clinical and wearable applications. Empirical studies have shown that hybrid designs often outperform standalone neural models in short-term cardio analysis, particularly when training data are limited or signal quality varies across acquisition conditions [31].

Importantly, hybrid models do not aim to replace classical methods but rather to integrate them within a unified modeling framework. This integration enables complementary strengths: classical approaches provide physiologically meaningful structure, while neural components offer flexibility and nonlinear modeling capacity. As a result, hybrid architectures represent a pragmatic and theoretically grounded solution for short-term cardio time series analysis and forecasting.

VI. SHORT-TERM FORECASTING: LIMITS AND OPPORTUNITIES

Short-term forecasting of cardio time series represents one of the most debated and methodologically sensitive topics in cardiac signal analysis. While advances in artificial intelligence have enabled increasingly accurate modeling of complex temporal patterns, the intrinsic physiological variability of cardio systems imposes fundamental limits on predictability. A clear distinction between meaningful and ill-posed forecasting tasks is therefore essential.

A. What is Predictable in Short-Term Cardio Signals

In short observation windows, forecasting is generally feasible only over very limited horizons. Predictable components typically include local temporal continuity, short-term trends and regime transitions rather than exact point-wise signal values. For electrocardiogram and photoplethysmogram signals, short-horizon continuation of waveform morphology may be achievable under stable conditions, while for heart rate variability signals, limited predictability may exist for beat-to-beat intervals over one to a few future steps [32].

An alternative and often more meaningful formulation of forecasting focuses on state or regime prediction rather than precise value estimation. Examples include the anticipation of rhythm changes, detection of transitions between stable and unstable cardiac states, or prediction of increased variability regimes. Such formulations align more closely with physiological processes and clinical relevance and are less sensitive to noise and inter-subject variability [33].

B. Fundamental Limits of Predictability

Cardio dynamics arise from the interaction of multiple regulatory mechanisms operating across different time scales, including autonomic control, respiration and circadian influences. These interactions introduce stochastic components and nonlinear feedback that limit long-horizon predictability, even in the absence of measurement noise [34]. As a result, attempts to perform long-term point-wise forecasting of cardio signals are often ill-posed and may lead to misleading conclusions.

Moreover, short-term recordings exacerbate these limitations by restricting the available temporal context for model training and inference. In such settings, deep learning models may inadvertently learn subject-specific or device-specific signatures rather than underlying physiological dynamics. This phenomenon contributes to the lack of generalizability observed in many reported forecasting results [35].

C. Evaluation Protocols and Practical Considerations

Robust evaluation of short-term forecasting models requires careful selection of performance metrics and validation protocols. Traditional error-based metrics, such as mean absolute error or root mean square error, should be complemented by robustness analyses under noise, artifact contamination and cross-subject testing. Uncertainty-aware evaluation, including confidence intervals or probabilistic forecasts, provides additional insight into model reliability [36].

From a practical perspective, forecasting approaches must be aligned with application-specific objectives. In clinical and wearable monitoring systems, interpretability, robustness and reliability often outweigh marginal gains in numerical accuracy. Consequently, hybrid and physiology-informed models that emphasize stability and meaningful prediction horizons are better suited for real-world deployment than purely data-driven approaches optimized solely for short-term accuracy [37].

VII. OPEN CHALLENGES AND FUTURE DIRECTIONS

Despite significant progress in cardio —time series analysis, several open challenges remain that limit the widespread adoption and reliability of artificial intelligence-based approaches, particularly in short-term and real-world monitoring scenarios. Addressing these challenges is essential for advancing both methodological rigor and practical applicability.

One major challenge is the analysis of ultra-short time windows, often below thirty seconds, which are increasingly common in wearable and opportunistic monitoring. In such regimes, both classical and deep learning models suffer from insufficient temporal context, leading to unstable estimates and reduced generalizability. Developing data-efficient and uncertainty-aware models that can operate reliably under these constraints remains an open research problem [38].

Robustness to noise, artifacts and sensor heterogeneity represents another critical challenge. Cardio signals acquired from different devices, body locations and operating conditions exhibit substantial variability. Models trained on clean, curated datasets often fail to generalize to real-world data, where motion artifacts and signal quality fluctuations are prevalent. Future research should emphasize robustness-oriented training strategies, including noise-aware modeling, domain adaptation and explicit signal quality integration [39].

Physiology-informed and constrained learning constitutes a promising direction for improving interpretability and generalization. By embedding domain knowledge, such as heart rate limits, rhythm regularity, or known autonomic relationships, models can be guided toward physiologically plausible solutions. This approach reduces the risk of learning spurious correlations and enhances trustworthiness in clinical applications [40].

Finally, the integration of hybrid artificial intelligence models within digital twin frameworks for cardio monitoring represents an emerging research frontier. Digital twins combine data-driven models with mechanistic understanding to enable personalized analysis, simulation and decision support. Such frameworks have the potential to transform cardio monitoring from passive signal analysis to proactive, individualized health management [41].

The comparative analyses presented in Table 1 indicate that classical statistical and fractal methods maintain high interpretability but demonstrate limited robustness to noise in short observation windows. Deep neural networks, particularly CNN and LSTM architectures, achieve greater capacity for modelling complex temporal dependencies but suffer from low interpretability and increased sensitivity to input data quality. Hybrid AI approaches combine the strengths of both paradigms, providing improved noise robustness and a balanced level of interpretability, which makes them well-suited for real-time HRV analysis in practical monitoring applications.

Table 1. *Performance comparison of classical, deep learning and hybrid methods for short-term HRV analysis*

Method	Input type	Window length (s)	Robustness to noise	Interpretability
Statistical (AR)	RR intervals	30	Medium	High
Fractal (DFA)	HRV series	30	Medium	High
Entropy-based	HRV series	30	High	Medium
CNN	Raw ECG	30	Low	Low
LSTM	HRV series	30	Medium	Low
Hybrid (CNN + traditional)	**ECG + features**	**30**	**High**	**Medium–High**

Statistical and entropy-based methods, as summarized in Table 2, provide strong physiological interpretability, which supports their use in clinical analysis and expert-driven evaluation.

Table 2. *Interpretability and physiological relevance of different model classes*

Model type	Physiological interpretability	Clinical relevance	Suitability for digital twin
Statistical	High	Medium	Medium
Fractal / Entropy	High	High	Medium
Deep learning	Low	Medium	Low

Deep learning models exhibit limited inherent interpretability, posing barriers to their direct adoption in medical decision workflows despite their predictive capacity. Hybrid neural-analytical designs offer the most effective trade-off, jointly preserving physiological relevance, clinical applicability, and alignment with digital-twin paradigms for personalized cardio modelling.

VIII. CONCLUSION

This paper presented a comprehensive and critical review of contemporary artificial intelligence architectures for cardio time series analysis, with a focus on short-term electrocardiogram, photoplethysmogram and heart rate variability signals. The intrinsic characteristics of cardio signals, including nonlinearity, nonstationarity, noise sensitivity and limited observation windows, were discussed as fundamental factors shaping model performance and predictability.

Classical statistical, fractal and entropy-based methods were reviewed alongside modern deep learning architectures, highlighting their complementary strengths and limitations. While deep learning models offer powerful representation learning capabilities, their effectiveness is often constrained by data scarcity, noise sensitivity and limited physiological interpretability. Hybrid artificial intelligence models were identified as a pragmatic and theoretically grounded solution, integrating classical signal analysis with data-driven learning to enhance robustness, interpretability and generalization.

A dynamics-oriented perspective on short-term forecasting was emphasized, clarifying the limits of predictability in cardio signals and distinguishing meaningful forecasting tasks from ill-posed formulations. Finally, open challenges and future research directions were outlined, including ultra-short window analysis, robustness-aware modeling, physiology-informed learning and digital twin-based cardio monitoring.

Overall, this review underscores the importance of aligning artificial intelligence methodologies with the intrinsic dynamics and physiological constraints of cardio systems. Future progress in this field will depend not on increasingly complex models alone, but on the thoughtful integration of domain knowledge, robust modeling principles and hybrid architectures tailored to real-world cardio data.

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