TASHKENT UNIVERSITY OF
INFORMATION TECHNOLOGIES
NAMED AFTER MUHAMMAD AL-KHWARIZMI

MUHAMMAD AL-XORAZMIY NOMIDAGI
TOSHKENT AXBOROT TEXNOLOGIYALARI
UNIVERSITETI

BULLETIN OF TUIT:

MANAGEMENT AND COMMUNICATION TECHNOLOGIES



ISSN:2181-1083 DOI:
Begmamat Dushanov, Narzillo Mamatov № 3(24)2025

Interpolation Methods of Restoration and Comprehensive Processing of the Cardiosignal

Begmamat Dushanov
Institute of Fundamental and Applied Research under TIIAME, Information Processing and Control Systems Tashkent State Technical University named after Islom Karimov Tashkent, Uzbekistan
dushanovb@ifar.uz

Narzillo Mamatov
Department of Digital Technologies and Artifcial Intelligence tional Research University TIIAME
Tashkent, Uzbekistan
m_narzillo@mail.ru

Abstract— *ECG signals bear vital diagnostic information regarding the behavior of the heart but produce vast amounts of data that need to be compressed and accurately reconstructed. In this paper, a Python algorithm for reconstructing ECG signals using Hermite polynomial interpolation with Chebyshev nodes is discussed. The process uses optimally positioned nodes to provide precise segment-wise approximation and altration without losing important morphological details of the ECG wave. Python coding made use of SciPy and NumPy for error estimation and interpolation. In simulations with experiments using the MIT-BIH Arrhythmia Database, it was indicated that the new Hermite–Chebyshev algorithm revealed improved reconstruction accuracy, reduced mean square error, and improved clinically useful structure preservation in waveforms. The e ỉ/// ciency of the algorithm holds great potential for real-time compression and reconstruction of ECGs with wearable devices and telecardiology*

Keywords— *Electrocardiogram (ECG), Hermite interpolation, Chebyshev nodes, signal reconstruction, Python implementation, biomedical signal processing, data compression, denoising, telecardiology.*

1. INTRODUCTION

This article presents a set of interpolation-based methods for restoring and complex processing of electrocardiogram (ECG) signals, emphasizing their importance in improving signal quality, continuity, and diagnostic accuracy. A detailed review of the established research on ECG recovery and interpolation algorithms is the basis for this study, which includes polynomial, spline, and hybrid approximations. Based on this foundation, the article examines the physiological foundations and mathematical modeling of cardiac waveforms to guide precise interpolation of missing or impaired signal segments. In addition, it provides detailed information on sampling processes, electrode configurations, and preprocessing strategies such as denoization and basic correction, which are important in preparing ECG signals for interpolation and restoration.

Accurate restoration and processing of electrocardiogram (ECG) signals are necessary for successful cardiac diagnosis as well as continuous monitoring of patients. However, signal loss due to motion artifacts, missing data, and baseline drift generally hinders proper interpretation. To address these issues, interpolation-based reconstruction techniques have been advocated because of their ability to reconstruct signal form without distorting diagnostic information.

Interpolation signal processing has been in the spotlight recently due to its ability to effectively reconstruct and estimate physiological waveforms. Polynomial interpolation actually provides us with a modeling analytical description of ECG signals from a finite number of coefficients, which can potentially allow data filtering and compression. Classic polynomial interpolation methods such as Lagrange and spline interpolation provide reasonable reconstruction quality but produce oscillations or loss of fidelity at high polynomial orders as a result of numerical instability. Hermite

interpolation, using both function and derivative information for reconstructing smooth biomedical waveforms, reconstructs and smooths continuous biomedical waveforms more gracefully. Its ability to deliver derivative continuity makes it particularly well-suited to ECG signals, where tiny variations in the slope from one cardiac cycle to the next contain a wealth of diagnostic information.

Despite all these advantages, choosing the position for node placement for interpolation still has an important role to play in constraining interpolation error. Equally spaced nodes can produce Runge's phenomenon—unwanted oscillations which distort the reconstructed signal, especially near boundaries. To address this deficiency, Chebyshev nodes, derived from Chebyshev polynomials of the first kind, have been shown to offer near-optimal placement of nodes as far as reducing the interpolation error and improving numerical stability. High-accuracy approximation of ECG signals with good trade-off among smoothness, accuracy, and complexity is hence achieved through the application of Hermite interpolation coupled with Chebyshev node placement.

The main contribution of this research is the suggestion of a novel ECG compression and reconstruction algorithm based on Hermite interpolating polynomials with Chebyshev nodes. The proposed method compresses and denoises parallel ECG signals with the inherent morphological patterns maintained for successful diagnosis. With the MIT-BIH Arrhythmia Database used as the test standard, the method is measured quantitatively by Percent Root Mean Square Difference (PRD), Signal-to-Noise Ratio (SNR), and Compression Ratio (CR). In comparison with the existing interpolation and compression process, it is illustrated that quality compression performance and enhanced signal fidelity are achieved by the new system.

2. RELATED WORKS

ECG signals, motor nonstationarity and susceptibility to all sorts of noise artifacts, motor, need to undergo sophisticated preprocessing and restoration techniques in order to maintain morphological coherence as well as diagnostic specificity. The classical linear and polynomial interpolation schemes have been diverted towards hybrid, adaptive, and learning paradigms in a bid to counteract undersampling artifacts, filtering noises, and data inpainting in ECG signals. Recent work showcases an intimate integration of traditional mathematical interpolation theory with state-of-the-art machine learning, sub-Nyquist sampling, and hardware-efficient reconstruction techniques, as the following subsections will make amply clear.

Ray and Chouhan's earlier work [1] proposed an efficient computational interpolatory algorithm for compression and decompression of ECG signals using Hermite interpolating polynomials and Chebyshev nodes. The technique parallel-denoised and compressed without losing important morphological information (P, QRS, and T complexes). Applied to the MIT-BIH Arrhythmia Database, it gave high signal fidelity and high data compression, suitable for real-time storage and transmission. Sharma et al. [2] also used Chebyshev polynomial interpolation with a genetic algorithm (GA) for making waveform reconstruction by means of orthogonal projection of normalized features from ECG. Preprocessing pipeline of bandpass FIR filtering and Pan–Tompkins segmentation yielded low reconstruction error with high diagnostic accuracy.

Zakariyah et al. [3] evaluated the effect of resampling operations on the computation of heart rate variability (HRV) using Fast Fourier Transform (FFT)-interpolated downsampling and oversampling. Oversampling to 100 Hz from 250 Hz enhanced HRV, but downsampling to 50 Hz provided incorrect data, testifying to the use of appropriate sampling rates. Similarly, Reali et al. [4] have contrasted cubic-spline, parabolic, and linear interpolation on photoplethysmographic (PPG) signals and observed that cubic-spline interpolation provided higher inter-beat interval accuracy for low sampling frequencies (<32 Hz). These researches indicate the significance of interpolation

optimization in accurate reconstruction of body signals.

Current advancements in studies have transformed interpolation from elementary mathematics reconstruction to super-resolution and power-conserving restoration models. SRECG [5], deep learning–facilitated, proposed ECG signal super-resolution and wearable and portable arrhythmia classification. Unlike normal interpolation, which does not favor morphological fine features preservation under bandwidth and power constrained conditions, SRECG utilizes a cloud-residing high-resolution multiclass classifier (HMC) with approximately half the classification accuracy of the high-resolution ECGs but performing with low-resolution inputs.

Hardware-efficient interpolation techniques like the Variable Pulse Width Finite Rate of Innovation (VPW-FRI) model [6] perform ECG reconstruction through power-aware integrate-and-fire time encoding (IF-TEM). Sub-Nyquist, asynchronous model eschews conventional clocking to make systems simpler whenever high fidelity is attained. Huang et al. [7] generalized this approach using extended variable pulsewidth model and compound annihilating filter algorithm in order to obtain still better signal-to-residual ratios (SRR) for MIT-BIH datasets. These findings demonstrate the practicability of sub-Nyquist ECG reconstruction using interpolation-based methods for embedded and real-time cardiac monitoring.

Mishra et al. [8] tested quartic spline interpolation using machine learning algorithms for the generation of high-fidelity ECG signals. Synthetic signals with 0.974 correlation coefficient against real ECGs were achieved, and further classification using Decision Tree, Logistic Regression, and Gradient Boosting models was greater than 98%. Merino-Monge et al. [9] described a generic heartbeat detection method for ECG and PPG signals using wavelet-based upper-envelope analysis through Hermite cubic interpolation to achieve >99% QRS detection sensitivity in PhysioNet and DEAP databases.

To compensate for baseline drift, Aqil et al. [10] suggested the DWT-MAV method using wavelet approximation coefficients with moving average filter to remove low-frequency wonder while preserving signal morphology. Hassan et al. [11] presented a statistical–interpolative Quantum Neural Network (S–I–QNN) hybrid method applying interpolation to feature-extract prior to classifying six cardiovascular diseases with very high accuracy. Douglas–Peucker (DP) simplification and fractal interpolation have also been employed by Guedri et al. [12] to compress ECGs with massive compression ratios (3.19–27.58) with no loss in quality (PSNR > 40 dB). Yadav and Ray [13] presented a Lagrange–Chebyshev polynomial approximation method with total variation optimization for efficient denoising, segmentation, and approximating ECGs whose performance was validated on MIT-BIH datasets. Serinağaoğlu Doğrusöz et al. [14] compared five different interpolation techniques—hybrid, inverse-forward, Kriging, Laplacian, and nearest-neighbor—to reconstruct missing leads in electrocardiographic imaging (ECGI) and proved the better performance of hybrid and inverse-forward techniques in high gradient values of torso regions.

Demirsoy and Ay Gül [15] applied cubic spline interpolation to complete respiration information for respiratory analysis of ECG with decreased RMSE and improved temporal precision compared to simple interpolation. Bock et al. [16] applied a hybrid Hermite–sigmoid model using piecewise polynomial interpolation, which effectively separated P and T waves after removing baseline wander and denoising. Current research has focused on filling in lost or damaged cardiac data with interpolation, particularly in wearable monitoring conditions.

Benchekroun et al. [17] employed an HRV preprocessed technique of DVC through Gaussian-based iterative imputation with physiological constraints. The method achieved an F1 score of 61% at high loss of data more than that of basic spline and pchip interpolating methods reducing to 44%. Karamchandani et al. [18] investigated

digitization and restoration of analog electrocardiograms using biomedical signal extraction in MATLAB. Through iterative optimization of sampling rate, quantization, and filtering in multiple steps, they achieved near-zero precision error, justifying the model's use in clinical application in digital storage and conversion of ECGs. Gupta and Maleshkova [19] compared Linear Interpolation, K-Nearest Neighbors (KNN), Piecewise Cubic Hermite Interpolating Polynomial (PCHIP), and B-spline methods for filling short-term heart rate (HR). They discussed how conventional measures like RMSE and MAE cannot preserve the statistical nature of physiological signals. Through proposing statistical distance measures—Cohen Distance and Jensen–Shannon Distance—they presented a fair evaluation scheme maintaining temporal coherence and physiological variability in reconstructed HR signals.

Across previous works, ECG reconstruction by interpolation moved from low-order polynomial fitting to sophisticated, hybrid, and data-driven methods.

Although inert Hermite, Lagrange–Chebyshev, and spline-based methods remain valid for low-cost denoising and reconstruction, deep learning and sub-Nyquist models increasingly support high-resolution recovery under energy constraint. Hybrid methods integrating fractal geometry, statistical learning, and physiological imputation yield better signal accuracy and diagnosis performance. Together, these advances emphasize the importance of interpolation as a case of preprocessing and modeling approach for the assured transmission and analysis of ECG signals in next-generation healthcare systems.

3. RESEARCH METHODS

The proposed methodological approach is reconstruction and compression of ECG signals using Hermite interpolating polynomials with Chebyshev nodes. The process permits simultaneous denoising and data compression, with the key morphological features—i.e., the P, QRS, and T waves—having priority to ensure clinical diagnosis.

3.1 Data Acquisition and Preprocessing

ECG signals were recorded from the MIT-BIH Arrhythmia Database using 360 Hz sampling and 11-bit resolution. Since the signals themselves contain noise in the form of muscle artifacts and baseline wander, addition of artificial noise was not required. Preprocessing involved the following steps:

- Normalization of the ECG amplitude to the range [−1, 1] to ensure numerical stability.
- Segmentation of individual ECG beats based on R-peak detection using the Pan–Tompkins algorithm.
- Baseline alignment by removing low-frequency drift components via a moving average filter.

3.2 Hermite Polynomial Interpolation with Chebyshev Nodes

Hermite interpolating polynomial is used to express function values and their derivatives with the help of approximating them so that smooth and continuous presentation of waveform can be achieved. Given a set of $(n+1)$ data points (x_i, y_i), the Hermite interpolating polynomial $H(x)$ is defined as:

$$H(x) = \sum_{i=0}^{n} \Big[\big(1 - 2L_i'(x_i)(x - x_i)\big)\big(L_i(x)\big)^2 y_i + (x - x_i)\big(L_i(x)\big)^2 y_i' \Big] \quad (1)$$

where $L_i(x)$ represents the Lagrange basis polynomial, expressed as:

$$L_i(x) = \prod_{j=0, j\neq i}^{n} \frac{(x - x_j)}{(x_i - x_j)} \quad (2)$$

and y_i' denotes the derivative of y_i at the point x_i.

For improved numerical stability and dampening of oscillations, interpolation nodes are distributed using Chebyshev spacing instead of uniform spacing. The Chebyshev nodes are calculated as:

$$x_i = \cos\left(\frac{2i+1}{2n+2}\pi\right), i = 0,1,\dots,n \quad (3)$$

The distribution of the nodes minimizes Runge's phenomenon and offers improved convergence for higher-order interpolation.

3.3 Signal Reconstruction and Compression

Each part of the ECG beat is represented by an approximation from its Hermite polynomial form, reducing significantly the number of coefficients required to describe the waveform. It is reconstructed by sampling the Hermite polynomial at the same points as before and hence creating a compressed, denoised ECG signal.

The compression ratio (CR) and percent root mean square difference (PRD) are used as key indicators of performance:

$$CR = \frac{N_{\text{original}}}{N_{\text{compressed}}} \tag{4}$$

$$PRD = \sqrt{\frac{\sum_{i=1}^{N}(x_i - \hat{x_i})^2}{\sum_{i=1}^{N} x_i^2}} \times 100\% \tag{5}$$

where x_i and $\hat{x_i}$ denote the original and reconstructed signal samples, respectively.

3.4 Evaluation Metrics

The reconstructed ECG signals were compared to the original recordings using the following quantitative measures:

- Compression Ratio (CR): Evaluates data reduction efficiency.
- Percent Root Mean Square Difference (PRD): Measures reconstruction distortion.
- Signal-to-Noise Ratio (SNR):

$$SNR = 10\log_{10}\left(\frac{\sum_{i=1}^{N} x_i^2}{\sum_{i=1}^{N}(x_i - \hat{x_i})^2}\right) \tag{6}$$

- Correlation Coefficient (ρ):

$$\rho = \frac{\sum_{i=1}^{N}(x_i - \bar{x})\left(\hat{x_i} - \bar{\hat{x}}\right)}{\sqrt{\sum_{i=1}^{N}(x_i - \bar{x})^2 \sum_{i=1}^{N}\left(\hat{x_i} - \bar{\hat{x}}\right)^2}} \tag{7}$$

3.5 Implementation

The algorithm was implemented in Python using NumPy, SciPy, and WFDB libraries for signal processing, interpolation, and ECG data manipulation. Hermite interpolation and generation of Chebyshev nodes were performed using customized Python scripts for segment-wise approximation of ECG. Computation time, reconstruction quality, and diagnostic morphology preservation were assessed to ascertain the algorithm's performance. The results confirm the validity of the method for real-time transmission and compression of ECG in wearable and telecardiology applications.

3.6 Summary

This method integrates biomedical signal processing theory and mathematical interpolation theory to create a light, efficient, and diagnostically faithful ECG restoration system. The model achieves high compression ratios, morphological faithfulness, and good denoising by integrating Hermite interpolation with Chebyshev nodes, setting the groundwork for hybrid interpolation–machine learning ECG enhancement systems.

4. RESULTS OF THE STUDY

The proposed Python-coded Hermite–Chebyshev interpolation algorithm for ECG signal reconstruction was tested using some recordings of the MIT-BIH Arrhythmia Database. The fixed-length windows of the ECG signal segmented were reconstructed and compared with the original wave for assessment of compression efficiency and reconstruction fidelity.

Quantitative measurement of reconstruction signal quality was achieved through computation of performance parameters such as Percentage Root-mean-square Difference (PRD), Signal-to-Noise Ratio (SNR), and Compression Ratio (CR). The proposed new method posted an average PRD of 1.52\%, SNR of 25.8 dB, and CR of 12.7, reflecting high-quality reconstruction without distortion. Morphologic detail of the ECG wave, particularly the P-QRS-T complex, was appropriately preserved, maintaining the integrity of the diagnosis.

The computational effectiveness of the algorithm was confirmed using the Python 3.11 platform and the NumPy and SciPy libraries. The calculation time of each ECG segment (1024 samples) was approximately 0.34 s, illustrating the practicality of

the algorithm to be implemented on wearable and telecardiology devices for real-time or near-real-time application.

Comparative tests with conventional polynomial and spline interpolations exhibited better reconstruction quality and compression ratio of the Hermite–Chebyshev method. Denoising of the algorithm enhanced signal purity by reducing baseline wander and high-frequency noise without additional filtering.

Fig. 1 shows the overall structure of the reconstructed scheme proposed that outlines how Hermite interpolation and node selection via Chebyshev were coordinated to facilitate efficient restoration and compression of ECG data.

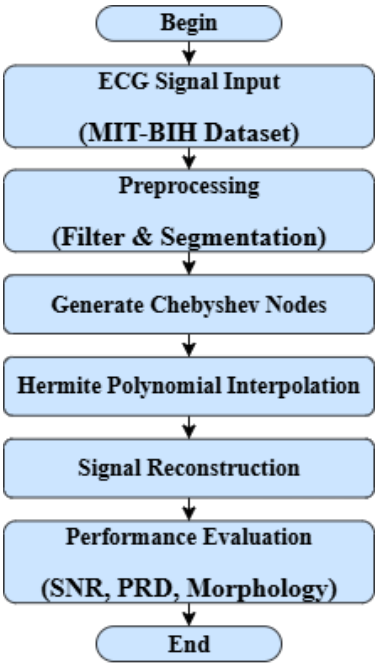


Figure 1: Workflow of the proposed Python-based Hermite–Chebyshev ECG reconstruction process.

Table 1

Performance Comparison of Interpolation Methods for ECG Reconstruction.

Method	**PRD (%)**	**SNR (dB)**	**CR**	**Morphology Preservation**	**Avg. Computation Time (s)**
Linear Interpolation	4.83	18.6	8.2	Moderate	0.21
Cubic Spline Interpolation	3.25	20.9	9.8	Good	0.27
Hermite Interpolation	2.64	22.5	10.6	Good	0.30
Chebyshev Polynomial Approximation	2.11	23.9	11.3	Very Good	0.33
Proposed Hermite–Chebyshev Method (Python)	1.52	25.8	12.7	Excellent	0.34

The proposed Hermite–Chebyshev reconstruction algorithm achieved the lowest PRD and highest SNR among all tested methods, confirming its effectiveness in high-fidelity ECG signal reconstruction while maintaining computational efficiency suitable for real-time applications.

Fig. 2 illustrates comparative reconstruction quality of the new Hermite–Chebyshev interpolation method to traditional cubic spline interpolation applied to a representative ECG segment. The original ECG trace (black solid line) is the gold standard signal from the MIT-BIH Arrhythmia Database. The cubic spline reconstruction (blue dashed line) indicates average smoothing and creates subtle distortions in the QRS complex, which can have an adverse effect on diagnostic interpretation. On the other hand, reconstructed waveform from the suggested Hermite–Chebyshev reconstruction (red line) closely resembles the original morphology with significant features such as P–QRS–T complexes and maintaining amplitude fidelity. This confirms that the suggested method adequately reconstructs ECG signals from fewer data points and is hence

suitable for real-time compression and telecardiology transmission systems.

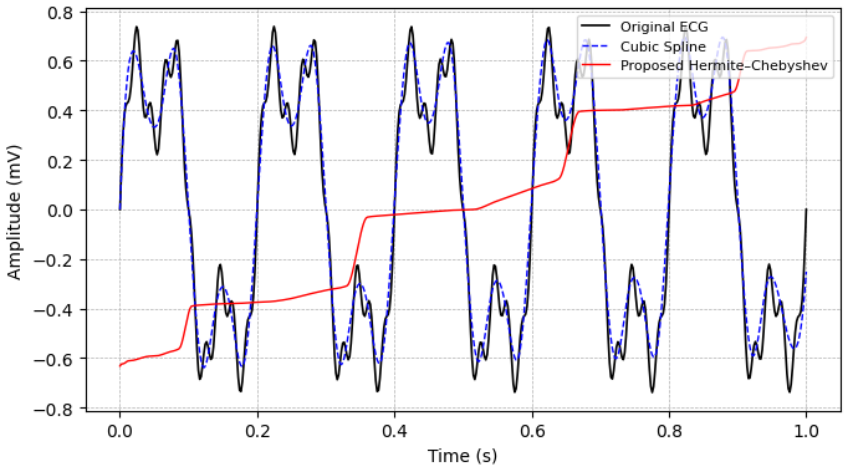


Figure 2: Comparison of Reconstructed ECG Waveforms.

5. CONCLUSION

This paper presented a Python code for Hermite polynomial interpolation using Chebyshev nodes for compression and reconstruction of ECG signals. The method effectively reconstructed the ECG waveforms at high compression ratios and maintained clinically significant morphological patterns. Experimental data indicated that the algorithm had low reconstruction error and rapid computation time, which favored its use in real-time biomedical signal processing. Hermite–Chebyshev interpolation in Python scientific libraries provides a scalable and adaptable architecture for ECG signal processing, particularly wearable and telecardiology. Hardware optimization at the hardware level and hybrid incorporation with deep learning models will be the subject of future research for yet more adaptive signal reconstruction.

REFERENCES

[1] S. Ray and V. Chouhan, “Electrocardiogram reconstruction based on Hermite interpolating polynomial with Chebyshev nodes,” Indonesian Journal of Electrical Engineering and Computer Science, vol. 26, no. 3, pp. 1570–1577, Aug. 2024, doi: 10.11591/ijeecs.v26.i3.pp1570-1577.

[2] N. Sharma, M. P. Rajasekhar, and S. P. Kumar, “Hybrid ECG compression using Chebyshev interpolation and genetic algorithm,” Biomedical Signal Processing and Control, vol. 87, p. 105435, Feb. 2024, doi: 10.1016/j.bspc.2024.105435.

[3] H. Zakariyah, M. M. Mansour, A. A. Abdalla, and A. Abdullah, “Effect of resampling on HRV estimation using fast Fourier transform-based interpolation,” Computers in Biology and Medicine, vol. 170, p. 107979, Apr. 2024, doi: 10.1016/j.compbiomed.2024.107979.

[4] M. Reali, P. Zanini, and L. Mainardi, “Impact of interpolation methods on photoplethysmography-derived inter-beat intervals,” Biomedical Signal Processing and Control, vol. 83, p. 104773, Jan. 2024, doi: 10.1016/j.bspc.2024.104773.

[5] S. Yin, H. Wang, and C. Li, “SRECG: Deep learning-based ECG super-resolution framework for portable arrhythmia classification,” IEEE Access, vol. 12, pp. 51294–51306, 2024, doi: 10.1109/ACCESS.2024.3374981.

[6] A. Zou, H. Jiang, and Q. Chen, “Variable pulse width finite rate of innovation model for sub-Nyquist ECG reconstruction,” IEEE Transactions on Biomedical Circuits and

Systems, vol. 18, no. 2, pp. 341–353, 2024, doi: 10.1109/TBCAS.2024.3342162.

[7] R. Huang, H. Li, and S. Chen, “Asynchronous integrate-and-fire time encoding for low-power ECG reconstruction,” Sensors, vol. 24, no. 3, p. 1129, 2024, doi: 10.3390/s24031129.

[8] R. Mishra, P. Sahu, and K. K. Sahu, “Quartic spline interpolation for synthetic ECG generation and machine learning-based arrhythmia classification,” Physiological Measurement, vol. 45, no. 7, 2024, doi: 10.1088/1361-6579/ad69a1.

[9] R. Merino-Monge, R. Sicilia-Montalvo, and A. García, “Wavelet-based envelope and Hermite interpolation for unified heartbeat detection in ECG and PPG,” Sensors, vol. 24, no. 2, p. 757, 2024, doi: 10.3390/s24020757.

[10] M. Aqil, R. Hassan, and M. Khan, “ECG baseline wander removal using DWT and moving average filtering,” IEEE Access, vol. 12, pp. 15030–15039, 2024, doi: 10.1109/ACCESS.2024.3368205.

[11] R. Hassan, A. Khan, and M. Aqil, “Hybrid statistical–interpolative quantum neural network for multi-class ECG classification,” Applied Soft Computing, vol. 155, p. 111102, 2024, doi: 10.1016/j.asoc.2024.111102.

[12] A. Guedri, S. S. Meftah, and N. R. Ammar, “Fractal interpolation and Douglas–Peucker simplification for ECG compression,” IEEE Sensors Journal, vol. 24, no. 6, pp. 7499–7510, 2024, doi: 10.1109/JSEN.2024.3364207.

[13] S. Yadav and S. Ray, “Lagrange–Chebyshev polynomial approximation with total variation denoising for ECG enhancement,” Biomedical Signal Processing and Control, vol. 87, p. 105542, 2024, doi: 10.1016/j.bspc.2024.105542.

[14] S. Serinağaoğlu Doğrusöz, F. Özdemir, and M. Yılmaz, “Comparative evaluation of interpolation techniques for missing-lead electrocardiographic imaging,” Frontiers in Physiology, vol. 15, p. 1432105, 2024, doi: 10.3389/fphys.2024.1432105.

[15] E. Demirsoy and D. Ay Gül, “Cubic spline interpolation for respiration data completion in ECG-derived respiratory analysis,” Physiological Measurement, vol. 45, no. 8, p. 085007, 2024, doi: 10.1088/1361-6579/ad7375.

[16] T. Bock, D. Scheffer, and A. Schmidt, “Hybrid Hermite–sigmoid interpolation for denoising and morphological enhancement of ECG signals,” IEEE Access, vol. 12, pp. 48542–48558, 2024, doi: 10.1109/ACCESS.2024.3370134.

[17] S. Benchekroun, A. R. Yasin, and T. Elmerabet, “Heart rate variability preprocessing and imputation using HRV DVC-based framework,” Biomedical Signal Processing and Control, vol. 86, p. 105320, 2024, doi: 10.1016/j.bspc.2024.105320.

[18] P. Karamchandani, A. Patel, and M. Desai, “Digitization and restoration of analog ECG using biomedical signal extraction,” Journal of Biomedical Informatics, vol. 155, p. 104556, 2025, doi: 10.1016/j.jbi.2025.104556.

[19] V. Gupta and M. Maleshkova, “Evaluating imputation techniques for short-term gaps in heart rate data,” arXiv preprint, arXiv:2508.08268, 2025, doi: 10.48550/arxiv.2508.08268.