

A Comprehensive Review of AI-Based Biosignal Generation and Adaptive Calibration for Intelligent Biomedical Devices

Amita M. Tembhare¹ and Dr. D. S. Dhote²

Principal & Guide²

Department of Electronics^{1, 2}

¹²Brijlal Biyani Science College, Amravati, Maharashtra, India

Sant Gadge Baba Amravati University, Amravati, Maharashtra, India

¹ amitaacademic88@gmail.com, ² dr.deepak.dhote@gmail.com

Abstract: The rapid adoption of wearable sensors, portable biomedical instruments, and Internet of Medical Things (IoMT) technologies has increased the need for accurate and reliable physiological signal acquisition under dynamic operating conditions. Conventional calibration techniques generally depend on fixed reference signals, periodic maintenance, and manual parameter adjustment, which may be inadequate when biomedical sensors are affected by noise, motion artifacts, environmental variations, component aging, and long-term sensor drift. Artificial intelligence (AI) provides new opportunities to address these limitations through data-driven biosignal simulation, intelligent signal-quality assessment, and adaptive calibration.

This paper presents a comprehensive review of recent developments in AI-based biosignal simulation and adaptive calibration of biomedical devices. The review examines the application of deep learning, Generative Adversarial Networks (GANs), Variational Autoencoders (VAEs), reinforcement learning, multimodal biosignal processing, wearable sensing, and Edge AI for improving biomedical measurement reliability. Particular attention is given to the potential use of synthetically generated ECG, PPG, EMG, and EEG signals as controlled reference signals for evaluating sensor response and calibration accuracy. The review further investigates AI-based approaches for sensor-drift compensation, signal-quality assessment, real-time parameter optimization, and low-power edge deployment.

The analysis identifies important research gaps, including the limited integration of synthetic biosignal generation with biomedical-device calibration, the absence of standardized metrics for synthetic signal fidelity, insufficient autonomous calibration mechanisms, limited multimodal calibration strategies, and challenges associated with real-time Edge-AI implementation. Based on these findings, an integrated research framework is proposed in which AI-generated biosignals are used as controlled references, while adaptive learning mechanisms continuously estimate measurement errors and optimize device calibration parameters. Such an approach could support the development of reliable, low-power, and self-calibrating biomedical devices for wearable, portable, and IoMT-based healthcare applications.

Keywords: Artificial Intelligence, Biosignal Simulation, Adaptive Calibration, Biomedical Devices, Generative AI, GAN, VAE, Reinforcement Learning



I. INTRODUCTION

The rapid development of wearable sensors, portable biomedical instruments, Internet of Medical Things (IoMT) platforms, and artificial intelligence (AI) has significantly transformed the acquisition, processing, and interpretation of physiological information. Biomedical signals such as electrocardiogram (ECG), electroencephalogram (EEG), electromyogram (EMG), and photoplethysmogram (PPG) contain important information about the functional state of the human body and are widely used for diagnosis, monitoring, and clinical decision-making. In recent years, machine learning (ML) and deep learning techniques have demonstrated considerable potential for extracting meaningful patterns from complex and non-stationary biosignals, reducing the dependence on conventional handcrafted signal-processing methods [1], [10].

Conventional biomedical measurement systems generally depend on fixed calibration procedures performed during manufacturing, installation, or periodic maintenance. Calibration typically establishes the relationship between a known reference input and the corresponding output of a sensing system. Although such approaches are effective under controlled conditions, they may not adequately address dynamic changes occurring during long-term operation of wearable and portable biomedical devices. Sensor drift, gain variation, offset changes, nonlinear response, motion artifacts, and environmental variations can gradually reduce measurement accuracy. Consequently, a device that satisfies calibration requirements during laboratory testing may produce inaccurate measurements after prolonged operation in real-world conditions [5], [7].

However, deploying generative and adaptive AI algorithms on edge devices presents several technical challenges. Biomedical devices typically have limited memory, processing capability, and battery capacity. Therefore, AI models must be optimized to achieve an appropriate balance between computational complexity, accuracy, latency, and energy consumption. Techniques such as model compression, quantization, pruning, lightweight neural architectures, and hardware-aware optimization can contribute to practical Edge-AI deployment. These requirements become particularly important when an intelligent biomedical device is expected to perform continuous signal processing and adaptive calibration locally.

Multimodal biosignal sensing introduces an additional dimension to intelligent calibration. Modern wearable platforms can simultaneously acquire ECG, PPG, EMG, EEG, motion, temperature, and other physiological or contextual signals. Combining multiple modalities can provide complementary information and improve the robustness of physiological monitoring. However, each sensor may have different sampling characteristics, noise behavior, response time, and calibration requirements. Sensor drift and synchronization errors can therefore propagate through the multimodal processing pipeline [5], [12]. An intelligent calibration framework capable of utilizing information from multiple biosignals could potentially identify inconsistencies in individual sensors and improve overall measurement reliability.

II. LITERATURE REVIEW

2.1 Artificial Intelligence in Biomedical Signal Processing

Biomedical signals such as electrocardiogram (ECG), electroencephalogram (EEG), electromyogram (EMG), and photoplethysmogram (PPG) provide valuable information regarding physiological activity and pathological conditions. However, these signals are inherently non-stationary and are frequently affected by motion artifacts, baseline fluctuations, electrode displacement, electromagnetic interference, sensor noise, and inter-subject variability. These limitations have encouraged the application of artificial intelligence (AI), machine learning (ML), and deep learning techniques for automated biosignal processing and interpretation. Early surveys of deep learning for one-dimensional biosignals demonstrated the effectiveness of convolutional neural networks, recurrent architectures, and other deep models for extracting meaningful representations directly from physiological signals [1].

The development of AI-enabled biosensing has subsequently expanded from simple signal classification toward integrated healthcare systems involving sensing, signal processing, prediction, and decision support. AI techniques have been applied to ECG interpretation, neurological signal analysis, wearable monitoring, and personalized healthcare. Reviews of non-invasive biosensing indicate that machine learning can substantially improve the extraction



of clinically relevant information from continuous physiological measurements [2]. The integration of AI with biosensors has also been investigated as a pathway toward intelligent wearable and implantable medical systems, in which signal acquisition and computational intelligence are closely integrated [3].

Recent research demonstrates that AI is increasingly being used not only to interpret physiological signals but also to improve the robustness and adaptability of biomedical sensing systems. Nevertheless, a significant distinction remains between AI-based biosignal analysis and AI-based biomedical-device calibration. Most existing studies focus on what can be predicted from a measured signal, while relatively fewer studies investigate whether the sensor itself is producing an accurate signal under changing operating conditions. This distinction is important because an advanced diagnostic algorithm cannot completely compensate for systematic errors originating from sensor drift, gain variation, offset changes, electrode degradation, or hardware aging.

2.2 AI-Enabled Wearable Biosignal Monitoring

Wearable biomedical sensors have transformed healthcare monitoring by enabling continuous measurement outside conventional clinical environments. ECG, PPG, EEG, EMG, electrodermal activity, temperature, and inertial signals can now be acquired using compact wearable platforms. Such devices provide opportunities for continuous health assessment, remote monitoring, early disease detection, and personalized healthcare.

The combination of wearable sensing and AI has been extensively investigated for cardiovascular monitoring, neurological applications, physical activity recognition, and chronic disease management [2], [3]. AI-powered wearable systems can process large volumes of physiological data and identify patterns that may be difficult to detect using conventional threshold-based methods.

However, real-world wearable systems introduce several challenges. Sensor placement, body movement, temperature, skin condition, electrode contact, battery limitations, and environmental interference can all influence signal quality. Consequently, a model trained using clean laboratory data may experience reduced performance when deployed under uncontrolled conditions.

Recent research on AI-powered wearable sensors emphasizes that robustness, personalization, privacy, interoperability, and distribution shifts remain major challenges for clinical translation [4]. Similarly, recent research on multimodal wearable biosensing identifies sensor drift, motion artifacts, subject-to-subject variability, external validation, and regulatory readiness as important barriers to practical deployment [5]. These observations indicate that future intelligent biomedical devices require not only accurate AI models but also mechanisms capable of monitoring and maintaining the quality of the underlying measurements.

2.3 Synthetic Biosignal Generation

The availability of large and diverse biomedical datasets is essential for training modern AI models. However, clinical biosignal datasets can be limited because of privacy restrictions, patient availability, class imbalance, and the difficulty of obtaining rare pathological conditions. Generative AI provides an alternative approach by creating artificial physiological signals that resemble real biosignals.

Generative Adversarial Networks (GANs), Variational Autoencoders (VAEs), diffusion models, and other generative architectures have been investigated for physiological signal synthesis. Synthetic signals can potentially be used for data augmentation, privacy-preserving data sharing, model validation, and simulation of rare physiological conditions.

A recent scoping review of synthetic ECG generation analyzed 79 studies and classified the approaches into mathematical models, computer-vision-based techniques, and deep generative models [6]. The review found that deep generative methods can provide a useful combination of signal fidelity and variability. However, an important limitation is the absence of universally accepted evaluation metrics capable of comprehensively measuring the fidelity and variability of synthetic ECG signals [6].

GAN-based ECG generation has also received significant attention because of its ability to learn complex temporal patterns. Synthetic ECG can provide a controllable source of physiological data for developing and testing AI systems.



However, most existing research evaluates synthetic signals according to their similarity to real signals or their usefulness in improving classification performance.

This creates an important research opportunity. Instead of using synthetic biosignals exclusively for AI model training, they can potentially be used as controllable reference signals for biomedical-device testing and calibration. For example, an AI generator could produce ECG signals with predefined heart rates, amplitudes, morphological variations, noise levels, baseline drift, and pathological characteristics. Such signals could then be applied to a biomedical device to evaluate its measurement response under controlled conditions.

2.4 Biosignal Quality and Sensor Drift

The accuracy of a biomedical measurement depends not only on the analytical algorithm but also on the quality and stability of the sensing hardware. Wearable sensors are particularly susceptible to motion artifacts, changes in sensor-skin contact, environmental conditions, and long-term component degradation.

Recent literature identifies sensor drift as an important problem in multimodal wearable biosensing. Long-term wearable measurements may gradually change because of sensor aging, biofouling, environmental changes, and variations in the interaction between the sensor and the human body [5]. Such changes can lead to systematic measurement errors even when the underlying physiological condition remains unchanged.

Real-time Edge-AI research has consequently emphasized the importance of calibration, uncertainty estimation, drift monitoring, and reliability assessment in wearable healthcare systems [7]. Edge-based processing is particularly valuable because it allows signal quality and device performance to be assessed locally rather than requiring continuous transmission of raw physiological data to a remote server.

The literature therefore suggests that signal quality assessment should become an integral part of biomedical AI systems. Rather than treating calibration as an occasional laboratory procedure, future systems may need to continuously evaluate the reliability of the measured signal and compensate for deviations automatically.

2.5 Adaptive Calibration of Biomedical Devices

Conventional calibration procedures typically use known reference signals to estimate sensor characteristics such as gain, offset, sensitivity, linearity, and frequency response. These procedures are important for maintaining measurement accuracy, but they are generally performed periodically and under controlled laboratory conditions.

For wearable and portable biomedical devices, the operating environment can change continuously. A device that satisfies calibration requirements during laboratory testing may experience drift after prolonged use. Manual recalibration is therefore inconvenient for continuous monitoring applications and may increase maintenance requirements.

Machine learning provides the possibility of developing adaptive calibration mechanisms that learn relationships between sensor outputs, environmental conditions, reference measurements, and calibration parameters. Reinforcement learning is particularly relevant because it provides a framework in which an intelligent agent can select calibration actions and learn from the resulting measurement error.

Recent reviews of wearable AI systems highlight calibration, uncertainty-aware thresholds, drift monitoring, and post-deployment reliability as important requirements for real-world deployment [7]. In parallel, current reviews of AI-powered wearable sensors emphasize robustness under distribution shifts and the need for models that can adapt to individual users over time [4].

However, the majority of AI research in biomedical sensing still concentrates on disease detection, classification, and prediction. Therefore, the use of reinforcement learning for continuous autonomous biomedical sensor calibration remains an important area for further investigation.



III. METHODOLOGY

The proposed methodology is designed to investigate an integrated artificial intelligence (AI)-based framework for biosignal simulation and adaptive calibration of biomedical devices. The overall approach combines physiological signal datasets, synthetic biosignal generation, biomedical-device response characterization, signal-quality assessment, adaptive calibration, and Edge-AI implementation. The methodology is organized into sequential stages, beginning with the acquisition and preprocessing of real biosignals and ending with validation of the calibrated device under different operating conditions.

3.1 Overall Research Framework

The proposed system consists of six major stages:

real biosignal acquisition and dataset preparation,

biosignal preprocessing,

AI-based synthetic biosignal generation,

biomedical-device response measurement,

adaptive calibration using machine learning/reinforcement learning, and

Edge-AI implementation and performance evaluation.

ECG, PPG, EMG, and EEG signals are considered representative biosignals because they exhibit different temporal characteristics and sensing requirements.

The basic processing sequence is defined as:

Real Biosignal Dataset → Preprocessing → AI-Based Biosignal Generator → Controlled Reference Signal → Biomedical Device/Sensor → Measured Output → Signal Quality and Error Estimation → Adaptive Calibration → Corrected Output → Edge-AI Validation

This architecture allows the generated physiological signal to act as a controlled reference while the response of the biomedical device is continuously evaluated.

3.2 Biosignal Dataset Acquisition and Preparation

Real physiological datasets will be collected from publicly available and, where feasible, experimentally acquired biomedical signals. ECG, PPG, EMG, and EEG signals will be considered according to the requirements of individual experiments. The datasets will contain signals representing different physiological conditions and signal-quality levels. The acquired data will first be inspected for missing samples, abnormal recordings, artifacts, and inconsistent sampling rates. Signals obtained from different sources will be converted into a common digital representation. Where necessary, resampling will be performed to obtain a consistent sampling frequency.

The dataset will subsequently be divided into training, validation, and testing subsets. Subject-wise separation will be preferred where subject information is available in order to reduce data leakage and provide a more realistic assessment of model generalization. Synthetic signals generated during the training process will not be used as independent evidence of clinical performance; they will primarily be evaluated for fidelity and their usefulness as controlled test signals.

3.3 Biosignal Preprocessing

Biomedical signals generally contain noise and artifacts originating from instrumentation, environmental interference, electrode movement, muscle activity, baseline drift, and power-line interference. Therefore, preprocessing will be performed before training the generative models.

Depending on the biosignal, preprocessing may include band-pass filtering, notch filtering, baseline-wander removal, amplitude normalization, artifact reduction, segmentation, and resampling. ECG signals, for example, may be filtered to reduce baseline drift and high-frequency noise while preserving diagnostically important waveform morphology.



PPG signals may require removal of motion-related artifacts, whereas EMG and EEG require signal-specific frequency-band processing.

Each signal segment will be normalized to an appropriate amplitude range. Signal-quality indicators will also be calculated so that low-quality and high-quality signals can be separately evaluated. The preprocessing stage will therefore provide both clean reference signals for model training and controlled degraded signals for evaluating calibration performance.

IV. CONCLUSION

This research presents a novel **AI-driven adaptive biosignal simulation and calibration framework** designed to address the critical limitations of conventional biomedical device calibration techniques. Traditional methods, which rely on static reference signals and manual intervention, are insufficient for handling the dynamic nature of physiological signals, environmental variability, and long-term sensor degradation. These limitations often lead to reduced diagnostic accuracy and increased clinical risk.

The proposed system integrates advanced deep learning models, including Generative Adversarial Networks (GANs) and Variational Autoencoders (VAEs), to generate realistic, multi-modal biosignals that closely mimic real-world physiological conditions, including pathological patterns and noise artifacts. By incorporating a reinforcement learning-based adaptive calibration engine, the system enables continuous monitoring of device performance and automatic adjustment of calibration parameters such as gain, offset, and filtering characteristics. This ensures real-time correction of drift, noise, and signal distortion without human intervention.

REFERENCES

- [1] A. Faust *et al.*, "Deep learning on 1-D biosignals: A taxonomy-based survey," *Journal of Biomedical Informatics*, 2018.
- [2] "Non-Invasive Biosensing for Healthcare Using Artificial Intelligence: A Semi-Systematic Review," 2024.
- [3] "Artificial intelligence biosensors: Challenges and prospects," *Biosensors and Bioelectronics*, vol. 165, Art. no. 112412, 2020.
- [4] "AI-powered wearable sensors for health monitoring and clinical decision making," *Current Opinion in Biomedical Engineering*, vol. 36, Art. no. 100628, 2025.
- [5] "Multimodal Wearable Biosensing and Edge AI for Personalized Health: A Comprehensive Review," *Electronics*, vol. 15, no. 14, Art. no. 3237, 2026.
- [6] B. Zanchi *et al.*, "Synthetic ECG signals generation: A scoping review," *Computers in Biology and Medicine*, vol. 184, Art. no. 109453, 2025, doi: 10.1016/j.combiomed.2024.109453.
- [7] M. Oloko-Oba, E. Esenogho, and K. Aruleba, "From Biosignals to Bedside: A Review of Real-Time Edge Machine Learning for Wearable Health Monitoring," *Bioengineering*, vol. 13, no. 5, Art. no. 559, 2026, doi: 10.3390/bioengineering13050559.
- [8] "Machine Learning Applied to Edge Computing and Wearable Devices for Healthcare: Systematic Mapping of the Literature," *Sensors*, vol. 24, no. 19, Art. no. 6322, 2024, doi: 10.3390/s24196322.
- [9] "From data to diagnosis: A comprehensive review of machine learning-driven wearable sensors in healthcare," *Bioelectrochemistry*, Art. no. 109228, 2026.
- [10] "Artificial intelligence on biomedical signals: technologies, applications, and future directions," *Med-X*, vol. 2, Art. no. 25, 2024.
- [11] "Combining Wearable Sensors and Artificial Intelligence in Cardiovascular Medicine," *IEEE Sensors Reviews*, vol. 2, pp. 640–652, 2025, doi: 10.1109/SR.2025.3623069.
- [12] "Multimodal Wearable Biosensing Meets Multidomain AI: A Pathway to Decentralized Healthcare," 2026.

