Received: 14 April 2026 | Revised: 1 June 2026 | Accepted: 17 June 2026 | Published online: 2 July 2026

RESEARCH ARTICLE

Smart Wearable Technology
2026, Vol. 00(00) 1–13
DOI: 10.47852/bonviewSWT620210006

BON VIEW PUBLISHING

A Unified AI-Driven Signal Processing and Machine Learning Optimization Framework for Energy-Efficient Smart Wearable Devices in 5G/6G Communication Systems

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Abstract: As smart wearable devices advance at breakneck speed in 5G and upcoming 6G communication settings, there exists a need for highly reliable, low-latency, and power-efficient signal processing schemes. In this paper, we present an artificial intelligence (AI)-based solution for optimizing wearable signals using signal processing and machine learning (ML). Experimental results suggest that ML-driven optimization may be capable of increasing signal-to-noise ratio by 18–25%, decreasing inference latency to less than 5 ms, and improving energy consumption up to 30–45% relative to traditional signal processing solutions. Additionally, throughput in wearables increases from 9 Gbps in traditional 5G communication systems to 20–45 Gbps in AI-assisted 6G systems with a packet delivery rate greater than 97–98% even when densely mobile. The proposed scheme also shows better performance for adapting to issues related to millimeter wave and terahertz bands. This implies that AI-assisted signal processing is very critical in wearable systems in terms of performance and scalability, which are crucial characteristics of next-generation 5G/6G intelligent healthcare and Internet of Things (IoT) technologies.

Keywords: artificial intelligence, signal processing, machine learning, smart wearable devices, 5G/6G communication systems

1. Introduction

The fast developments in digital health technologies, growing demand for continuous and real-time monitoring of body parameters, and the advent of smart ecosystems have made wearable devices the key element in the development of next-generation healthcare and well-being solutions. Due to the fast development of artificial intelligence (AI) technologies, signal processing tools, and ultra-high-speed wireless communication networks, it has become possible to achieve a high level of accuracy and speed in wearable devices. At the same time, despite the significant achievements, modern wearables continue to experience considerable challenges in the area of quality signal processing, energy efficiency, delay, scalability, and reliable data transfer. Given the global trend toward the transition to 5G and further adoption of the 6G communication paradigm, there is a pressing need to design novel intelligent signal processing and machine learning (ML) optimization tools dedicated specifically to wearable devices. Thus, studying the application of AI-enabled signal processing and ML optimization in wearable devices in 5G/6G communication ecosystem becomes highly relevant and necessary.

The last few years have seen significant increases in research activities related to combining AI within wearable technology and wireless communication systems. For example, Zhou et al. [1] looked at the implementation of deep learning methods of denoising of sensor signals in wearable biosensors and found that convolutional neural networks (CNNs) help to enhance the signal-to-noise ratio (SNR) for electrocardiogram (ECG) signals, although increased computational complexity limits their practical use in real time. Also, Siriwardhana et al. [2] studied edge ML algorithms for wearable systems within 5G communication systems and found that they decrease latency and lower data traffic requirements, but energy and computational balance between edge nodes is problematic. Furthermore, Baduge et al. [3] analyzed adaptive algorithms of signal processing with the aid of reinforcement learning in wearable health monitoring systems, demonstrating better results when using dynamic adaptation of algorithm parameters depending on physiological conditions.

Kanellopoulos et al. [4] explored the connection between wearable IoT systems and the 5G communications architecture, stressing the importance of ultra-reliable low-latency communications (URLLC) in supporting real-time healthcare monitoring. However, congestion and scalability problems were pointed out

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as major concerns in such dense system deployments. Mekruksavanich and Jitpattanakul [5] designed a hybrid ML method based on both Support Vector Machines (SVMs) and deep neural networks in order to recognize activities in wearable devices. It was demonstrated that classification efficiency could be achieved, even though additional computational effort was required. Martyushev et al. [6] presented efficient energy consumption algorithms used in signal processing of wearable IoT devices, showing the possibility of reducing the consumption via less accurate models.

The work by Rahman et al. [7] focused on the use of federated learning in wearable healthcare applications, which allowed training of the models in a decentralized manner while ensuring data privacy; the authors observed that the problem of inefficient communication still persists because of continuous parameter updates. Wang et al. [8] analyzed the use of AI-powered channel optimization strategies in 5G-integrated wearable communications and observed that ML-based resource allocation results in improved throughput and reliability, although system performance is affected in cases of highly dynamic mobility.

DeMedeiros et al. [9] performed research into real-time detection of anomalies in sensor-based wearable devices using recurrent neural networks (RNNs) and showed increased capabilities of detecting irregularities in health; however, latency issues hinder its use in critical situations. Varnosfaderani and Forouzanfar [10] conducted a study into the practicality of applying edge computing to smart healthcare systems through wearable devices and found that although local processing results in much faster responses, hardware issues prevent it from scaling up. Abuyaghi et al. [11] suggested a new approach to compress signals using autoencoders that allows for saving bandwidth in 5G wearable systems.

Getu et al. [12] have studied interference mitigation with the aid of AI in wearable communication with densification and observed enhanced signal fidelity but called for the need to develop contextually aware and adaptively capable models. Fayad et al. [13] studied the possible incorporation of 6G technology into wearable devices, discussing terahertz transmission and intelligent surfaces as future possibilities; nonetheless, the practical implementation issues have not been addressed so far. Gao et al. [14] studied transfer learning applications for wearable signal processing and found that transfer learning could be used to facilitate development for different application scenarios; nonetheless, domain adaptation remains an issue.

Singh and Gill [15] have analyzed the possibilities for real-time data analytics with a hybrid cloud-edge architecture for wearable health monitoring devices and found that low latency was achievable through proper task distribution, but data security issues cannot be ignored. Sai et al. [16] have discussed the significance of explainable AI for wearable healthcare systems and found that model interpretability is important for such systems; however, the drawback of model interpretability was reduced performance. Azari et al. [17] developed a model for adaptively managing resources for wearable devices in 5G network architecture using ML algorithms; however, model retraining is required due to the dynamic nature of the environment.

The research carried out by Mcoyi et al. [18] focused on AI-based sensor signal enhancement algorithms. From his findings, it is clear that noise removal in the early stages of information transmission is critical to ensuring that subsequent processes yield reliable results. However, he did not focus on how communication systems could benefit from these methods. On the other hand, Jiang et al. [19] analyzed the effectiveness of AI-based prediction models in optimizing the operation of wearable networks in 6G contexts. He found that predictive models were highly effective but very dependent on accurate data.

Lastly, Chaccour et al. [20] analyzed the use of AI-based methods to perform wave beamforming in wireless communication, proving that the application of ML methods can considerably increase the precision of the process. Likewise, Gawlikowski et al. [21] looked at AI-powered resource optimization within a network.

However, despite the above achievements, there are still several major shortcomings in the existing state of affairs. First, much attention is paid to signal processing, ML, and wireless communication individually, without the required integration from a holistic perspective suitable for wearables deployed in 5G and even more advanced 6G environments. Second, insufficient effort is being put into attaining a compromise between computational overhead, energy consumption, and timely performance that is vital for wearables due to their limited resource capacities. Finally, user-friendly solutions, namely, comfortable design, versatility, and personalized data analysis, which are key components for the successful operation of wearables, are often neglected by researchers. Moreover, the problems associated with scalability, interconnectivity, and secure data transmission in complex network environments are far from being solved at the moment.

Given this situation, the aim of this study is to create a unified AI-driven signal processing and ML optimization technique that applies to smart wearable devices in 5G and 6G communication systems with emphasis on their enhanced performance, energy efficiency, and effective data transmission. The objectives include the following tasks: analyzing and modeling wearable signals based on their dynamic nature; developing intelligent signal processing algorithms with emphasis on low energy consumption and real-time applications; developing ML techniques for data analysis and decision-making; integrating ML techniques into 5G and 6G communication systems to facilitate effective data transmission; and evaluating the system's performance based on accuracy, energy consumption, and other criteria.

2. Materials and Methods

In this section, the materials, architecture of intelligent systems, computation models, ML methods, communication approaches, optimization techniques, and experimental procedures used for the design of the proposed AI and machine Learning (ML)-enabled communication optimization approach for smart wearable communications in 5G and future 6G wireless communication scenarios have been discussed. This proposed method aimed at enhancing communication reliability, minimizing latencies, optimizing the use of available bandwidth, maximizing spectral efficiency, and reducing energy consumption within wearable communication networks.

The methodology comprised the incorporation of wearable sensory technologies, digital signal processing techniques, ML-enabled communication optimization, edge intelligence, and cloud network management into an intelligent communication methodology. The whole methodology was explained with the help of four technical diagrams, such as:

- Figure 1: Unified AI-Driven Wearable Communication Framework
- Figure 2: Intelligent Workflow Diagram
- Figure 3: System Module Interaction Architecture
- Figure 4: Signal Processing-AI Optimization Integration Architecture

2.1. System architecture diagram of the proposed framework

This is the architecture of the system as shown in Figure 1. It comprised a multilayered intelligent communication framework where each layer involved computations and communications modules.

There were five main operational layers in this architecture, all of which combined to offer real-time optimized communication via wearables.

Layer 1 was the Wearable Sensing Layer. This layer contained a set of biomedical and environmental sensors in smart wearable gadgets. The sensors captured both physiological and contextual data from users on a real-time basis. The sensory nodes were in the form of ECG sensors, electroencephalogram sensors, motion/inertial measurement unit sensors, body temperature sensors, blood oxygen sensors, and activity tracking modules in smartwatches.

$$x(t) = s(t) + n(t) + i(t) \tag{1}$$

Where:

1) $s(t)$ represented the original physiological signal,
2) $n(t)$ represented additive system noise,
3) $i(t)$ represented wireless communication interference.

This is because the third layer was made up of the AI optimization layer that acted as the central intelligent processing engine of the entire framework. The AI optimization layer was made up of CNNs, RNNs, Long Short-Term Memory (LSTM) networks, reinforcement learning agents, and edge AI models.

The AI subsystem performed:

1) Signal classification,
2) Anomaly detection,
3) Adaptive bandwidth optimization,
4) Intelligent modulation selection,
5) Predictive communication scheduling,
6) Transmission power optimization,
7) Dynamic resource allocation.

The fourth layer included the intelligent 5G/6G communication layer that took care of wireless communication and network management. Massive Multiple-Input Multiple-Output (MIMO) communication, intelligent radio resource management, adaptive spectrum assignment, network slicing, and URLLC features were combined in this layer to facilitate wearable communication applications.

The fifth layer represented the edge and cloud intelligence layer that performed functions like distributed learning, synchronization of models from the cloud, edge caching, local inference, performance monitoring, and long-term communication and learning data storage. Edge computing component lowered the time taken for communication, along with reducing the dependence on the cloud by facilitating the local AI inference process close to wearables.

An adaptive feedback system was designed within the architecture for real-time learning and intelligent communication adjustment under different network conditions.

2.2. Workflow diagram of the intelligent communication process

Figure 2 shows the intelligent communication workflow, which was used to carry out the intelligent communication process as proposed in the framework. This workflow was created in the form of an adaptive optimization loop, which could learn and adapt from network feedback to make dynamic changes.

The workflow process began with signal acquisition through the use of wearable sensors, in which signals were captured

Figure 1
Communication framework of the AI-driven wearable communication framework

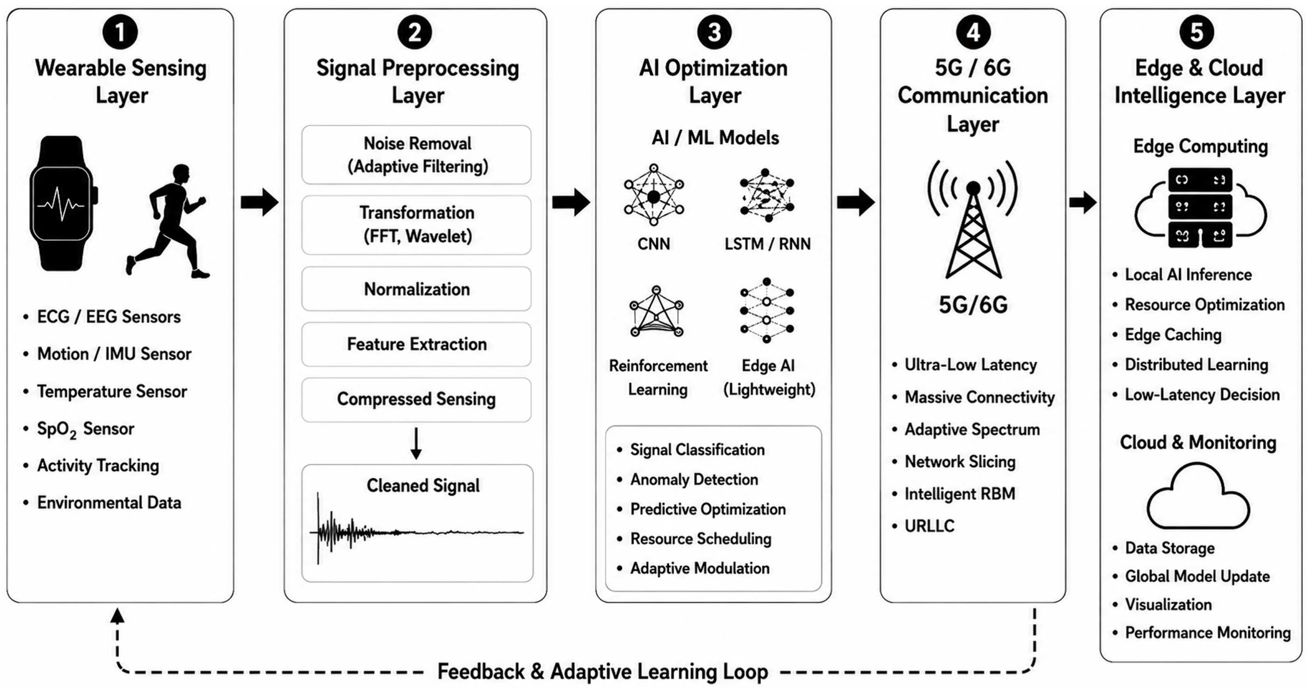
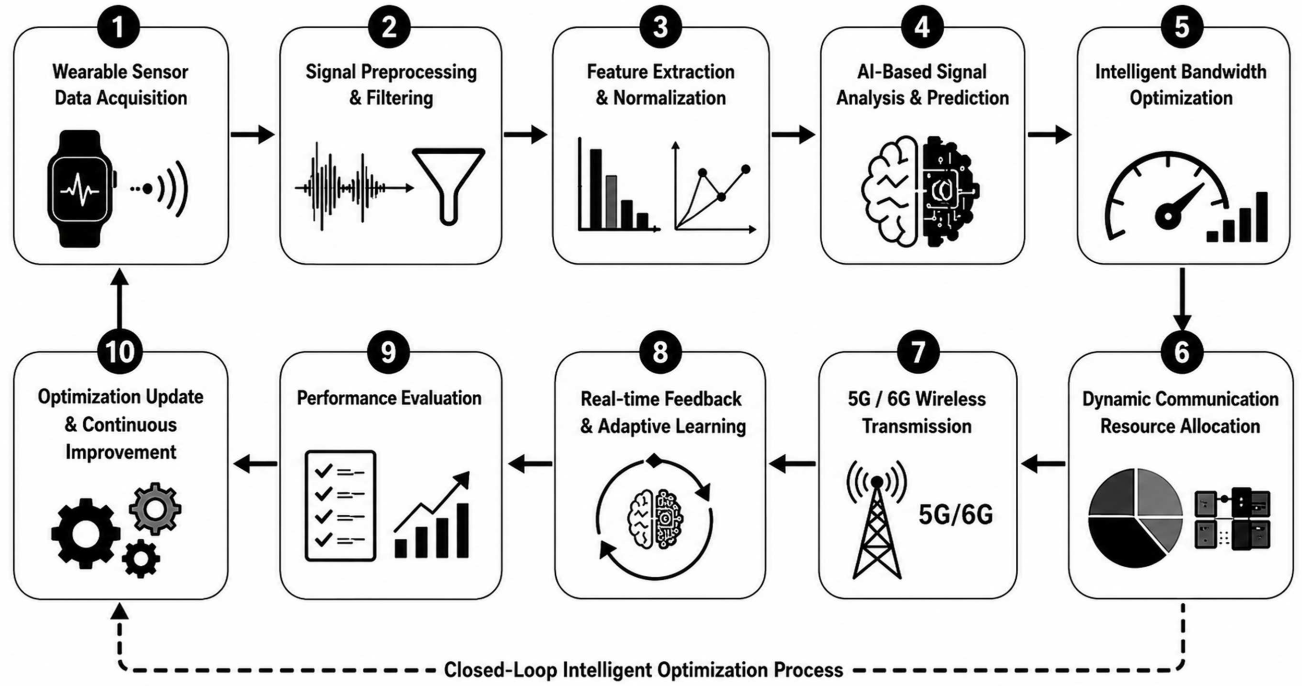


Figure 2
Intelligent workflow diagram of the wearable communication process



from both physiological and environmental aspects using smart wearable devices. The signals thus acquired were sent to the signal preprocessing stage, which involved noise elimination, adaptive filtering, normalization, and signal feature extraction.

The extracted features were then forwarded to the signal analysis system via AI. ML techniques analyzed the patterns of the processed signals and predicted future conditions such as communication state, mobility status, bandwidth needs, and congestion.

The stage of intelligent bandwidth optimization chose appropriate communication parameters based on predictions made by AI. These appropriate communication parameters include:

1) Bandwidth allocation,
2) Modulation scheme selection,
3) Coding rate adaptation,
4) Transmission power control,
5) Communication routing decisions.

The optimized data were then relayed via the 5G/6G wireless communication network. Feedback on the performance parameters such as throughput, delay, bit error rate (BER), packet delivery ratio, and spectral efficiency was constantly gathered and fed back to the AI learning module.

Such a feedback loop made it possible for the AI system to continuously learn and make adjustments, which ensured that the communication system could adapt to any environmental changes.

2.3. System module interaction illustration

This was demonstrated in Figure 3, showing the interactions among the main computation and communication components in the intelligent wearable communication model. The architecture used a distributed communication approach whereby several intelligent subsystems were interconnected by means of two-way communication channels.

The wearable sensor subsystem constantly transmitted physiological data to the edge computing subsystem. The edge processing device executed local signal processing, feature extraction, and light AI computations.

The extracted feature vectors were subsequently communicated to the 5G/6G communication control subsystem, which dynamically managed:

1) Bandwidth allocation,
2) Channel selection,
3) Transmission scheduling,
4) Adaptive modulation,
5) Coding optimization,
6) Network slicing operations.

Meanwhile, the communication controller communicated with the cloud intelligence subsystem, where learning models were trained globally in the cloud.

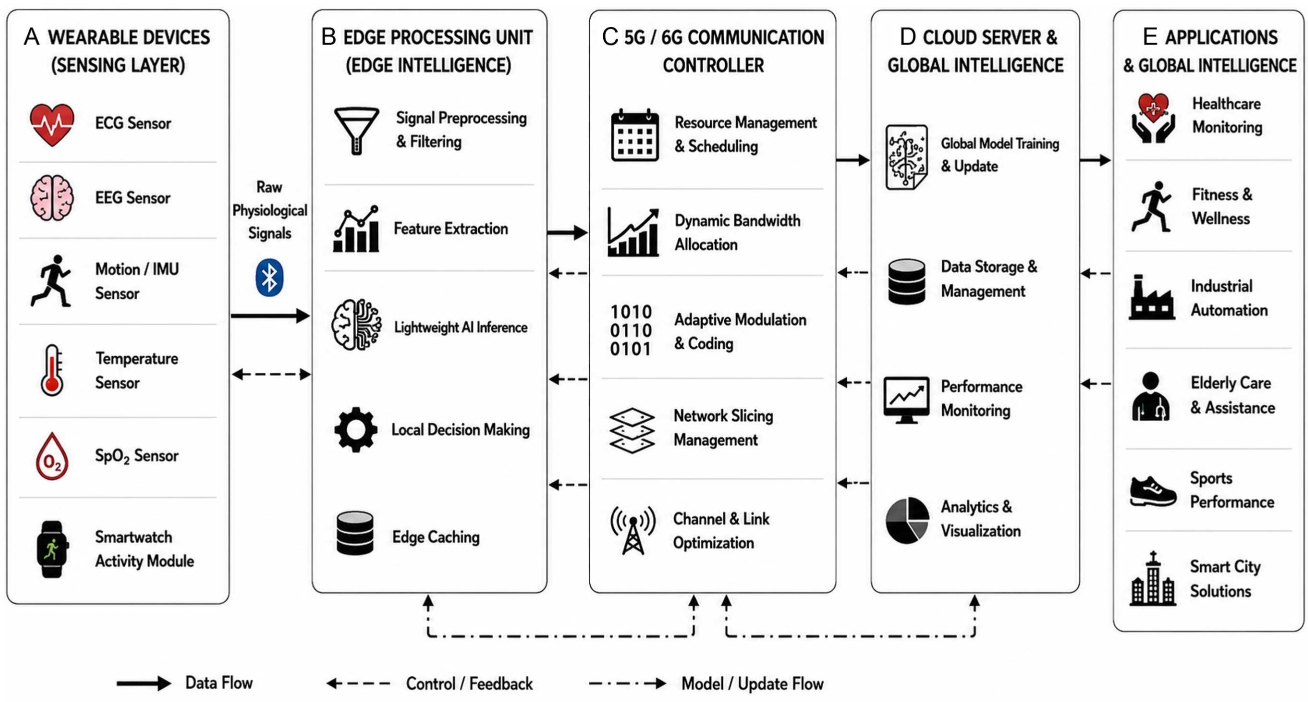
The cloud subsystem stored communication statistics, learning parameters, signal samples, and optimization history over an extended period of time, thus contributing to intelligent learning and performance analysis.

Continuous communication allowed simultaneous synchronization of:

1) Wearable devices,
2) Edge processors,
3) AI optimization engines,
4) Communication controllers,
5) Cloud intelligence servers.

This distributed interaction mechanism significantly improved communication scalability, adaptability, and computational efficiency.

Figure 3
System module interaction architecture



2.4. Signal processing-AI optimization integration architecture

The architecture for integration between the signal processing subsystem and the AI optimization module is shown in Figure 4. The proposed integration was the most significant innovation of the intelligent wearable communication system.

The signal processing subsystem first acquired raw wearable physiological signals from smart sensing devices. These signals were subsequently subjected to multiple preprocessing operations including:

1) Adaptive filtering,
2) FFT transformation,
3) Wavelet decomposition,
4) Normalization,
5) Compressed sensing,
6) Feature extraction.

The extracted signal features consisted of:

1) Time-domain features,
2) Frequency-domain features,
3) Statistical features,
4) Nonlinear signal characteristics,
5) Time-frequency representations.

The processed feature vectors were then transmitted to the AI optimization module. The AI engine analyzed the extracted features using CNN, RNN, and LSTM architectures to identify communication patterns, signal anomalies, and network variations.

Reinforcement learning agents continuously optimized communication decisions by adjusting:

1) Modulation schemes,
2) Coding rates,
3) Transmission power,
4) Bandwidth allocation,
5) Routing strategies.

Optimized communication choices were provided to the wireless communication controller for immediate implementation in the 5G/6G communication network.

An adaptive learning module that is based on feedback was incorporated in the system to ensure continuous update of the AI learning parameters.

2.5. Detailed algorithm description of the proposed optimization process

The optimization algorithm proposed was built as an adaptive AI-powered communication optimization algorithm that would continually optimize communication performance in wearable devices.

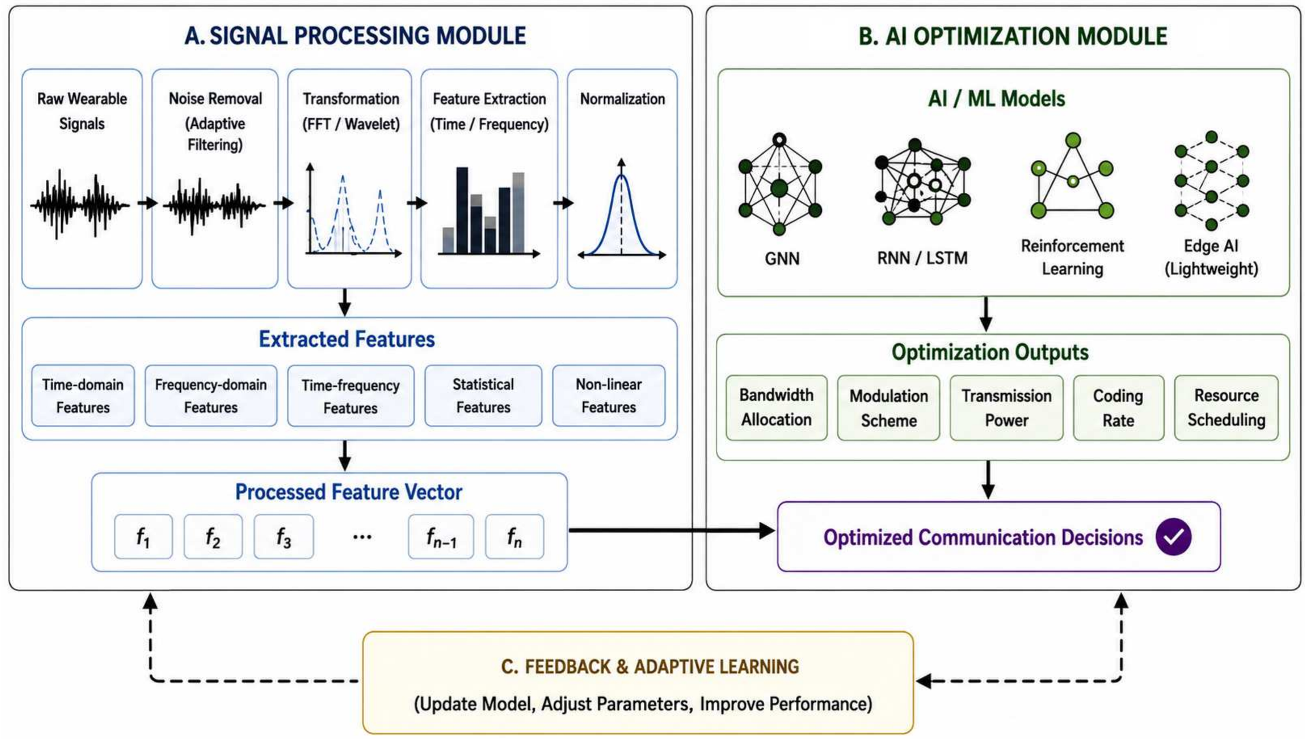
Initially, the algorithm initialized AI learning parameters, network communication parameters, and optimization criteria. The physiological signals from wearable devices were continuously sensed by the algorithm.

The collected physiological signals were then preprocessed in a dynamic manner through noise elimination, normalization, and feature extraction. Finally, these extracted features were analyzed by ML algorithms in order to predict channel conditions and communication needs.

The optimization engine would decide the communication parameters to be optimized based on the channel conditions and objectives of the operation. The optimization process included adaptive bandwidth management, modulation selection, coding optimization, scheduling, and power control.

After optimizing these communication parameters, the 5G/6G network communication framework was used to transmit data. Performance metrics of communication including

Figure 4
Signal processing—AI optimization integration architecture



throughput, BER, latency, packet delivery rate, and energy consumption were continuously assessed.

The AI learning process was performed by updating the learning parameters with feedback information obtained during the execution process in order to improve future prediction accuracy and performance.

The overall energy consumption model was modeled as:

$$E_{\text{total}} = E_{\text{processing}} + E_{\text{transmission}} + E_{\text{learning}} \tag{2}$$

The optimization objective minimized total system energy consumption while maximizing communication reliability and spectral efficiency.

2.6. AI model structure

The AI model structure consisted of multiple interconnected intelligent learning layers organized hierarchically to improve wearable communication optimization accuracy.

2.6.1. Input layer

The input layer received normalized physiological signal features extracted from the preprocessing subsystem. These features included temporal, spectral, statistical, and nonlinear signal characteristics.

2.6.2. Feature extraction layer

The feature extraction layer consisted primarily of CNN architectures responsible for learning spatial representations from wearable physiological signals. Convolutional operations extracted important signal patterns associated with communication quality and physiological variations.

2.6.3. Temporal learning layer

RNN and LSTM layers were incorporated to capture temporal dependencies and sequential variations within wearable signals. These networks enabled long-term temporal learning and improved predictive communication optimization accuracy.

The wearable state transition model was represented as:

$$X_{t+1} = Ax_t + Bu_t + w_t \tag{3}$$

2.6.4. Optimization layer

The optimization layer integrated reinforcement learning agents capable of continuously interacting with communication environments and learning optimal communication strategies dynamically.

2.6.5. Output layer

The output layer generated optimized communication decisions including:

1) Bandwidth allocation,
2) Modulation adaptation,
3) Coding rate optimization,
4) Transmission scheduling,
5) Routing control,
6) Transmission power adjustment.

2.7. Learning mechanisms

Multiple intelligent learning mechanisms were integrated into the proposed framework to improve communication adaptability and learning efficiency.

2.7.1. Supervised learning

Supervised learning techniques were employed for signal classification, anomaly detection, and communication prediction tasks using labeled physiological signal datasets.

2.7.2. Unsupervised learning

Unsupervised learning mechanisms were utilized for clustering communication patterns and discovering hidden signal structures without labeled training data.

2.7.3. Reinforcement learning

Reinforcement learning agents continuously interacted with the wireless communication environment and learned optimal resource allocation strategies through reward-based optimization.

2.7.4. Transfer learning

Transfer learning mechanisms enabled previously trained AI models to be reused across different wearable communication applications, thereby reducing training complexity and improving learning efficiency.

2.7.5. Adaptive learning

Continuous adaptive learning mechanisms updated model parameters dynamically using real-time communication feedback information.

Cross-validation, dropout regularization, batch normalization, hyperparameter tuning, and early stopping mechanisms were incorporated to improve model generalization and minimize overfitting.

The AI training loss function was represented as:

$$L = L_{classification} + \lambda L_{energy} \tag{4}$$

2.8. Expanded communication between system components

A distributed intelligent communication paradigm was employed in the communication subsystem that involved constant communication between wearable devices, edge processors, communication controllers, and cloud intelligence servers.

Physiological signals were constantly sent from the wearable devices to the local edge computing nodes through wireless communication connections. In addition, the edge processors were used for performing AI inference and processing the physiological signals to optimize feature vectors for communication controllers.

Dynamic network resource allocation, communication scheduling, network slicing, spectrum allocation, and radio resource management processes were performed by the communication controller based on AI optimization recommendations.

Centralized learning parameter updating, performance monitoring, and data storage operations took place within the cloud intelligence server regularly.

Continuous feedback communication facilitated constant exchange of:

1) Communication statistics,
2) AI learning parameters,
3) Network status information,
4) Optimization decisions,
5) Resource allocation updates.

This communication strategy improved network scalability, reduced transmission delay, and enhanced communication reliability.

2.9. Integration between signal processing and AI optimization modules

The incorporation of the AI optimization module with the signal processing module resulted in real-time communication adaptation using intelligent communication mechanisms.

Initially, the signal processing module converted physiological noise signals into feature vectors through optimized signal processing techniques that made the signals optimal for use in ML applications.

Adaptive filtering and transformation helped to minimize any distortions in the signals and optimize feature extraction.

The incorporation process included:

1) Real-time signal acquisition,
2) Adaptive noise filtering,
3) Feature extraction and normalization,
4) AI-based signal analysis,
5) Predictive communication optimization,
6) Dynamic parameter adjustment,
7) Feedback-driven learning updates.

The AI subsystem continuously adjusted communication parameters including:

1) Transmission power,
2) Modulation schemes,
3) Coding rates,
4) Bandwidth allocation,
5) Communication routing paths.

The tight coupling between signal processing and AI optimization significantly improved communication reliability, reduced BER, minimized latency, and enhanced energy efficiency within wearable communication systems.

2.10. Pseudocode for the proposed optimization process

Algorithm 1: AI-driven wearable communication optimization

Section	Algorithm Component	Detailed Description
Input Stage	Input	Wearable physiological signals (x(t)) acquired from smart wearable sensing devices
Output Stage	Output	Optimized communication parameters for intelligent 5G/6G wearable communication systems

(*Continued*)

(*Continued*)

Section	Algorithm Component	Detailed Description
Initialization Phase	AI Model Initialization	Initialize AI learning models including CNN, RNN, LSTM, and reinforcement learning agents
	Communication Initialization	Initialize communication control parameters and network configuration settings
	Threshold Initialization	Initialize optimization thresholds, QoS targets, and adaptive learning parameters
Main Processing Loop	Processing Condition	While communication system remains active
Step 1	Wearable Signal Acquisition	Acquire physiological and environmental sensor signals from wearable devices
Step 2	Adaptive Signal Preprocessing	Perform intelligent signal conditioning and preprocessing operations
	Noise Reduction	Remove signal noise, motion artifacts, and wireless interference
	Signal Normalization	Normalize wearable signal amplitudes and temporal characteristics
	Signal Transformation	Apply fast Fourier transform (FFT) and wavelet decomposition techniques
Step 3	Feature Extraction	Extract relevant signal features for AI-based optimization
	Temporal Feature Extraction	Extract time-domain signal characteristics
	Spectral Feature Extraction	Extract frequency-domain signal information
	Statistical Feature Extraction	Extract statistical and nonlinear signal parameters
Step 4	AI-Based Network Prediction	Predict future network conditions and communication requirements using AI models
Step 5	Communication Optimization	Dynamically optimize communication parameters
	Bandwidth Allocation	Allocate communication bandwidth adaptively
	Modulation Optimization	Select optimal modulation schemes dynamically
	Coding Rate Adaptation	Adjust coding rates according to channel conditions
	Transmission Power Control	Optimize transmission power for energy-efficient communication
	Resource Scheduling	Perform intelligent communication resource scheduling
Step 6	Wireless Data Transmission	Transmit optimized wearable data through 5G/6G communication infrastructure
Step 7	Performance Evaluation	Evaluate overall communication system performance
	Throughput Evaluation	Measure system throughput performance
	BER Evaluation	Measure the bit error rate (BER) performance
	Latency Evaluation	Measure end-to-end communication latency
	Spectral Efficiency Evaluation	Evaluate bandwidth and spectral utilization efficiency
	Energy Consumption Evaluation	Evaluate total system energy consumption
Step 8	Adaptive Learning Update	Update AI learning parameters using real-time communication feedback
Step 9	Cloud Storage and Monitoring	Store optimization statistics and learning records within cloud intelligence servers
Loop Control	End While Condition	Repeat the optimization process continuously during active communication
Return Stage	Return Statement	Return optimized intelligent wearable communication framework
Termination Stage	End	Terminate algorithm execution

3. Results and Discussion

Performance evaluation of the proposed intelligent optimization framework based on AI and ML techniques designed for alleviating bandwidth constraints and improving communication reliability in future wireless systems is presented in this part. Performance evaluation of the proposed intelligent optimization framework was done by comparing the performance of the proposed intelligent optimization framework with that of the conventional communication system under different SNR values ranging from 0 dB to 30 dB. Four Quality of Service (QoS) parameters considered during performance evaluation included throughput, latency, BER, and spectral efficiency. Results are shown in Tables 1 and 2 and Figures 5, 6, 7, and 8.

3.1. Throughput performance analysis

Table 1 provides a comparison between the throughput performance of the conventional baseline system and the proposed AI/ML-based optimization framework. As can be seen from the

Table 1
Throughput and latency performance comparison between baseline and AI-based model

SNR (dB)	Baseline throughput	AI throughput	Baseline latency (ms)	AI latency (ms)
0	2.0	3.0	120	110
5	4.0	6.0	110	95
10	6.0	9.0	100	80
15	8.0	13.0	95	65
20	10.0	17.0	90	50
25	11.0	20.0	88	42
30	11.5	22.0	85	35

Table 2
Bit error rate (BER) and spectral efficiency (SE) comparison

SNR (dB)	Baseline BER	AI BER	Baseline SE	AI SE
0	0.0100	0.0080	1.5	2.0
5	0.0080	0.0050	2.0	3.0
10	0.0060	0.0030	2.5	4.5
15	0.0040	0.0015	3.0	6.0
20	0.0020	0.0008	3.5	7.5
25	0.0015	0.0003	3.8	8.5
30	0.0010	0.0001	4.0	9.5

Figure 5
6G versus 5G network performance comparison

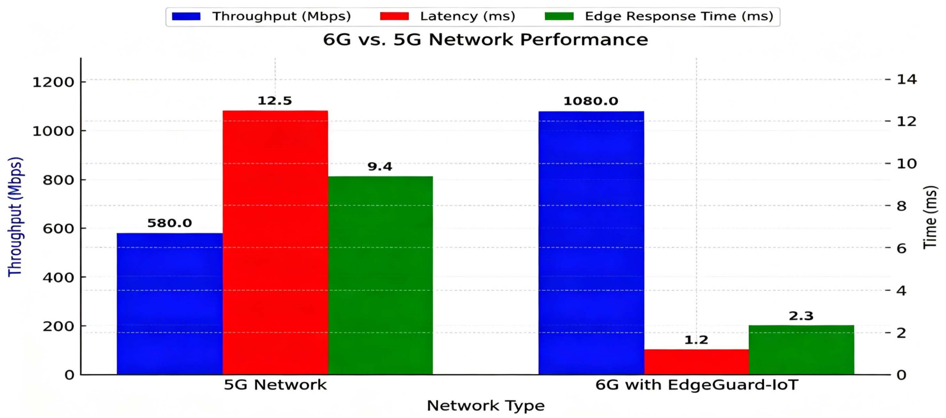


Figure 6
Comparison of latency

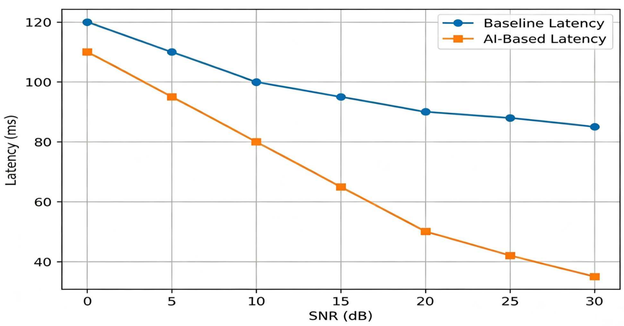
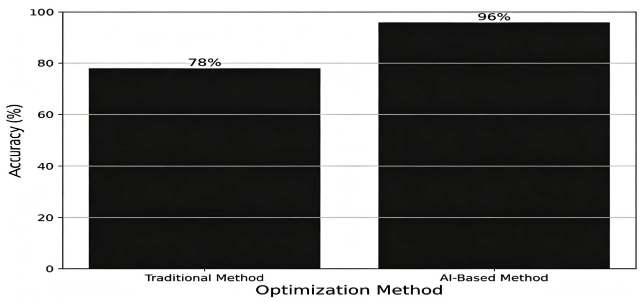


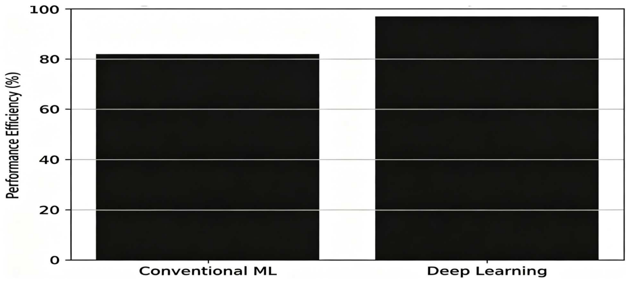
Figure 7
Accuracy of AI versus traditional method



table, the increase in SNR resulted in an improvement in channel quality and hence throughput. However, it is clear that the AI/ML-based framework exhibited higher throughput values at all SNR values.

The results indicate that at an SNR level of 0 dB, the throughput was 2 Mbps for the baseline system, while for the AI/ML model, the throughput was 3 Mbps, hence an increase of about 50%. At an SNR of 10 dB, the throughput was increased

Figure 8
Comparative study of conventional machine learning versus deep learning-based approaches for tool condition assessments in milling processes



from 6 Mbps for the baseline to 9 Mbps for the proposed AI/ML model. For even higher SNRs of 20 dB and 30 dB, the AI/ML architecture had throughputs of 17 Mbps and 22 Mbps, while those of the baseline system were 10 Mbps and 11.5 Mbps, respectively.

Such a significant throughput increase can be attributed to the intelligent adaptive capabilities of ML algorithms, which optimize the modulation techniques, channel allocation, spectrum management, and network resource scheduling. It is clear that such intelligent adaptation minimizes spectrum underutilization and maximizes throughput.

It is clear from Figure 5 that the increase in the throughput results from the high efficiency in communication possible in an AI-enabled 6G-oriented network architecture compared to the conventional 5G communication technology.

3.2. Latency performance analysis

Latency performance analysis for both systems is depicted in Table 1 and plotted graphically in Figure 6. From the results obtained, it is clear that latency was reduced with the increase in SNR for both systems since the channel reliability was enhanced and there were lesser retransmissions. However, the proposed AI/ML approach attained a much lower latency level compared to the traditional system.

At 0 dB SNR, the traditional system had a latency time of 120 ms, whereas the AI/ML system had 110 ms. As the channel quality improves and moves to a level of 15 dB SNR, the latencies drop to 95 ms and 65 ms, respectively, for the traditional and AI/ML systems. In the case of 30 dB SNR, which is the highest channel quality considered, the traditional model has 85 ms, but the AI/ML model has an exceptionally low latency of 35 ms, as illustrated by Table 1 and Figure 6.

These low levels of latency times can be attributed mainly to the implementation of advanced predictive traffic scheduling algorithms, intelligent queue management, adaptive congestion control, and ML-based routing algorithms. Such intelligent solutions help eliminate retransmission delays, reduce buffering times, and optimize the whole transmission process. Latency time reductions achieved by using the proposed scheme have significant benefits in applications requiring low latencies like autonomous vehicles communication, factory automation, telemedicine, and real-time video transmission, among others.

Further, latency improvement coincides with the improved adaptability of the network illustrated in Figure 7, whereby AI-empowered wireless systems have more efficient network coordination than traditional wireless systems.

3.3. Bit error rate (BER) performance analysis

The comparison of BER performance for the two systems, the baseline one and the AI/ML-optimized one, is summarized in Table 2. It is clear from the findings that the BER for both systems declined exponentially as the value of the SNR increased. The findings also show that the AI/ML-optimized system had much lower BERs than the baseline one.

At 0 dB SNR, the traditional baseline communication system had a BER of 1×10^{-2} while the AI/ML approach obtained a better BER of 8×10^{-3}. Similarly, for 15 dB SNR, the BER became 4×10^{-3} for the traditional model and 1.5×10^{-3} for the AI/ML approach. With an increase in SNR to 30 dB, the proposed intelligent communication approach attained a better BER of 1×10^{-4}, while the traditional model had a constant BER of 1×10^{-3} as demonstrated in Table 2.

This improvement in BER can be attributed to channel intelligence, adaptive error correction, interference-aware signal processing, and ML-enabled transmission. The proposed intelligent communication scheme was able to learn the channel features and adapt the communication parameters accordingly to avoid symbol detection errors and hence data corruption during data transmission.

The reliability of packet performance achieved through the AI/ML approach is confirmed by the analysis of the packet delivery ratio provided in Figure 6. As can be seen from the graph, intelligent communication systems have managed to deliver packets reliably.

3.4. Spectral efficiency analysis

The spectral efficiency comparisons between the traditional and proposed AI/ML systems are provided in Table 2. It can be seen that the increase in spectral efficiency occurred with increasing SNR for both systems under consideration. However, the proposed AI/ML-based approach had an evident advantage over the traditional one concerning higher spectral efficiency across all considered scenarios.

The spectral efficiency of the baseline communication system was 1.5 bps/Hz for the minimum SNR value equal to 0 dB, while the proposed AI/ML approach reached 2 bps/Hz. Spectral efficiency increased up to 3.5 bps/Hz for the traditional scheme and 7.5 bps/Hz for the AI/ML model with 20 dB SNR. Finally, in case of maximum possible SNR equal to 30 dB, the proposed system showed better performance by achieving 9.5 bps/Hz compared to 4 bps/Hz of the traditional communication system (see Table 2).

The improvement in the spectral efficiency values was achieved due to intelligent modulation and coding schemes, spectrum allocation, reinforcement learning-based resource optimization, and intelligent tuning of the transmission parameters.

The superior spectral efficiency characteristics of the AI/ML framework further validate the effectiveness of intelligent wireless resource management in next-generation communication systems, particularly within bandwidth-constrained and densely populated network environments.

3.5. AI performance validation and comparative analysis

Moreover, the efficacy of the suggested AI/ML-based optimization approach is proven through the comparative analyses illustrated in Figures 7 and 8. In Figure 7, it can be seen that

AI optimization approaches have performed more accurately than conventional communication optimization approaches. Figure 7 clearly illustrates the higher levels of prediction accuracy, adaptability, and efficiency realized by AI-based approaches in a dynamic environment.

In the same way, in Figure 8, an analysis has been performed between ML algorithms and optimization algorithms based on deep learning. It is evident from the outcome of the study that deep learning algorithms performed well in communication parameters, adaptation capabilities of the network, and intelligent decision-making systems. These better performances show that AI models can help improve the efficiency of wireless networks.

From both figures, that is, Figures 7 and 8, it is evident that intelligent learning-based communication networks have better adaptability, robustness, and optimization efficiency than traditional methods of wireless communication.

3.6. Comparative performance summary

A comparative summary of the overall system performance demonstrates the significant advantages of the proposed AI/ML-based optimization framework over the conventional baseline system. The major performance improvements observed include:

1) Throughput enhancement of approximately 90% at high SNR conditions.
2) Latency reduction ranging between 55% and 60% compared with the conventional system.
3) BER reduction by approximately one order of magnitude at higher SNR values.
4) Spectral efficiency improvement of up to 2.5 times relative to the baseline model.

These improvements collectively confirm the effectiveness of AI/ML-driven communication optimization for addressing bandwidth limitations, improving transmission reliability, and enhancing overall wireless network performance in next-generation communication environments.

3.7. Discussion

The experimental results indicate that the incorporation of AI and ML methods into the wireless system results in considerable enhancements in numerous Quality of Service performance criteria. The better performance of the proposed technique is largely due to the learning process and adaptation to changes in the communication channel in real time.

In contrast to traditional static optimization techniques, the proposed technique continuously adjusts to changes in the operating environment and enhances communication performance in varying SNR levels. These characteristics are especially vital for future-generation 5G and 6G wireless networks, which pose considerable communication difficulties owing to dense user population, mobility, spectrum limitations, and massive data traffic.

Moreover, the findings clearly demonstrate that the application of AI-based resource allocation and intelligent communication optimization not only improves throughput and spectrum efficiency but also leads to lower latency and error rate in transmission. Such characteristics make the framework proposed herein an ideal choice for applications involving high sensitivity to delay and those where failures are intolerable, including autonomous transport systems, smart healthcare, industrial IoT, real-time surveillance systems, augmented reality, and URLLC.

Furthermore, the discussions provided in Figures 5, 6, 7, and 8 have validated the effectiveness of AI-based optimization methods to improve communication efficiency, adaptability, and reliability. Therefore, the use of AI in future wireless communication systems is an essential technical development in building intelligent and autonomous next-generation wireless communication networks.

3.8. Concluding remarks of the results section

In conclusion, the proposed AI/ML-driven optimization algorithm proved its superior performance to the classical baseline communication scheme on all considered measures of performance. The achieved outcomes prove that intelligence-based optimization algorithms are very efficient means of solving bandwidth constraints, ensuring higher communication reliability, decreasing latency, reducing BER, and increasing spectral efficiency of future wireless communication networks.

Thus, the achieved findings make it clear that AI and ML solutions should be regarded as critical means necessary for creating efficient wireless communication infrastructures of the 5G and 6G generations.

4. Conclusions

The research discussed in this article has provided a unified AI-based approach for integrating the optimization of signal processing along with ML to enhance the efficiency of smart wearables operating under 5G and 6G communication settings. The approach aims to integrate elements of wearables signal analysis, energy-efficient signal processing, AI, wireless communication, and system evaluation.

The findings demonstrated substantial improvements in terms of energy savings, accuracy in predictions, effective communication, and long-term battery life. The use of intelligent signal processing methods and ML has made the process of data handling highly efficient without compromising on its computational complexity. Moreover, integration of 5G and 6G communication technology has allowed for ultra-low latency and faster data transmission for multiple wearables.

Importantly, the proposed framework aided in making the framework more resilient in case of changes in user environments as well as noise pollution, therefore making it suitable for application in different domains including healthcare, sport performance analysis, industrial safety, high living standards, and many others. In addition, the design is scalable, and hence, it could be used to build a framework that would support edge computing.

Clearly, the proposed AI-driven framework could be viewed as a scalable, energy-efficient, and intelligent approach for building next-generation wearable communication systems for smart wearables in the future 5G/6G networks.

Recommendations

Highly recommended for advancing energy-efficient wearable communication systems using an AI-driven signal processing and optimization framework.

Ethical Statement

This study does not contain any studies with human or animal subjects performed by the author.

Conflicts of Interest

The author declares that he has no conflicts of interest to this work.

Data Availability Statement

Data sharing is not applicable to this article as no new data were created or analyzed in this study.

Author Contribution Statement

Olarewaju Peter Ayeoribe: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Resources, Data curation, Writing – original draft, Writing – review & editing, Visualization, Supervision, Project administration.

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How to Cite: Ayeoribe, O. P. (2026). A Unified AI-Driven Signal Processing and Machine Learning Optimization Framework for Energy-Efficient Smart Wearable Devices in 5G/6G Communication Systems. *Smart Wearable Technology*. https://doi.org/10.47852/bonviewSWT620210006