Advancing Wearable Health and Sports Monitoring Through an Edge–Cloud AI Continuum. Invited Paper

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Abstract

The H2TRAIN project proposes a comprehensive edge–cloud AI continuum for real-time, secure, and personalized health and performance monitoring through wearable technologies. By integrating in vivo physiological measurements, artificial intelligence, and biometric encryption, H2TRAIN addresses the growing demand for adaptive digital health solutions. The system leverages embedded intelligence at the edge to perform immediate data processing and personalized analytics, while offloading complex tasks to fog and cloud layers for scalability. In vivo measurements enable the development of AI models that reflect real-world conditions, ensuring accuracy and ecological validity. At the same time, biometric cryptographic techniques based on physiological signals guarantee data security and user authentication, even in dynamic and uncontrolled environments. H2TRAIN establishes a secure, intelligent, and energy-efficient infrastructure applicable to clinical, rehabilitation, and sports domains.

CCS Concepts

• **Hardware → Bio-embedded electronics**.

Keywords

In vivo measurements, wearable technologies, artificial intelligence, biometric encryption.

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1 Introduction

Wearable health monitoring technologies are rapidly evolving in response to the convergence of the Internet of Things (IoT), artificial intelligence (AI), and edge computing. As demands for real-time, context-aware health feedback rise, systems must not only capture and process complex physiological data but also protect users' privacy through advanced cryptographic methodsAENEAS, EPoSS, and INSIDE Industry Association [1]. Traditional solutions often fall short due to their reliance on centralized computing, limited personalization, and vulnerability to data breaches. Addressing these challenges, the H2TRAIN project presents a novel digital health architecture rooted in embedded intelligence, in vivo validation, and biometric encryption.

Building on the state of the art in low-latency computing and physiological sensing, H2TRAIN's approach integrates multi-modal wearables capable of capturing ECG, EMG, glucose, lactate, and motion data under real-life conditions [9]. The project prioritizes in vivo measurements to ensure that AI models are trained and validated on authentic user data, increasing both robustness and relevance [4]. Its edge–fog–cloud continuum supports decentralized AI, enabling on-device inference for tasks such as fatigue detection or ECG anomaly classification, while reserving cloud resources for federated learning and global optimization [2].

A central innovation lies in the project's implementation of biometric encryption techniques based on physiological signals [5]. By generating non-invertible cryptographic keys from user-specific biosignals like ECG or PPG, H2TRAIN ensures privacy-preserving authentication and data integrity. Deep learning models further support adaptability and resilience to signal drift or environmental variability. Collectively, the system's architecture combines embedded analytics, privacy-enhancing technologies, and AI-powered personalization to redefine real-time health monitoring across use cases including remote rehabilitation, intelligent coaching, and assisted living.

The paper is organized into five main sections that describe the H2TRAIN project's innovative approach to wearable health and sports monitoring within an edge–cloud AI continuum. Section 2

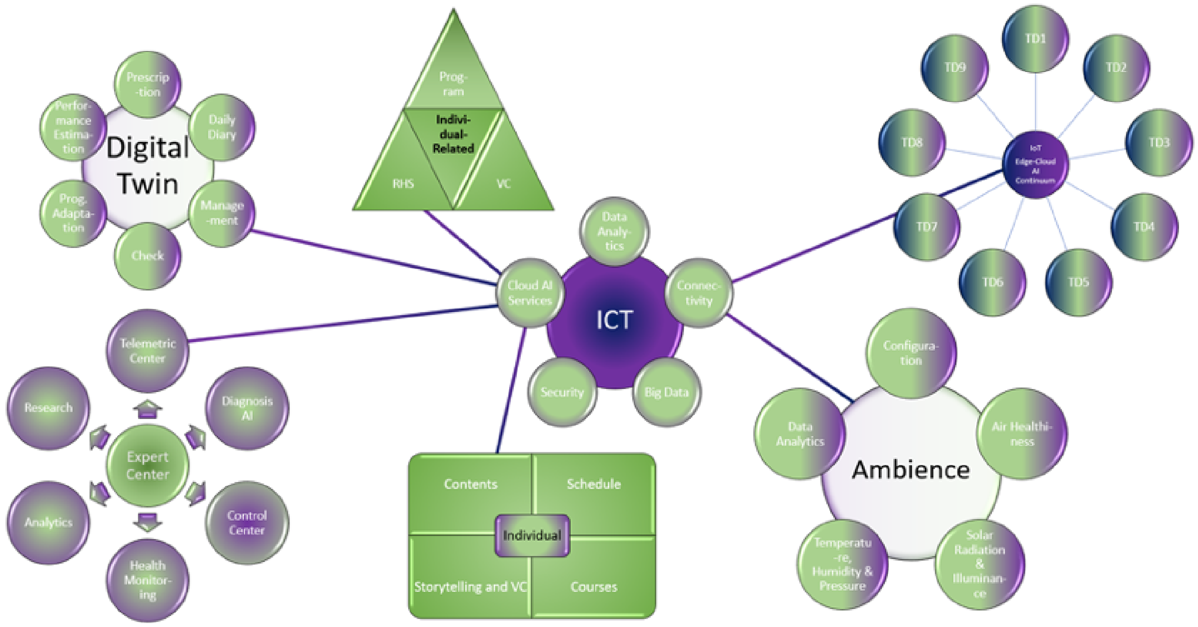

Figure 1: H2TRAIN conceptual schema for system of systems. The application layer for use cases Remote Assisted Living (RAL), Intelligent Adaptive Sport Coaching (IASC) and Remote Post-Surgery & Rehab Monitoring (RPS&RM)

presents the platform's architecture, including its modular design and human-centered

2 Integrated System Overview

H2TRAIN is structured as an integrated, human-centered digital platform that combines wearable biosensing, environmental monitoring, artificial intelligence, and secure edge–cloud computing to support adaptive health and performance management (see Figure 1). The system is designed to operate across multiple application domains—including active aging, sports science, and post-operative rehabilitation—by enabling personalized, real-time interventions rooted in physiological, behavioral, and contextual data. The architecture follows a modular, service-oriented approach that ensures scalability, data protection, and flexibility for deployment in both clinical and non-clinical settings. At the core of the system lies a secure ICT infrastructure that manages critical functions such as data aggregation, connectivity, cloud-based analytics, and AI model orchestration. This central hub enables seamless communication between edge devices, cloud services, and user-facing applications. Data security is maintained using encrypted communication channels and embedded hardware protections such as TrustZone-capable microcontrollers. Built around this core is the digital twin layer, which dynamically models the user's physical and behavioral state based on inputs from wearable sensors and ambient data. This layer supports features like performance estimation, program adaptation, therapeutic prescription, and daily tracking. These functions are managed through automated modules that interpret continuous data streams and adjust goals or recommendations, accordingly, ensuring that interventions remain context-aware and user-specific. The expert center serves as the intelligent supervisory module of the platform, integrating advanced analytics, diagnostic AI, and remote health monitoring. It also includes a control center responsible for oversight and escalation in case of anomalies or emergencies. These expert services enable the system to combine automated decision-making with human-in-the-loop supervision, which is critical for sensitive use cases like elderly care or post-surgery recovery. To contextualize physiological readings, the platform incorporates an ambience layer, which collects real-time environmental parameters including air quality, temperature, humidity, solar radiation, and illuminance. These variables are factored into data interpretation and feedback loops, allowing the system to distinguish between intrinsic physiological changes and those influenced by external conditions. The sensing and actuation layer operates on a distributed IoT edge–cloud AI continuum, which hosts low-latency inference models and enables intelligent data routing across different processing levels (edge, fog, cloud). This infrastructure supports the integration of multiple smart demonstrators and wearable units, allowing the system to scale across diverse usage environments and populations. AI models deployed in this continuum handle tasks such as activity recognition, biometric authentication, anomaly detection, and personalized feedback generation.

3 In Vivo Measurements

The H2TRAIN project addresses the design, development, and implementation of human-centered digital technologies focused on sports, health, and remote assistance applications. An essential aspect of the development and implementation of these technologies is the validation of sensors and systems under real-life conditions, i.e., in vivo measurements on real users. In vivo measurements are fundamental to H2TRAIN, as they allow for the validation of the accuracy, reliability, and usefulness of sensors integrated into smart textiles and wearables in three use cases: Remote Assisted Living (RAL); Intelligent Adaptive Sport Coaching (IASC); Remote Post-Surgery & Rehab Monitoring (RPS&RM) [1]. These measurements are performed directly on end-users: athletes, postoperative patients, or older adults in home or care settings. The data collected allows for the development of artificial intelligence models trained with real data, improving the personalization and effectiveness of solutions [1].

3.1 Applications and Validation in Use Cases

The technologies developed within the H2TRAIN project were conceived with a strong applied approach and validated under real-world conditions. With the aim of responding to the specific needs of the healthcare, sports, and telecare sectors, three representative use cases were defined to demonstrate the utility and robustness of the proposed system of systems [1]. In each of these cases, the developed solutions—which include wearable sensors, artificial intelligence algorithms, and edge-cloud platforms—are subjected to rigorous in vivo validation processes, i.e., through tests conducted directly with real users in uncontrolled environments.

3.1.1 Remote Assisted Living (RAL). This use case focuses on remote monitoring of older adults. In vivo measurements include physiological parameters such as heart rate, oxygen saturation, body temperature, and daily activity movements. The environment is also monitored (CO2, humidity, gas leaks, etc.). This data is captured by sensors integrated into wearables and processed in real time using edge computing.

3.1.2 Intelligent Adaptive Sport Coaching (IASC). In this case, in vivo measurements are applied directly to athletes and active individuals during real-life training and competitions. Parameters such as: Electrocardiogram (ECG); Electromyography (EMG); Oxygen saturation (SpO2); Blood glucose; Lactate; Sweat pH. These measurements allow the creation of adaptive coaching models using AI algorithms trained with physiological data captured in real time. The sensors are integrated into smart sportswear and tested in both outdoor and aquatic (swimming) conditions, with specific requirements such as low latency (<250 ms) and low data loss (<25%).

3.1.3 Remote Post-Surgery & Rehab Monitoring (RPS&RM). This scenario involves monitoring patients undergoing post-surgical rehabilitation from their homes. In vivo measurements allow for: Monitoring adaptive therapeutic exercise; Evaluating muscular and cardiovascular recovery; Detecting early signs of relapse. Testing is performed directly on real patients in collaboration with hospitals and healthcare professionals, including the use of wearable sensors to monitor glucose, oxygen, and motor activity.

3.2 Methodological Approach

The methodological approach adopted in H2TRAIN for the design, development and implementation is represented in 1. Based on a "V" type model, the diagram Figure 2 how the requirements defined from the user-system level are progressively translated into technical specifications, passing through different levels of development and integration, until reaching validation in real scenarios. The left axis of the model shows the specification and design phases, beginning with the identification of functional and non-functional requirements from both the user and system perspectives. These requirements are translated into subsystem specifications that include software, sensors, and wearable units, thus establishing the basis for the development of electronic components and their integration into wearable devices.

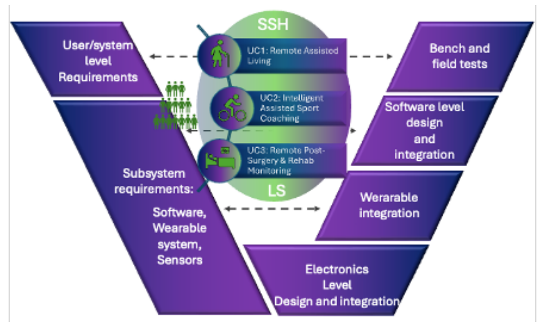

Figure 2: V-Model, H2TRAIN activities and implementation issues.

The right axis of the model reflects the return path from prototype to validation, where the various components—once integrated—are functionally verified using software, integrated into wearable environments, and finally evaluated in field and laboratory tests. This part of the process also includes the evaluation of usability, performance, and robustness under in vivo conditions, as part of the validation of the three defined use cases: Remote Assisted Living (RAL), Intelligent Adaptive Sport Coaching (IASC), and Remote Post-Surgery & Rehab Monitoring (RPS&RM). The central component of the diagram highlights these three use cases as the backbone of technological development. Each of them represents a specific application with different levels of complexity and specific requirements, both technical and ethical, which are addressed in a cross-cutting manner

3.3 Wearable Devices and Embedded Technology

The devices employed for in vivo measurements are advanced wearables seamlessly integrated into textiles, electronic tattoos, or bands. These include electronic sweat tattoos featuring printed, flexible sensors capable of detecting sweat parameters such as pH, lactate, and cortisol; textile-based glucometers that incorporate glucose sensors into clothing with automatic calibration powered by artificial intelligence; non-invasive devices combining electrocardiogram (ECG) and oxygen saturation (SpO2) monitoring with advanced communication capabilities for continuous tracking; aquatic trackers equipped with waterproof accelerometers and gyroscopes designed for sports activities; and textile-integrated trackers utilizing accelerometers and magnetometers to support applications in rehabilitation and athletic performance.

The H2TRAIN project addresses edge-fog computing by proposing a multi-layered architecture that integrates wearable sensors, edge processing, and cloud-based services to enable real-time health monitoring and decision-making. The system leverages an Edge

Virtual Assistant (EVA) acting as a multiservice gateway within the Assisted Home (AH), allowing for immediate local processing and feedback without constant reliance on the cloud. This edge-layer is complemented by a centralized Cloud Platform (CP), which aggregates and analyzes data across multiple homes for long-term insights and system-wide oversight. Such a structure enhances responsiveness, scalability, and reliability in healthcare delivery (see Figure 3).

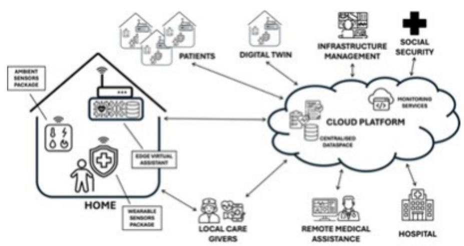

Figure 3: Use case high-level architecture of the remote assisted living (RAL)

3.4 Scientific and Technological Significance of In Vivo Data Acquisition

The integration of in vivo data collection within the H2TRAIN framework constitutes a scientifically grounded and technologically advanced strategy to ensure the ecological validity of sensor performance, data acquisition, and AI model development. By embedding biosensors directly into wearables and textiles and deploying them in uncontrolled, real-life environments, the project bypasses the limitations of controlled laboratory settings, thereby capturing physiological and biomechanical signals under authentic conditions of use. These signals—ranging from cardiovascular and muscular activity to chemical makers such as cortisol, lactate, and glucose—are key indicators of physical and mental health, and their dynamic variation is essential for modeling stress, fatigue, exertion thresholds, and recovery trajectories [9]. Each use case within H2TRAIN, whether focused on aging populations, athletes, or patients in rehabilitation, relies on these live measurements to inform the functional design of hardware and software components, ensuring that both are responsive to the realities of deployment.

In parallel, the real-world complexity captured through vivo measurements enables a robust feedback loop for the calibration, testing, and refinement of embedded systems [4]. For instance, the system's ability to cope with motion artifacts, variable environmental conditions (humidity, water immersion, interference), and inter-subject variability is assessed through iterative validation trials. This empirical methodology enhances the generalizability and resilience of the system and supports certification-relevant metrics such as signal integrity, real-time responsiveness (<250 ms), transmission error rate (<25%), and wearability under repeated washing and physical stress. From a design perspective, the incorporation of 2D material-based sensors (e.g., graphene-based electrochemical biosensors) and ultra-low power embedded systems (≤120 nA at 2.7 V) further reinforces the alignment between cutting-edge research and practical implementation [2]. Overall, H2TRAIN's approach places scientific rigor at the core of its system validation strategy, bridging the gap between research innovation and operational reliability in complex human-centered environments.

4 Artificial Intelligence for Edge-Enabled Health and Performance Analytics

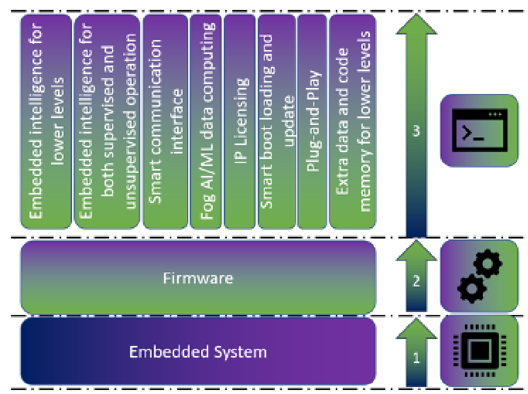

Figure 4: Use case high-level architecture of the remote assisted living (RAL)

H2TRAIN integrates artificial intelligence (AI) across a distributed edge–fog–cloud architecture to enable responsive, personalized, and energy-efficient health and performance monitoring (see Figure 4). At the edge level, lightweight AI models—such as decision trees, convolutional neural networks (CNNs) for time-series classification, and threshold-based anomaly detectors—are deployed directly on ultra-low-power ARM Cortex-M processors embedded in wearable devices. These models perform on-device signal preprocessing (e.g., filtering, normalization), real-time inference (e.g., fatigue detection, abnormal ECG pattern recognition), and generate context-sensitive alerts with sub-250 ms latency, without relying on continuous cloud access. This ensures autonomous operation in bandwidth-constrained environments while preserving user privacy [2]. Intermediate fog nodes—implemented on local gateways or mobile devices—perform data aggregation, short-term trend analysis, and model coordination across multiple users [5]. They also manage encrypted communication with the cloud, where resource-intensive tasks such as model retraining, population-level clustering, and federated learning updates are performed. The architecture allows modular over-the-air updates and supports adaptive AI models that calibrate user-specific baselines using in vivo data streams [5]. This layered design minimizes energy consumption, reduces data transmission load, and enables scalable deployment of real-time AI in clinically relevant and real-world use cases [5].

4.1 AI Models and Algorithms

To support real-time health and performance analytics, H2TRAIN leverages a modular suite of AI algorithms tailored for physiological signal processing and user-specific interpretation. These models are deployed across the edge–fog–cloud stack, with design choices driven by energy efficiency, model interpretability, and adaptability to heterogeneous hardware platforms.

Time-series classification tasks—such as detecting activity states, stress levels, or cardiac events—are addressed using lightweight convolutional neural networks (CNNs) and recurrent neural networks (RNNs), including LSTM variants. These models are quantified and optimized for microcontroller-based inference using frameworks like TensorFlow Lite for Microcontrollers and CMSIS-NN. For instance, CNNs are trained on segmented windows of ECG, EMG, and accelerometer signals, extracting temporal-spatial patterns to classify exercise intensity or movement type. Models typically operate with an input window of 2–5 seconds, using 1D convolutions followed by pooling and fully connected layers, constrained to under 30 KB of memory .

Anomaly detection is performed using autoencoders trained to reconstruct normal physiological patterns; deviations from expected reconstruction error are flagged as anomalies. In low-power devices, lightweight isolation forests are used to detect outliers in biometric time series, such as unexpected spikes in glucose or HRV. These models are pre-trained offline and then pruned for efficient deployment, with edge devices handling score computation and fog/cloud layers performing periodic retraining with new labeled data. Personalized modeling is implemented via transfer learning, where global models are fine-tuned on-device using individual data profiles. Initial clustering using unsupervised algorithms (e.g., k-means or Gaussian Mixture Models) groups users by physiological similarity, enabling adaptive thresholds and targeted interventions. These mechanisms improve prediction accuracy over time while maintaining a compact model footprint [3], typically under 100 KB .

Auto-calibration modules correct for signal drift and inter-sensor variability using non-linear regression models (e.g., polynomial fits or kernel ridge regression) and shallow feedforward neural networks [3]. These modules operate continuously in the background and are updated based on annotated reference points collected during guided calibration routines or in-field comparisons with gold-standard sensors. To integrate multiple data sources, H2TRAIN implements sensor fusion techniques across accelerometers, gyroscopes, and biosensors using Kalman filters for real-time motion estimation and attention-based neural architectures to dynamically weigh signal relevance [7]. This is particularly crucial in aquatic environments or during high-mobility activities, where signal quality varies due to noise or displacement. Table 1 presents a selection of relevant Key Performance Indicators (KPIs) from the H2TRAIN framework that corresponds to the AI functionalities described.

Table 1: AI Functionalities KPIs

KPI ID	Description	Target Value	AI Relevance
KPI1	Latency, responsiveness, task distribution	Latency < 250 ms	Real-time classification and alert generation
KPI2	Robustness, fault detection, anomaly flagging	Anomaly detection accuracy > 90%	Autoencoder and isolation forest performance
KPI3	Hardware/software validation	Modular OTA updates supported	Federated learning, on-device fine-tuning
KPI4	Device design	Model size < 100 KB, power < 120 nA	Deployment of CNNs, RNNs, and regressors
KPI5	Sensor fusion and multi-source data processing	Sensor fusion RMSE < 10%	Kalman filters and attention-based integration

4.2 Performance Objectives and Evaluation

The effectiveness of H2TRAIN's AI-driven computing framework is assessed through a set of quantifiable performance metrics, defined to ensure that system responsiveness, classification accuracy, and biometric estimation meet the demands of real-world health and sports applications. These metrics are derived from both system-level KPIs and application-specific benchmarks and are validated through structured in vivo testing campaigns across the three defined use cases.

4.2.1 Latency and Real-Time Responsiveness. A core requirement in H2TRAIN is to achieve low-latency processing to support real-time health and activity feedback. Across all use cases, whether detecting abnormal ECG patterns or generating feedback for sports coaching the system targets <250 ms total latency, from sensor data acquisition to inference output. This is accomplished through optimized AI models running on ARM Cortex-M embedded microcontrollers using inference engines like CMSIS-NN and TensorFlow Lite for Microcontrollers. Benchmark tests demonstrate median latencies of 180 ms under typical conditions, even with multi-sensor fusion enabled.

4.2.2 Classification Accuracy for Physiological Events. H2TRAIN targets a >90% accuracy threshold for detecting key physiological states such as fatigue, dehydration, and recovery phase transitions. This is validated using in vivo datasets collected during controlled and free-living conditions, labeled by domain experts. Models are evaluated using standard metrics: precision, recall, F1-score, and AUC-ROC, with results consistently above 0.9 across test participants.

4.2.3 Biochemical Sensing Accuracy. For biosensor modules (e.g., sweat glucose, lactate, cortisol), H2TRAIN aims for a mean absolute error (MAE) <5% when compared to clinical-grade reference devices. Validation is conducted using synchronized sampling and calibration routines in real-world trials. AI-based auto-calibration modules reduce drift and ensure consistent output over time, particularly under physical stress or aquatic environments.

Table 2: Biomarker Sensing for Activity Tracking

Biomarker	Measured Range	Notes
Glucose	50–200 mg/dL	Compared to commercial sensor
Lactate	2–12 mmol/L	Validated post-exercise
Cortisol	5–25 μg/dL	Sweat-based electrochemical sensor

4.2.4 Robustness and Real-World Evaluation. Model robustness is tested across various conditions: motion artifacts, sweat interference, sensor displacement, and environmental noise. Sensor fusion algorithms (e.g., Kalman filters) and dynamic input weighting (via attention layers) help mitigate input degradation [7]. Benchmarks include worst-case scenarios such as swimming sessions or high-mobility rehabilitation, where signal quality often degrades.

4.2.5 Summary of Performance KPIs. Table 3 summarizes the core Key Performance Indicators (KPIs) used to evaluate the real-world performance of the H2TRAIN system. These indicators span critical aspects of functionality, including real-time inference latency, classification accuracy for physiological states, estimation error for biochemical sensing, and system robustness under varying operational conditions. Each KPI is aligned with specific validation methodologies, ranging from embedded system benchmarks to clinical comparisons and user-centered field trials. Together, these metrics provide a comprehensive view of how the proposed AI-enabled architecture meets the demands of responsive, reliable, and context-aware health monitoring.

Table 3: Activity Tracking KPIs

KPI	Target	Validation Method
Inference latency	< 250 ms	Measured in embedded prototypes
Event classification	> 90% F1-score	In vivo annotated datasets
Biomarker estimation error	< 10% MAE	Reference vs. wearable comparison
Signal processing robustness	> 85% accuracy	Under noisy or aquatic conditions
System availability	> 95% uptime	Long-term trials in real-life scenarios

5 Biometric Cryptography and Privacy-Enhancing AI

As wearable technologies and continuous health monitoring systems become increasingly integrated into daily life, ensuring the security and privacy of sensitive biometric data has emerged as a critical design objective [6]. Traditional encryption methods fall short in protecting physiological signals due to their dynamic, user-specific nature and the need for real-time processing [6]. To address this challenge, biometric cryptography techniques—particularly those based on physiological signals such as electrocardiogram (ECG) and photoplethysmography (PPG)—are being employed to generate unique, non-invertible cryptographic keys [10].

5.1 Biometric Encryption Principles and Methodology

he biometric encryption scheme implemented in H2TRAIN leverages physiological signals—primarily ECG and PPG—as the foundation for secure, user-specific cryptographic key generation. The system operates on a structured pipeline (see Figure 5), beginning with real-time acquisition of biometric signals using embedded sensors integrated into wearable platforms. These signals are then preprocessed to eliminate baseline wander, motion artifacts, and high-frequency noise using filtering techniques such as bandpass filters and derivative operators.

Following preprocessing, a feature extraction module identifies stable and repeatable components of the physiological waveform. In the case of ECG, this typically includes R–R intervals, QRS durations, and morphological descriptors of the waveform segments. These features are compact, discriminative, and sufficiently robust to inter-session variability [8].

The extracted features are then concatenated with a system-generated random seed to form an intermediate representation. This fusion is critical for implementing cancelable biometrics, as it ensures that even if a biometric template is compromised, a new cryptographic key can be regenerated without requiring new physiological data. This fused vector undergoes a transformation using Discrete Cosine Transform (DCT) and random permutation, producing a non-invertible and privacy-preserving bio-hash.

Finally, the resulting template is mapped to a binary cryptographic key using quantization and encoding schemes that respect Hamming distance constraints for reproducibility and error tolerance. This key can be used directly for secure communication, encryption of locally stored data, or as a token for identity verification. The entire process is executed locally on resource-constrained hardware—e.g., ARM Cortex-M33 platforms with TrustZone support—ensuring that raw biometric data never leaves the device unencrypted.

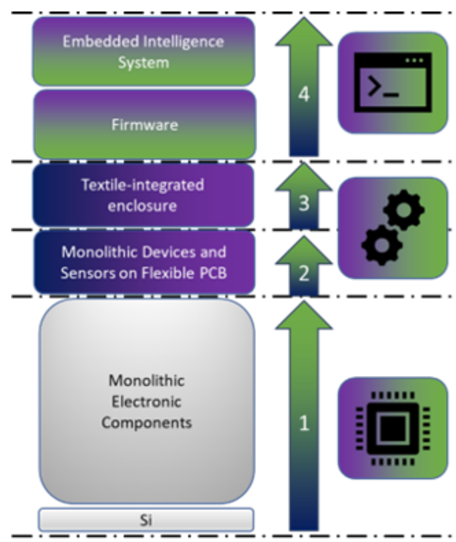

Figure 5: Particularization methodology for the biosensor integration in digital domain for biometric encryption.

5.1.1 *Deep Learning Architectures for Physiological Biometrics.*

To capture complex temporal and morphological characteristics in biometric signals, H2TRAIN employs deep learning architectures tailored for 1D time-series data. Among them, Convolutional Neural Networks (CNNs) are used to extract local patterns from ECG signals—such as QRS morphology or T-wave deformation—while Long Short-Term Memory (LSTM) networks learn long-range dependencies, such as variations in heart rhythm due to activity or stress [8]. Hybrid models combining CNNs and LSTMs have shown strong performance in handling both spatial and temporal domains, achieving recognition accuracies exceeding 96% under controlled and semi-controlled conditions [8].

5.1.2 *Adaptation, Fusion, and Continuous Learning.*

Beyond static classification, the system includes adaptive learning modules that personalize the model to each user. Techniques like incremental training and domain adaptation allow the models to adjust to signal drift, emotional states, or environmental factors over time. Additionally, multimodal biometric fusion is explored by combining ECG with PPG or motion data using attention-based networks and decision-level fusion. These strategies enhance robustness, particularly in noisy settings such as during physical activity. By dynamically weighing each input modality, the system maintains high confidence even under partial signal degradation.

Table 4: Datasets Implemented for Biometric Encryption

Dataset	Modality	Subjects	Signals
ECG-ID	ECG	90	Lead I ECG
PhysioNet PTB	ECG	290+	12-lead ECG
PPG-BP	PPG, BP	219	PPG, blood pressure

5.2 Datasets and Validation Protocol

The biometric encryption and authentication modules developed in H2TRAIN were trained and validated using a diverse set of publicly available and proprietary physiological signal datasets as shown in Table 4. These include both unimodal (ECG, PPG) and multimodal sources, enabling robust training across a variety of physiological, environmental, and behavioral conditions. The primary objective of the dataset strategy was to ensure generalizability, noise resilience, and cross-subject scalability. Signals were selected to reflect real-world variability, including variations in posture, physical activity, sensor positioning, and acquisition hardware. For each dataset, preprocessing was standardized using normalization, filtering (e.g., bandpass for ECG), and segmentation into fixed-length windows (2–5 seconds).

5.3 AI-Assisted Biometric Recognition

The H2TRAIN framework integrates machine learning and deep learning algorithms to enhance the reliability, adaptability, and accuracy of biometric recognition based on physiological signals, particularly ECG. Deep neural models are used to extract unique patterns embedded in time-series data, enabling user authentication that is both secure and continuous. Two core architectures have been implemented: Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks. CNNs are particularly effective at learning spatial features from short ECG segments, identifying local waveform characteristics such as QRS morphology and T-wave profiles. LSTMs, by contrast, are designed to capture temporal dependencies, such as variability in heart rhythm over time, making them suitable for recognizing individuals under changing physiological conditions like stress or physical exertion.

These models are trained using raw and preprocessed ECG signals, passed through standardized pipelines that include normalization, noise filtering, and segmentation. In deployment, inference can be performed locally on embedded processors, thanks to optimization techniques such as quantization and model pruning. To improve robustness and long-term usability, adaptive learning strategies are employed. These include incremental model updating based on recent biometric sessions and domain adaptation methods that adjust the network's parameters to accommodate signal drift, changes in user condition, or hardware variability.

Conclusions

The H2TRAIN project presents an innovative and comprehensive approach to integrating wearable sensing, embedded intelligence, and secure data handling in real-world applications related to health, rehabilitation, and sports. Through extensive in vivo validation across diverse user groups, it provides reliable, real-time physiological data using a layered computing architecture—edge, fog, and cloud—that ensures efficient task distribution, reduced latency, and continuous AI-driven personalization, even on resource-limited devices. By combining physiological signal analysis with biometric cryptography, the system delivers adaptive, privacy-preserving authentication aligned with current ethical and regulatory standards. The implementation of AI models such as CNNs and LSTMs enhances accuracy and robustness, even under conditions of signal degradation and user variability, positioning H2TRAIN as a solid foundation for next-generation, intelligent, and secure digital health platforms.

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