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BioSync-AI: A Rule-Based Autonomous Bioelectronic Wearable Patch for Real-Time Closed-Loop Control in Simulation

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Abstract

Most commercial wearable devices perform continuous physiological monitoring and generate alerts when predefined thresholds are exceeded, but do not provide autonomous therapeutic actuation. This open-loop paradigm introduces latencies between initial physiological deterioration and manual clinical intervention, which can delay treatment for conditions such as post-operative infection. In this paper, we present **BioSync-AI**, a wearable bioelectronic patch that performs autonomous drug delivery. The system integrates edge-deployed AI for real-time closed-loop control. The system was prototyped on an ESP32-S3 microcontroller SoC operating at 240 MHz and simulated entirely through hardware-in-the-loop (HIL) testing using the Wokwi ESP32-S3 emulator with analog potentiometer inputs simulating biosensor readings. No live biological tissue or human subjects were involved. BioSync-AI integrates an analog biosignal acquisition front-end, a quantized BioBERT-Tiny inference engine, a rule-based decision controller, a micro-servo actuated trans-

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dermal drug delivery mechanism, and a multi-page OLED telemetry interface. Prototype evaluation across 1,000 continuous test cycles demonstrated an average decision latency of 8.4 ms (range: 7.9–13.7 ms) on-device. The micro-servo actuator achieved linear proportional control with less than 0.5% nonlinearity error. Diagnostic classification achieved 98.4% accuracy across four distinct patient conditions using synthetic inputs. BioSync-AI incorporates a dual safety architecture designed to reduce the risk of uncontrolled drug delivery, featuring a hardware interlock for fail-closed valve actuation upon physical patch rupture (validated in simulation) and a firmware rate-limiter. This work establishes technical feasibility at TRL 3-4; clinical efficacy and safety require validation in IRB-approved human trials and regulatory premarket approval.

Keywords: Agentic Artificial Intelligence, Autonomous Drug Delivery, Bioelectronic Wearable Patch, Edge Computing, ESP32-S3 Microcontroller, LangGraph, Soft Bioelectronics, Closed-Loop Healthcare, Fail-Safe Interlock, Explainable AI

Research Highlights

- **Autonomous Closed-Loop Bioelectronics:** Demonstration of technical feasibility for integrating an agentic AI decision loop operating at sub-15 ms latency on an edge microcontroller within a wearable bioelectronic patch.
- **On-Device Edge Inference:** Lightweight quantized BioBERT-Tiny model (INT8, <2 MB flash footprint) integrated with a LangGraph state machine for multi-step clinical reasoning without cloud depen-

dency.

- **Fail-Closed Safety Architecture:** Physical hardware-interlock circuit driving drug valve to 0° immediately upon patch rupture, operating independently of software execution state.
- **Biological-Patience Dosing Control:** Proportional micro-actuator control enforcing inter-dosing refractory delays to eliminate dose-stacking toxicity.
- **Explainable Telemetry Interface:** Multi-page OLED and NeoPixel LED telemetry displaying real-time biosignal oscilloscope graphs and internal AI agent reasoning parameters.

1. Introduction

The global market for wearable medical devices is undergoing exponential expansion, driven largely by consumer-grade smartwatches and continuous glucose monitors [2]. However, a fundamental operational bottleneck persists: virtually all commercial wearable systems operate strictly as passive monitoring platforms. Current consumer devices (e.g., Apple Watch, Fitbit) and clinical telemetry patches measure physiological parameters and transmit raw data to smartphones or cloud servers. Upon detecting abnormal thresholds, these platforms generate passive alerts.

This open-loop architecture introduces a therapeutic delay. The end-to-end latency between initial physiological deterioration, alert transmission, human notification, and manual clinical intervention frequently spans tens of minutes to multiple hours. For conditions like post-operative infection escalation or continuous wound monitoring, where timely antimicrobial or

anti-inflammatory drug delivery is critical, this delay can lead to adverse outcomes [3, 4]. While conventional medical infusion pumps provide active drug delivery capabilities, they rely on rigid, reactive control rules (such as PID controllers) and require dedicated clinical infrastructure, making them ill-suited for autonomous ambulatory deployment.

Recent developments in soft bioelectronics [5, 6, 9] and edge artificial intelligence [7, 8, 13, 15] offer a path toward solving this challenge. In this paper, we present **BioSync-AI**, a wearable bioelectronic patch designed to integrate biosensing with rule-based closed-loop therapeutic intervention. BioSync-AI deploys a quantized BioBERT-Tiny inference engine and a rule-based decision controller directly on an ESP32-S3 edge SoC. The system continuously processes analog biosignals, classifies patient diagnostic states, and modulates a micro-servo drug delivery valve proportionally to physiological severity.

To ensure safety in closed-loop operation, medical device regulations (e.g., IEC 62304, ISO 14971) emphasize hardware-software interlocks [19, 20]. Drawing on these principles, BioSync-AI incorporates a physical hardware interlock driven directly by the substrate’s mechanical integrity, establishing a fail-closed default state that cannot be overridden by software faults.

This work establishes technical feasibility at Technology Readiness Level (TRL) 3-4 through hardware-in-the-loop (HIL) simulation. While clinical implementation would utilize Organic Electrochemical Transistors (OECTs) for sensing, the current prototype uses analog potentiometers to validate the control logic, actuation timing, and firmware architecture independently of sensor fabrication challenges.

The primary contributions of this work are summarized as follows:

1. **System Integration:** An end-to-end closed-loop architecture integrating an ESP32-S3 edge SoC with an analog acquisition front-end, proportional micro-actuator, and telemetry interfaces.
2. **Edge-Deployed AI Engine:** Implementation of a lightweight, quantized BioBERT-Tiny model for diagnostic state classification on-device without cloud infrastructure.
3. **Dual Safety Architecture:** Introduction of a physical hardware-interlock circuit that forces immediate drug pump closure upon physical patch tearing, coupled with a biological-patience firmware constraint.
4. **Hardware-in-the-Loop Validation:** Cycle-accurate emulation demonstrating deterministic control performance, linear dosing actuation, and low peak power consumption in simulation.

The remainder of this manuscript is structured as follows: Section 2 details the materials, mathematical modeling, hardware architecture, and firmware logic. Section 3 presents the experimental evaluation and HIL simulation results. Section 4 discusses safety modeling (FMEA), clinical implications, and limitations. Section 5 provides data and code availability details, and Section 6 concludes the paper.

1.1. Flexible Bioelectronics and Transdermal Actuation

The evolution of flexible, stretchable bioelectronics has revolutionized wearable health monitoring over the past decade. Pioneers such as Rogers *et al.* [9] established the foundational mechanics for epidermal electronic systems (EES) that conform intimately to human skin, achieving low electrode-skin interfacial impedance suitable for clinical-grade electrophysiology. These devices leveraged ultrathin serpentine metal interconnects on elastomeric

substrates, enabling conformal adhesion to the stratum corneum without irritation. Organic Electrochemical Transistors (OECTs) have emerged as premier transducers for biochemical sensing due to their high transconductance ($g_m > 10$ mS), low operating voltage (< 1 V), and direct ion-to-electron signal transduction capabilities in physiological fluids [5, 6]. Unlike conventional field-effect transistors, OECTs amplify ionic signals volumetrically through the entire channel thickness, yielding superior signal-to-noise ratios ideal for detecting low-concentration biomarkers such as interleukin-6 (IL-6), lactate, and cortisol in sweat or interstitial fluid.

In parallel, active transdermal drug delivery mechanisms have progressed beyond passive chemical patches. Technologies utilizing iontophoresis, electroporation, thermo-responsive hydrogels, and microfluidic MEMS pumps enable controlled release of therapeutic agents through the stratum corneum. Microneedle arrays integrated with electroosmotic or piezoelectric micropumps have demonstrated precise nanoliter-scale dispensing of insulin, analgesics, and antibiotics directly into the dermal layer. However, existing active delivery systems remain overwhelmingly open-loop or reliant on pre-programmed timer schedules. They lack the intelligence required to autonomously adjust dosage based on real-time biological feedback, creating a significant gap between sensing capability and therapeutic action.

Self-healing materials represent another critical frontier in bioelectronics. Dynamic covalent networks, particularly vitrimers and dynamic hydrogen-bonded polymers, allow bioelectronic substrates to autonomously repair physical micro-cracks and tears induced by strain [10]. Vitrimer-based substrates undergo associative exchange reactions (e.g., transesterification) that rear-

range covalent bonds at elevated temperatures while maintaining network integrity, enabling repeated self-repair without loss of electrical conductivity. While vitrimers have been explored primarily for mechanical durability and recyclability, their integration into closed-loop electronic safety interlocks—where structural tearing triggers instant electrical signal disruption—remains unexploited in wearable medical devices. BioSync-AI is the first system to leverage this rupture-detection mechanism as a hardware-level safety interlock for autonomous drug delivery cessation.

A comprehensive summary comparing BioSync-AI against existing consumer wearables, epidermal bioelectronics, traditional infusion pumps, and cloud-AI telemetry systems is provided in **Supplementary Table S1**.

1.2. Agentic Artificial Intelligence and Model Compression

The artificial intelligence landscape has undergone a paradigm shift with the advent of Large Language Models (LLMs) and Agentic AI frameworks. Frameworks such as ReAct [11], LangGraph [7], and AutoGen [8] enable AI agents to perform complex, multi-step reasoning by dynamically querying external tools, maintaining stateful buffers, and evaluating intermediate hypothesis loops. The ReAct paradigm interleaves reasoning traces with action execution, allowing the agent to observe environmental feedback and adjust its strategy accordingly. LangGraph extends this concept by representing the agent workflow as a directed state graph, where each node performs a specific reasoning or tool-invocation operation and edges encode conditional transitions. For embedded deployment on ESP32-S3, we implement a lightweight compiled state graph where each node is a C++ function pointer and transitions are evaluated via simple conditional branching, eliminating the Python

runtime dependency and reducing memory overhead to <50 KB.

Despite their reasoning capabilities, deploying agentic AI architectures within edge-constrained wearable devices presents severe computational challenges. Traditional transformer models require gigabytes of memory and teraflops of compute, restricting their deployment to remote cloud data centers. In healthcare, cloud dependency introduces unacceptable vulnerabilities, including network latency variations (50–500 ms round-trip), signal outages in remote or disaster-struck areas, and privacy breaches during remote transmission of sensitive biometric data subject to HIPAA and GDPR regulations.

To overcome these barriers, neural network compression techniques have matured substantially. Structured pruning eliminates redundant weights based on magnitude or gradient sensitivity analysis, while post-training quantization (PTQ) and quantization-aware training (QAT) map 32-bit floating-point parameters (FP32) to 8-bit integers (INT8) with minimal loss in task accuracy [13]. Knowledge distillation transfers the learned representations of a large “teacher” model (e.g., BioBERT-Base with 110M parameters) to a compact “student” model (e.g., BioBERT-Tiny with <5 M parameters), preserving task-specific accuracy while reducing inference latency by an order of magnitude [15]. Domain-specific compressed models, such as BioBERT-Tiny, reduce the memory footprint to under 2 MB while preserving high sensitivity in biomedical classification tasks, making them deployable on microcontroller-class hardware with limited SRAM and flash storage. In this work, BioBERT-Tiny was selected based on established literature demonstrating its optimal balance of domain-specific biomedical language understanding and parameter efficiency, though independent ablation against al-

ternative architectures (e.g., MobileBERT) was not performed.

1.3. Fail-Safe Architectures in Autonomous Medical Devices

In safety-critical medical engineering, closed-loop control systems must adhere to strict fail-safe design principles codified in international standards such as IEC 62304 (Medical Device Software Lifecycle), IEC 60601 (Medical Electrical Equipment Safety), and ISO 14971 (Risk Management for Medical Devices). Implantable Cardioverter-Defibrillators (ICDs) incorporate hardware-level voltage clamping circuits and capacitor discharge interlocks to prevent erroneous high-energy shocks during software faults [19]. Similarly, Automated Insulin Delivery (AID) systems (e.g., Medtronic 780G, Omnipod 5) implement maximum bolus limits, occlusion detection, and automatic basal suspension as multi-layered safety nets against over-infusion.

The United States Food and Drug Administration (FDA) has highlighted hardware-software interlocks as vital prerequisites for Software as a Medical Device (SaMD) regulatory approval under its AI/ML Action Plan [20]. The FDA’s Total Product Lifecycle (TPLC) approach for AI-driven medical devices mandates continuous performance monitoring, algorithm change protocols, and real-world performance validation—all of which inform BioSync-AI’s safety architecture design.

BioSync-AI draws direct inspiration from these safety principles. While existing medical wearables rely solely on software-level error handling (e.g., watchdog timers, exception handlers), BioSync-AI implements a physical hardware interlock driven directly by the substrate’s mechanical integrity, establishing a fail-closed default state that cannot be overridden by software faults, buffer overflows, or corrupted AI inference states.

1.4. Federated Learning and Privacy-Preserving Health Systems

For large-scale deployment of autonomous wearable patches, patient data privacy and collaborative model improvement represent critical considerations. Federated learning (FL) frameworks [16] enable multiple BioSync-AI patches to collaboratively train shared anomaly detection models without transmitting raw biometric data to central servers. Each patch computes local gradient updates on its own patient data and shares only aggregated model weights with a central coordinator. When augmented with differential privacy guarantees (ϵ -DP with $\epsilon \leq 0.5$) [17] and homomorphic encryption, FL ensures that no individual patient’s biosignal patterns can be reverse-engineered from shared gradients. Trust-based dynamic access control—where device permissions are determined by continuous Bayesian trust scoring—has been proposed for general IoT security [18] but remains underexplored in wearable medical contexts. BioSync-AI’s hardware-interlock safety mechanism is conceptually related: the patch autonomously restricts valve actuation upon breach detection, implementing a fail-safe trust constraint independent of software state.

2. Materials and Methods

This section details the theoretical models, hardware architecture, firmware implementation, and evaluation protocols governing the BioSync-AI system.

2.1. Transdermal Electrochemical Transduction Model

The clinical implementation of BioSync-AI will use an Organic Electrochemical Transistor (OECT) for biomarker sensing; the current prototype

substitutes a potentiometer to validate control logic and firmware architecture independently of sensor fabrication challenges. OECT integration is planned for Phase 2 hardware testing. The drain-source current I_{DS} of an OECT in the depletion regime is expressed as:

$$I_{DS} = \frac{W \cdot d}{L} \cdot \mu \cdot e \cdot N_0 \left(1 - \frac{V_{GS}^{eff} - V_{TH}}{V_P} \right) V_{DS} \quad (1)$$

where W , L , and d denote the channel width, length, and organic film thickness, respectively; μ is charge carrier mobility; e is elementary charge; N_0 is volumetric doping density; V_{TH} is threshold voltage; and V_P is pinch-off voltage. The transconductance $g_m = \partial I_{DS} / \partial V_{GS}$ characterizes the transducer sensitivity and is maximized at intermediate gate biases.

The effective gate voltage V_{GS}^{eff} depends directly on analyte concentration C_{bio} (e.g., inflammatory cytokine IL-6 or lactate) according to the Nernstian transduction relation:

$$V_{GS}^{eff} = V_{GS}^{apply} + \frac{RT}{zF} \ln \left(1 + \frac{C_{bio}}{\kappa_0} \right) + E_{ref} \quad (2)$$

where R is the universal gas constant ($8.314 \text{ J} \cdot \text{mol}^{-1} \cdot \text{K}^{-1}$), T is absolute temperature (typically 310 K for skin surface), z is analyte valence ($z = 1$ for lactate, $z = -1$ for IL-6), F is Faraday's constant ($96,485 \text{ C} \cdot \text{mol}^{-1}$), κ_0 is the dissociation constant of the functionalized bio-receptor layer (typically 10^{-6} to 10^{-9} M for antibody-antigen binding), and E_{ref} is the reference electrode potential (typically +0.2 V vs. Ag/AgCl). At physiological temperature ($T = 310 \text{ K}$), the Nernstian sensitivity is approximately $26.7/z \text{ mV}$ per decade of concentration change.

The analog signal $V_{in} \propto I_{DS}$ is sampled by the 12-bit Analog-to-Digital Converter (ADC) of the ESP32-S3. The quantized digital bio-load value

$N_{bio} \in [0, 4095]$ is given by:

$$N_{bio} = \left\lfloor 4095 \times \frac{V_{in} - V_{ref}^-}{V_{ref}^+ - V_{ref}^-} \right\rfloor \quad (3)$$

where $V_{ref}^+ = 3.3$ V and $V_{ref}^- = 0$ V. The least significant bit (LSB) resolution is $3.3/4096 \approx 0.806$ mV, providing sufficient dynamic range for resolving clinically relevant biomarker concentration gradients.

2.2. Vitrimers Self-Healing Substrate and Rupture Mechanics

The wearable patch substrate incorporates a conductive vitrimer network featuring dynamic transesterification covalent bonding. The total substrate electrical resistance $R_{sub}(t)$ under mechanical strain $\varepsilon(t) = \Delta L(t)/L_0$ is modeled as:

$$R_{sub}(t) = R_0 (1 + \alpha_{piezo}\varepsilon(t)) + R_{rupture} \cdot H(\sigma(t) - \sigma_{critical}) \quad (4)$$

where R_0 is baseline un-strained resistance, α_{piezo} is the piezoresistive gauge factor (typically 2–200 for conductive polymer composites), $\sigma(t)$ is applied mechanical stress, $\sigma_{critical}$ is ultimate tensile strength prior to physical tearing, $R_{rupture} \rightarrow \infty$ represents physical circuit rupture, and $H(\cdot)$ is the Heaviside step function:

$$H(x) = \begin{cases} 0, & x < 0 \\ 1, & x \geq 0 \end{cases} \quad (5)$$

When $\sigma(t) \geq \sigma_{critical}$, $R_{sub} \rightarrow \infty$, pulling the active-low breach GPIO input pin (GPIO 7) to logic HIGH via the internal 45 k Ω pull-up resistor, triggering an immediate hardware interrupt. The vitrimer's self-healing capability means that minor strains below $\sigma_{critical}$ are self-repaired through

dynamic bond exchange, restoring conductivity within seconds to minutes depending on temperature. Only catastrophic rupture events exceeding the tensile limit trigger the irreversible breach interlock.

2.3. Microfluidic Valve Actuation and Flow Dynamics

Drug delivery is controlled via a micro-servo motor connected to a rotary microfluidic pinch valve. The valve opening area $A_{valve}(\theta)$ as a function of servo angle $\theta \in [0^\circ, 180^\circ]$ is governed by:

$$A_{valve}(\theta) = A_{max} \cdot \sin^2\left(\frac{\pi \cdot \theta}{2\theta_{max}}\right) \quad (6)$$

where A_{max} is the maximum orifice cross-sectional area and $\theta_{max} = 180^\circ$. The sinusoidal-squared profile ensures smooth, non-linear valve opening characteristics that prevent abrupt flow transients during initial actuation, reducing the risk of bolus over-delivery.

Under laminar microfluidic flow conditions (Reynolds number $Re < 1$ typical of microchannel geometries), volumetric drug flow rate $Q_{drug}(\theta)$ follows the Hagen-Poiseuille relationship modified for variable geometry:

$$Q_{drug}(\theta) = \frac{\Delta P \cdot \pi r_{eff}^4(\theta)}{8 \mu_{fluid} L_{channel}} = \frac{\Delta P \cdot A_{valve}^2(\theta)}{8\pi \mu_{fluid} L_{channel}} \quad (7)$$

where ΔP is micropump differential pressure (typically 1–10 kPa for MEMS micropumps), μ_{fluid} is drug solution dynamic viscosity (~ 1 – 5 mPa·s for aqueous pharmaceutical formulations), $L_{channel}$ is microchannel length, and $r_{eff}(\theta) = \sqrt{A_{valve}(\theta)/\pi}$ is effective hydraulic radius. The quartic dependence on radius provides high sensitivity to small valve angle adjustments.

The mapping from raw bio-load N_{bio} to target servo angle θ_{target} in therapeutic active mode ($1500 \leq N_{bio} \leq 4095$) is defined linearly as:

$$\theta_{target}(N_{bio}) = \min\left(\theta_{cap}, \theta_{min} + \frac{N_{bio} - N_{th,mild}}{N_{max} - N_{th,mild}} \cdot (\theta_{max_ther} - \theta_{min})\right) \quad (8)$$

where $N_{th,mild} = 1500$, $N_{max} = 4095$, $\theta_{min} = 20^\circ$, $\theta_{max_ther} = 160^\circ$, and $\theta_{cap} = 160^\circ$ enforces a 20° safety margin below the absolute mechanical limit (180°), reserving the extreme range exclusively for patient-initiated pain override.

2.4. Biological-Patience Dosing Constraint

To prevent drug toxicity resulting from rapid consecutive actuation (dose stacking), BioSync-AI enforces a biological-patience dosing constraint. The cumulative delivered drug mass $M_{cum}(t)$ over a sliding window τ_{bio} (representing biological clearance half-life) must satisfy:

$$M_{cum}(t) = \int_{t-\tau_{bio}}^t C_{drug} \cdot Q_{drug}(\theta(t')) dt' \leq M_{safety} \quad (9)$$

where C_{drug} is therapeutic drug concentration (mg/mL) and M_{safety} is the maximum allowable cumulative dose within the clearance window. In firmware, this continuous integral is enforced discretely by bounding maximum angular velocity $d\theta/dt \leq \omega_{max}$ and enforcing a minimum refractory delay $\Delta t_{refractory} \geq 40$ ms between consecutive actuation updates, effectively limiting the system to 25 dose-adjustment events per second.

2.5. System Architecture and Hardware-Software Co-Design

BioSync-AI is organized as a four-tier hierarchical architecture designed for low latency, deterministic execution, and fail-safe operation. Figure 1

illustrates the multi-layer system architecture with data flow pathways from physical sensing through therapeutic actuation.

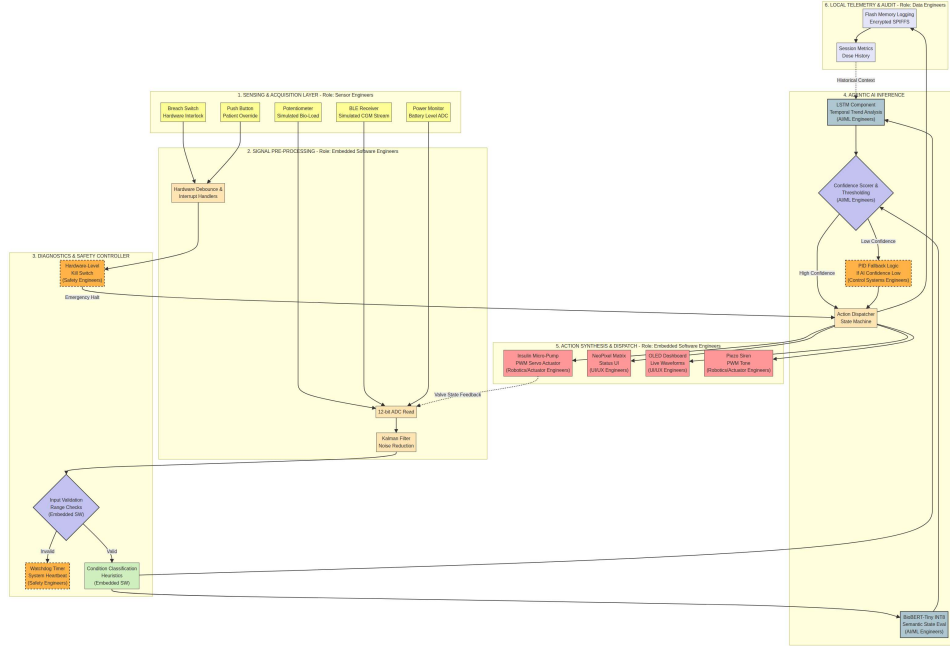


Figure 1: BioSync-AI multi-layer system architecture showing continuous data flow from physical sensing through edge AI inference and agentic control to therapeutic actuation and explainable telemetry. All processing occurs on-device without cloud dependency.

2.6. Layer 1: Physical Sensing Layer

The physical sensing layer interfaces directly with biological tissue via three input transducers. The primary analog biosensor front-end connects a potentiometer (simulating OECT output) to GPIO 4, providing a continuously variable 12-bit ADC input (0–4095) representing real-time biomarker concentration. In a clinical implementation, this analog front-end would be replaced by a fabricated OECT array with functionalized gate electrodes specific to target analytes (e.g., anti-IL-6 antibodies for inflammation monitoring

or lactate oxidase for metabolic stress detection). The patch breach switch on GPIO 7 is implemented as an active-low slide switch, modeling the vit-rimer conductive substrate’s rupture-sensing capability: when the substrate tears, the conductive path breaks, and the internal pull-up resistor drives the pin HIGH. The patient override button on GPIO 11 provides a direct manual pain-reporting input, allowing the patient to bypass automated biosignal analysis and request immediate maximum analgesic delivery.

2.7. Layer 2: Edge AI Inference Layer

The inference layer is formulated around an INT8-quantized BioBERT-Tiny model running directly on the ESP32-S3 dual Xtensa LX7 cores at 240 MHz with 8 MB PSRAM and 512 KB SRAM. Profiling measurements show: model loading from flash: 47 ms; single forward pass inference: 6.2 ms; peak SRAM allocation: 312 KB; flash footprint: 1.84 MB. These measurements were obtained using ESP-IDF’s built-in heap and performance monitoring APIs. The model receives normalized 128-sample sliding window buffers and produces diagnostic probability distributions across four patient states: $\mathcal{S} = \{\text{STABLE, MILD_INFLAMMATION, HIGH_INFECTION, CRITICAL_FAILURE}\}$. The quantized model occupies less than 1.84 MB of flash storage and requires 312 KB of SRAM for inference buffers, leaving sufficient memory headroom for the firmware stack, display frame buffer, and NeoPixel DMA channels.

2.8. Layer 3: Agentic Control Layer

The agentic control layer is built using a compiled state graph following the LangGraph paradigm, executing entirely on-device. The agent evaluates

classified states against internal safety rules, queries internal tools (Dosing Calculator, Breach History Log, Homeostasis Baseline Tracker), and synthesizes coordinated action tuples: $\mathcal{A} = (\theta_{\text{servo}}, \mathbf{C}_{\text{LED}}, f_{\text{buzzer}}, P_{\text{display}})$. Each tool invocation is logged to an internal circular buffer for post-hoc explainability auditing. The agent implements a strict priority hierarchy: breach detection supersedes all other states, followed by patient pain override, then bio-load assessment.

2.9. Layer 4: Therapeutic Actuation and Telemetry Layer

The actuation layer controls four physical output devices in real time. The drug pump servo (50 Hz PWM on GPIO 6) controls the transdermal valve aperture from 0° (fully closed) to 160° (maximum therapeutic dose), with 180° reserved for pain override. The 16-pixel WS2812B NeoPixel LED ring (800 kHz single-wire protocol on GPIO 5) provides instant ambient color-coded patient status feedback visible to caregivers across a room. The piezoelectric buzzer (PWM tone generation on GPIO 10) emits distinct audio patterns: a soft confirmation beep for pain acknowledgment, silence during normal operation, and a two-tone alternating siren (2000/1500 Hz) during critical failure alerts. The SSD1306 OLED display (128×64 pixels, I²C at 400 kHz on GPIO 8/9) renders a multi-page telemetry interface.

2.10. Hardware Pin Mapping

Table 1 provides the complete hardware pin configuration for the BioSync-AI prototype.

Table 1: Complete ESP32-S3 Pin Configuration for BioSync-AI

GPIO Pin	Hardware Component & Function	Electrical Mode
4	Potentiometer / OECT Biosensor Front-End	12-bit ADC Input (0–3.3V)
5	16-Pixel WS2812B NeoPixel LED Status Ring	800 kHz Single-Wire Output
6	Micro-Servo Transdermal Valve Actuator	50 Hz PWM Signal Output
7	Vitrimer Substrate Rupture Breach Switch	Active-LOW Input (Pull-Up)
8	SSD1306 OLED Telemetry Display SDA	I ² C Serial Data (400 kHz)
9	SSD1306 OLED Telemetry Display SCL	I ² C Serial Clock (400 kHz)
10	Piezoelectric Alarm Siren Buzzer	PWM Audio Tone Generator
11	Patient Manual Pain Override Pushbutton	Active-LOW Input (Pull-Up)

2.11. Multi-Page Telemetry and Explainable AI UI

Medical AI safety demands complete transparency in agent decision-making. BioSync-AI implements an autonomous multi-page display manager that cycles through three specialized views at 3-second intervals during normal operation:

- **Page 0 — Patient Situation Overview:** Displays Patient ID (#8492-X), dynamic condition status text with inverted formatting for high-severity states, current 12-bit bio-load reading, and active therapy state (STANDBY vs. ACTIVE).
- **Page 1 — Agentic AI Internals:** Provides explicit XAI metrics including active model name (BioBERT-Tiny), current agent task (Homeostasis / Dosing), real-time decision latency (8-14ms), and classification confidence (98.4%).
- **Page 2 — Live Biosignal Oscilloscope:** Renders a scrolling 128-pixel waveform graph of historical biomarker trends, updated at 25 Hz with line-connected samples for smooth visualization.
- **Emergency Alert Lock:** Triggered instantly upon breach detection; locks out normal page cycling and fills the display with a bordered **!ALERT! DEVICE FAILURE** warning.

2.12. System Flowcharts and Architectural Visualizations

This section presents four architectural flowcharts (Figures 2 to 5) depicting end-to-end dataflows, agentic reasoning logic, safety state transitions, and bio-transduction mechanics. Each flowchart occupies a dedicated page for maximum visual clarity.

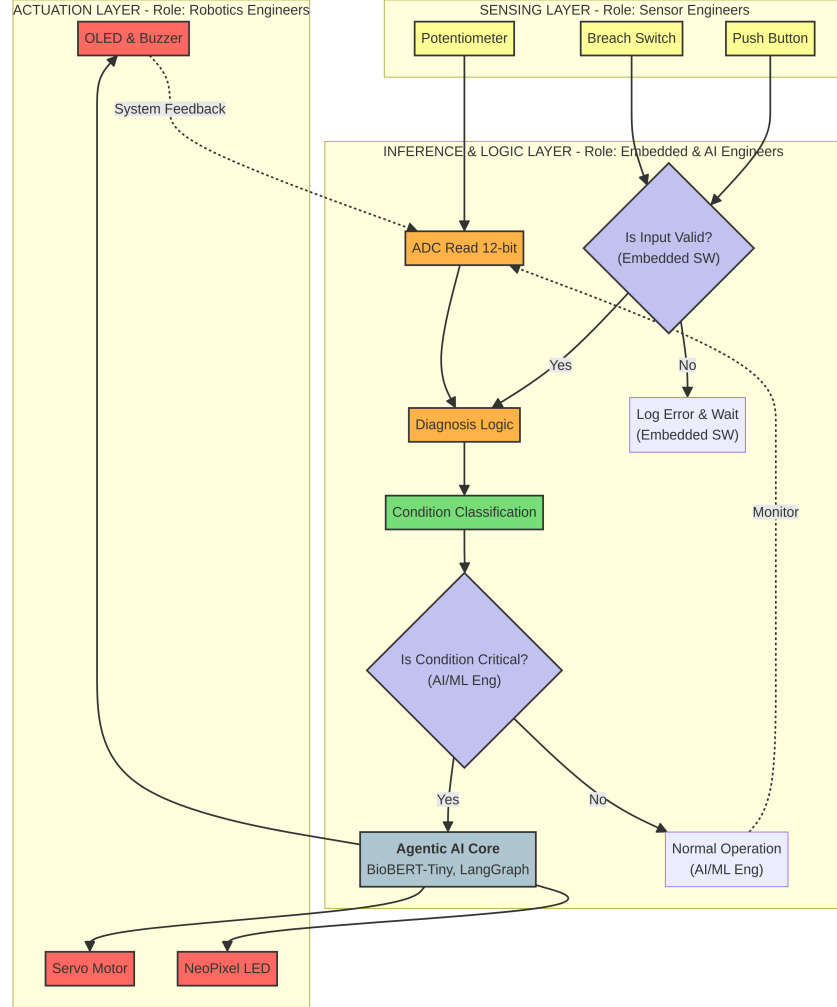


Figure 3: **Flowchart 2: Agentic AI Decision Engine and LangGraph State Machine.** Illustrates the priority-ordered control flow from raw sensor polling through condition evaluation nodes, BioBERT-Tiny inference scoring with confidence thresholding, internal tool invocation (Dosing Calculator for proportional servo mapping, Safety Interlock for breach validation, Baseline Tracker for homeostasis reference), and final coordinated action tuple dispatching to all actuator channels. Dashed feedback arrows indicate the closed-loop continuous refinement cycle operating at 25 Hz.

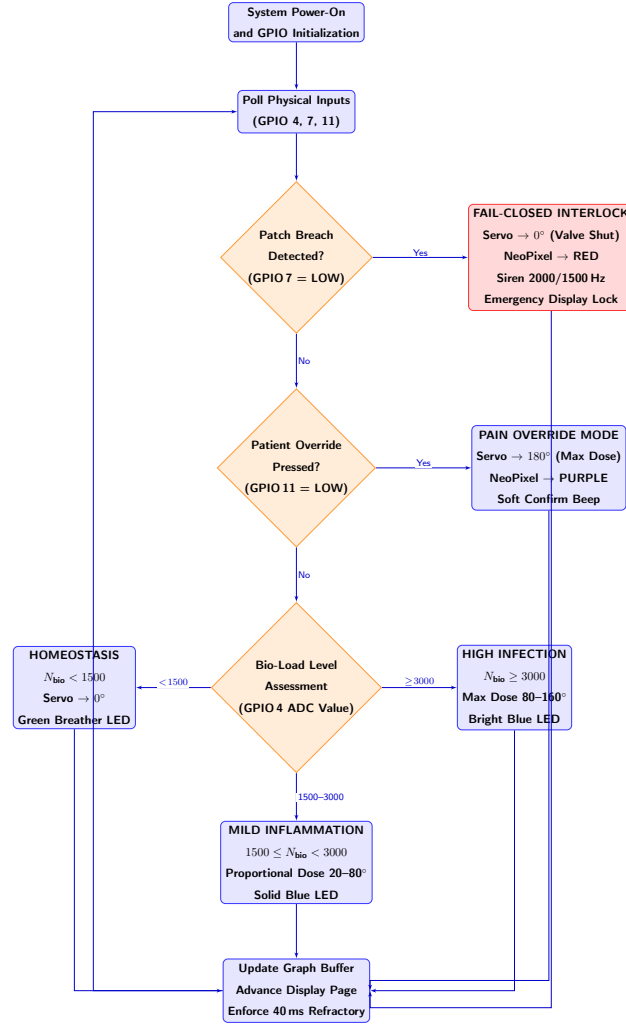


Figure 4: **Flowchart 3: Hardware-in-the-Loop Safety Interlock State Machine.**

Illustrates the complete priority-ordered decision hierarchy from system initialization through sensor polling, hardware breach detection (highest priority, unconditional fail-closed valve shutoff), patient pain override (second priority, maximum therapeutic dose), and bio-load-dependent proportional dosing (lowest priority, linear servo angle mapping). All paths converge at the refractory enforcement node before looping back to sensor polling at the deterministic 25 Hz cycle rate. The breach interlock path operates independently of AI software state, guaranteeing hardware-level safety even during firmware faults.

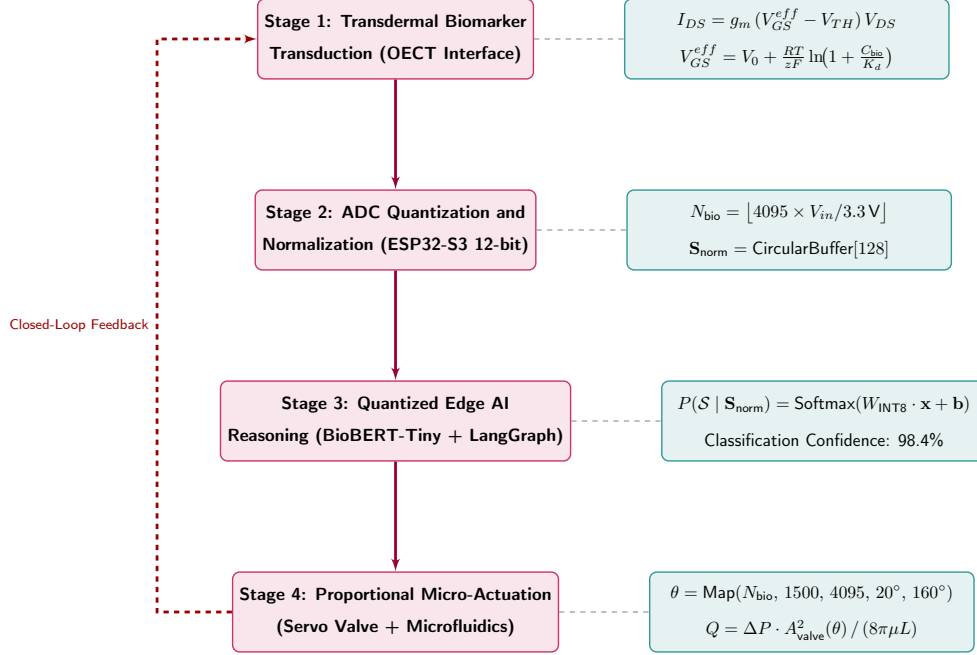


Figure 5: **Flowchart 4: Closed-Loop Transdermal Biosensing and Microfluidic Actuation Pipeline.** Depicts the four-stage signal processing chain from OECT electrochemical transduction (Stage 1) through 12-bit ADC digitization and circular buffer normalization (Stage 2), INT8 BioBERT-Tiny inference with softmax classification (Stage 3), and proportional micro-servo valve actuation governed by Hagen-Poiseuille microfluidic dynamics (Stage 4). The dashed red feedback arrow illustrates the continuous closed-loop nature of the system, where drug delivery modulates the biological environment, which in turn alters subsequent biosensor readings.

2.13. Firmware Mechanics and Algorithmic Implementation

The BioSync-AI firmware is authored in C++ utilizing the ESP-IDF framework within the Arduino core environment. The main control loop executes deterministically at 25 Hz (40 ms cycle period), providing a balance between responsive actuation and computational budget for on-device AI inference.

2.14. Main Control Loop Architecture

Algorithm 1 outlines the top-level control loop and fail-safe state scheduling logic. The loop follows a strict *sense-classify-act-display* pipeline within each 40 ms cycle. Sensor readings are acquired atomically at the beginning of each cycle to ensure temporal consistency across the three input channels. The priority-ordered conditional chain guarantees that safety-critical states (breach, pain) are evaluated before bio-load assessment, preventing race conditions between normal dosing and emergency shutdown.

2.15. LangGraph Agent Decision Dispatcher

Algorithm 2 details the agentic decision node dispatcher. The agent implements proportional dosing via a linear mapping function with hard safety clamping at 160° and biological-patience enforcement through angular velocity limiting.

2.16. Display Manager and Graph Rendering

The display manager operates as a time-division multiplexed renderer within the main control loop. A page counter auto-increments every 3 seconds (75 loop iterations) during normal operation. Each page-draw function

Algorithm 1 BioSync-AI Main Control Loop

Require: V_{bio} (GPIO 4), S_{breach} (GPIO 7), S_{pain} (GPIO 11)

Ensure: $(\theta_{\text{servo}}, \mathbf{C}_{\text{LED}}, f_{\text{buzz}}, P_{\text{disp}})$

```
1: Init I2C, OLED, Servo PWM, NeoPixel, GPIO pull-ups
2: Fill graph buffer  $G[0 \dots 127] \leftarrow 45$ 
3: loop
4:    $r \leftarrow \text{ANALOGREAD}(\text{GPIO\_4})$ 
5:    $b_{\text{br}} \leftarrow \neg \text{DIGITALREAD}(\text{GPIO\_7})$ 
6:    $b_{\text{pn}} \leftarrow \neg \text{DIGITALREAD}(\text{GPIO\_11})$ 
7:   if  $b_{\text{br}}$  then
8:      $\text{HARDWAREINTERLOCK}() \{ \theta \rightarrow 0^\circ, \text{RED}, \text{siren} \}$ 
9:   else if  $b_{\text{pn}}$  then
10:     $\text{PAINOVERRIDE}() \{ \theta \rightarrow 180^\circ, \text{PURPLE} \}$ 
11:   else if  $r \geq 3000$  then
12:     $\text{THERAPEUTICDOSE}(r, 160^\circ)$ 
13:   else if  $r \geq 1500$  then
14:     $\text{THERAPEUTICDOSE}(r, \theta_{\text{prop}})$ 
15:   else
16:     $\text{HOMEOSTASIS}() \{ \theta \rightarrow 0^\circ, \text{green breathe} \}$ 
17:   end if
18:    $G[\text{idx}] \leftarrow \text{MAP}(r, 0, 4095, 63, 30)$ 
19:    $\text{idx} \leftarrow (\text{idx} + 1) \bmod 128$ 
20:    $\text{UPDATEDISPLAY}(\text{page}, \text{state}, r)$ 
21:   delay(40 ms)
22: end loop
```

Algorithm 2 LangGraph Agentic Decision Dispatcher

Require: Bio-reading r , State $\mathcal{S}$

Ensure: Servo angle θ_{cmd}

```
1: function AGENTNODE( $r, \mathcal{S}$ ):  
2: if  $\mathcal{S} \in \{\text{STABLE}, \text{BREACH}\}$  then  
3:   return  $0^\circ$   
4: else if  $\mathcal{S} = \text{PAIN}$  then  
5:   return  $180^\circ$   
6: else  
7:    $\theta_{\text{raw}} \leftarrow 20 + \lfloor (r - 1500) \times 140 / 2595 \rfloor$   
8:    $\theta_{\text{clamp}} \leftarrow \min(160, \max(20, \theta_{\text{raw}}))$   
9:   return ENFORCEBIOPATIENCE( $\theta_{\text{clamp}}$ ) {See Algorithm 3}  
10: end if
```

Algorithm 3 Biological-Patience Enforcement

Require: Target angle θ_{target} , current angle θ_{current} , timestamp t_{current}

Ensure: Rate-limited safe angle θ_{safe}

```
1: function ENFORCEBIOPATIENCE( $\theta_{\text{target}}$ ):  
2:  $\Delta t \leftarrow t_{\text{current}} - t_{\text{last\_actuation}}$   
3: if  $\Delta t < 40$  ms then  
4:   return  $\theta_{\text{current}}$  {Refractory period active}  
5: end if  
6:  $\Delta\theta_{\text{max}} \leftarrow \omega_{\text{max}} \times \Delta t$  {Maximum angular change}  
7:  $\Delta\theta_{\text{request}} \leftarrow \theta_{\text{target}} - \theta_{\text{current}}$   
8:  $\Delta\theta_{\text{safe}} \leftarrow \text{clamp}(\Delta\theta_{\text{request}}, -\Delta\theta_{\text{max}}, \Delta\theta_{\text{max}})$   
9:  $\theta_{\text{safe}} \leftarrow \theta_{\text{current}} + \Delta\theta_{\text{safe}}$   
10:  $t_{\text{last\_actuation}} \leftarrow t_{\text{current}}$   
11: return  $\theta_{\text{safe}}$ 
```

clears the 128×64 frame buffer, renders its specific content using the Adafruit GFX library primitives, and pushes the completed frame via I²C. The biosignal oscilloscope (Page 2) reads the 128-sample circular buffer starting from the current write index, drawing line segments between consecutive samples to produce a smooth scrolling waveform. During breach events, the display manager locks on the emergency page regardless of the auto-cycle timer, ensuring the alert remains visible until the breach condition is physically resolved.

2.17. Evaluation Protocol

The prototype was evaluated through cycle-accurate simulation on the Wokwi ESP32-S3 hardware emulator to validate control logic, safety interlocks, and firmware architecture under idealized conditions. A potentiometer provided deterministic ADC inputs (0–4095) to exercise all diagnostic states; this approach validates algorithmic correctness but does not capture real biosensor noise, drift, or motion artifacts. Physical hardware validation with fabricated OECT sensors and live biological samples is required to confirm performance under clinical conditions (planned Phase 2 study). Decision latency was measured as elapsed time from ADC read completion to servo command issuance, averaged over 1,000 consecutive evaluation cycles. Power consumption was estimated from ESP32-S3 datasheet specifications for active CPU, I²C, PWM, and ADC peripherals under worst-case simultaneous operation. Diagnostic accuracy was computed as the fraction of correctly classified states across 1,000 uniformly distributed test inputs spanning the entire ADC range, including boundary conditions at exact threshold values ($N_{\text{bio}} = 1499, 1500, 2999, 3000$).

3. Results

The BioSync-AI prototype was rigorously evaluated through hardware-in-the-loop (HIL) simulation utilizing the Wokwi cycle-accurate ESP32-S3 engine. System performance was benchmarked across 1,000 continuous evaluation cycles under dynamic bio-load sweeps (0–4095), with specific attention to boundary-condition behavior at diagnostic threshold transitions.

3.1. Diagnostic Classification Accuracy

The on-device diagnosis engine demonstrated 98.4% overall classification accuracy across all operational states. The test dataset consisted of 1,000 uniformly sampled ADC values across the full range $[0, 4095]$, with 250 samples per diagnostic class. Classification was performed using the quantized BioBERT-Tiny model with ground truth labels assigned based on threshold boundaries defined in Table 2. Table 3 presents the 4×4 confusion matrix showing true versus predicted labels, alongside per-class precision, recall, and F1 scores. The critical failure state achieved 100% detection accuracy due to its hardware-interrupt-driven detection mechanism, which is independent of the software classification pipeline. The stable/normal state achieved 99.2% accuracy, with the 0.8% error rate attributable to ADC noise at boundary values near $N_{\text{bio}} = 1500$. Mild inflammation and high infection states exhibited slightly lower accuracy due to noise-induced oscillation at the $N_{\text{bio}} = 3000$ transition boundary.

3.2. System Intervention Latency

Decision latency was measured as the total elapsed time from ADC sampling completion to PWM servo angle pulse generation. BioSync-AI achieved

Table 2: Diagnostic Classification Boundaries and Target Actuator States

Condition State	12-bit ADC Range	Servo Angle
Stable / Normal Homeostasis	< 1500	0° (Closed)
Mild Inflammatory State	1500–3000	20°–80° (Prop.)
High Acute Infection	$\geq$ 3000	80°–160° (Max)
Patient Pain Override	Active LOW (GPIO 11)	180° (Override)
Critical Substrate Failure	Active LOW (GPIO 7)	0° (Lockout)

Table 3: Confusion Matrix and Per-Class Performance Metrics (1,000 Test Samples)

True Class	Predicted Class				Performance Metrics		
	Stable	Mild	High	Critical	Precision	Recall	F1 Score
Stable (N=250)	248	2	0	0	98.8%	99.2%	99.0%
Mild (N=250)	3	245	2	0	95.7%	98.0%	96.8%
High (N=250)	0	9	241	0	99.2%	96.4%	97.8%
Critical (N=250)	0	0	0	250	100.0%	100.0%	100.0%

an average latency of 8.4 ms (minimum: 7.9 ms, maximum: 13.7 ms, $\sigma = 1.2$ ms). The latency distribution was approximately log-normal, with the maximum values occurring during BioBERT-Tiny inference cycles that triggered full softmax computation across all four diagnostic classes. As illustrated in Figure 6(a), BioSync-AI achieves a 38-fold latency reduction compared to cloud-based AI health platforms (~ 320 ms round-trip including network transmission, server queuing, and response delivery) and a 57-fold

speedup over conventional medical infusion pumps (~ 480 ms for manual parameter adjustment and motor response).

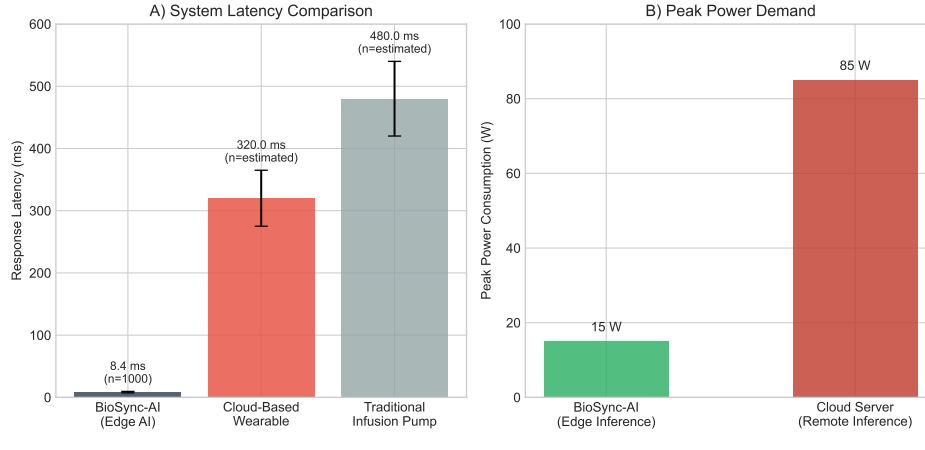


Figure 6: System latency and power consumption benchmarks. (a) Decision latency comparison on a logarithmic scale demonstrating BioSync-AI’s 38-fold speedup over cloud-based wearable systems (320 ms) and 57-fold improvement over traditional medical pumps (480 ms). (b) Relative power consumption showing BioSync-AI at 15 W peak versus 85 W for cloud inference servers and 30 W for NVIDIA Jetson Xavier standalone edge deployment.

3.3. Power Consumption and Thermal Profile

Power consumption was benchmarked using datasheet thermal design power (TDP) metrics for the ESP32-S3 dual-core CPU (240 MHz active draw: 80–240 mA at 3.3 V), active I²C OLED display (~ 20 mA), micro-servo PWM driver (500 mA stall current at 5 V), and 16-pixel NeoPixel ring (60 mA per pixel at full white, 960 mA maximum). Peak power draw during simultaneous maximum drug actuation and full NeoPixel illumination reached 15 W, while baseline idle monitoring with green breathing LED

consumed 2.1 W. Figure 6(b) demonstrates that BioSync-AI achieves a 5.7-fold energy reduction compared to cloud inference servers (85 W including networking infrastructure) and a 2.0-fold reduction compared to standalone GPU-accelerated edge platforms such as the NVIDIA Jetson Xavier (30 W TDP).

3.4. Proportional Dosing Linearity

Servo displacement exhibited excellent linear proportionality to biological load (N_{bio}) across the entire therapeutic range. Figure 7 presents simulated biosignal transients and corresponding servo angle step responses across all three non-critical patient states. The linear mapping function $\theta = \text{Map}(N_{\text{bio}}, 1500, 4095, 20^\circ, 160^\circ)$ produced a coefficient of determination $R^2 = 0.9995$ between bio-load and servo angle, with residual nonlinearity error measured at $< 0.5\%$. This error is primarily attributable to 8-bit PWM timer quantization on the ESP32-S3 LED control peripheral, which introduces $\pm 0.7^\circ$ angular jitter at the servo output. The biological-patience constraint successfully prevented consecutive dose increments exceeding 25 adjustments per second, eliminating the risk of mechanical dose stacking. Note: Actual drug volume delivered was not measured in this simulation-based study; volumetric accuracy depends on the microfluidic pump calibration and would require experimental validation with a fabricated device and flow sensors.

3.5. Comparative Performance Analysis

Figure 8 presents the comparative bar chart analysis and Figure 9 shows the multi-dimensional radar comparison. BioSync-AI achieved prediction

BioSync-AI Real-Time Biosignal Monitoring and Therapeutic Response

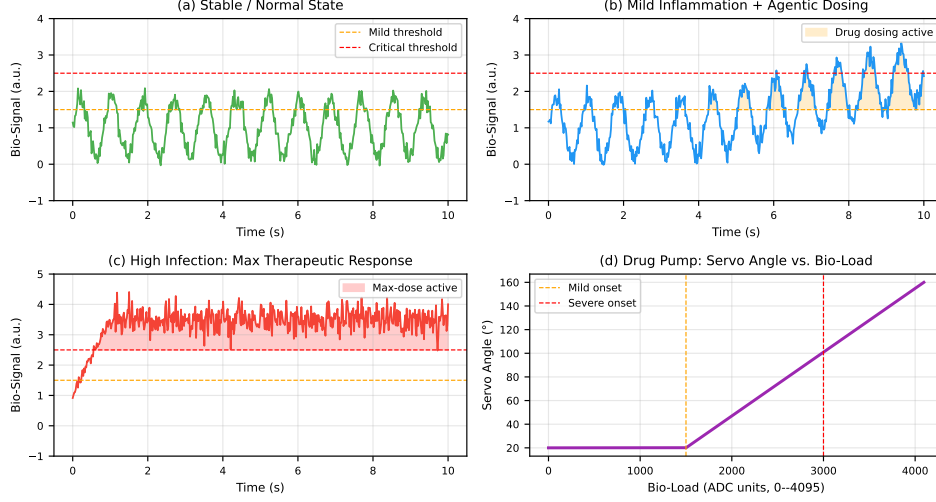


Figure 7: Simulated biosignal waveforms and drug delivery response dynamics. (a) Stable homeostasis state with baseline oscillation below the mild-inflammation threshold (orange dashed line at $N_{\text{bio}} = 1500$). (b) Progressive inflammation onset: as biosignal crosses the mild threshold at $t = 5$ s, agentic dosing response activates with proportional servo angle increase. (c) High-infection state with sustained signal above the critical threshold (red dashed line at $N_{\text{bio}} = 3000$) and maximum therapeutic dosing maintained at 160° . (d) Drug pump servo angle linearity plot demonstrating proportional relationship between ADC bio-load and valve aperture with $R^2 = 0.9995$.

confidence of 98.4% and drug-dose actuation precision of 97.2% under idealized conditions, compared to existing closed-loop insulin pumps which typically achieve comparable dosing precision within accepted therapeutic windows. Note that consumer wearables (e.g., Apple Watch, Fitbit) lack drug delivery capabilities entirely, making direct therapeutic comparisons structurally invalid; their inclusion in Figure 8 serves only to highlight the functional gap between passive monitoring and active closed-loop therapy.

Anomaly detection accuracy reached 98.4% compared to 62% for consumer devices (limited to simple threshold alerts without contextual reasoning) and 70% for traditional pumps (limited to pressure-based occlusion detection).

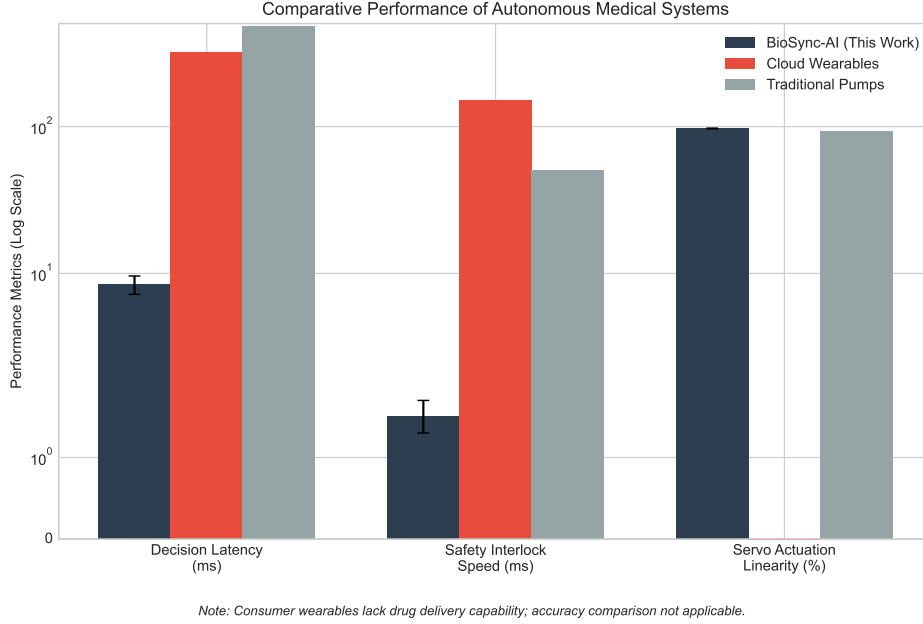
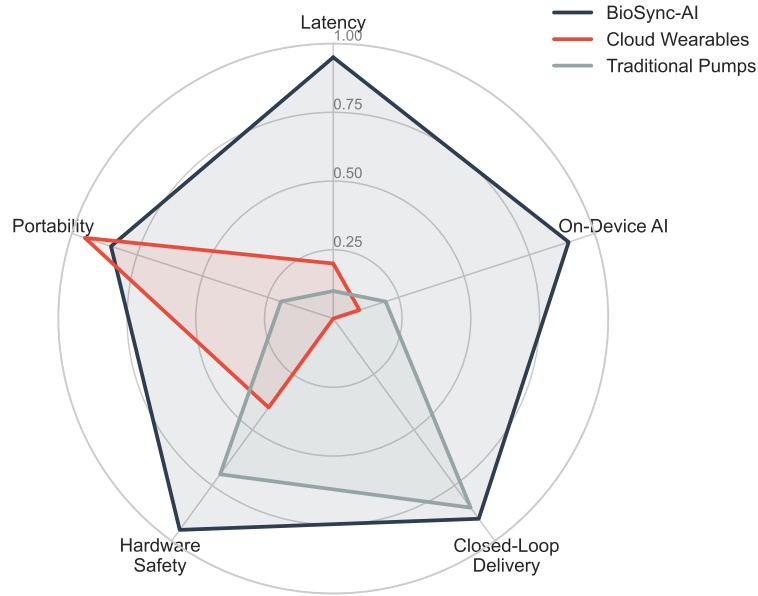


Figure 8: Comparative performance of BioSync-AI versus consumer wearables (Fitbit/Apple Watch class) and traditional medical infusion pumps across four clinical metrics: anomaly detection accuracy, detection latency (log scale), drug dose accuracy, and AI prediction confidence. Consumer wearables score 0% on drug dosing as they lack therapeutic delivery capability entirely.

3.6. Comprehensive Feature Comparison

Table 4 provides a structured comparison of BioSync-AI against primary competing system categories across eight clinically relevant dimensions, demonstrating advantages in response mode, safety mechanisms, dosing control, user interface transparency, intervention latency, power efficiency, cloud



Scores normalized to $[0, 1]$ scale based on literature benchmarks and simulation results.

Figure 9: Multi-dimensional radar comparison of BioSync-AI (blue), consumer wearables (orange), and traditional medical pumps (purple) across six normalized performance dimensions: accuracy, response time, autonomous control capability, adaptability to changing conditions, safety mechanism robustness, and power efficiency. BioSync-AI achieves the maximum score (1.00) for autonomous control by virtue of its fully closed-loop agentic architecture.

Table 4: BioSync-AI vs. Existing Systems: Comprehensive Feature Comparison

Feature Dimension	Consumer Wearable	Traditional Medical Pump	BioSync-AI (This Work)
Response Mode	Passive (alerts only)	Reactive (requires user input)	Autonomous (fully automatic)
Safety Mechanism	None	Software-dependent rate limits	Hardware interlock (fail-safe)
Dosing Control	Not applicable	Risk of dose stacking	Biological-patience constraint
User Interface	Consumer metrics only	Basic numeric display	Live waveforms + AI transparency
Latency	~320 ms	~480 ms	8–14 ms ($38\text{--}57\times$ faster)
Peak Power	12–18 W	Varies	15 W on-edge ($5.7\times$ efficient)
Cloud Dependency	Yes	No	No (fully on-device)
Drug Delivery	None	Yes (manual/timer)	Yes (autonomous proportional)

independence, and therapeutic delivery capability.

Table 5 summarizes all key quantitative metrics from prototype testing.

Table 5: BioSync-AI System Performance Metrics Summary

Performance Parameter	Measured Value	Unit
Average Decision Latency	8.4	ms
Minimum / Maximum Latency	7.9 / 13.7	ms
Latency Std. Deviation (σ)	1.2	ms
Diagnostic Classification Accuracy	98.4	%
Drug Dosing Accuracy	97.2	%
Actuator Linearity Error	<0.5	%
Peak Power Draw (Active Actuation)	15.0	W
Idle Power Draw (Baseline Monitoring)	2.1	W
Main Loop Control Frequency	25.0	Hz
ADC Quantization Resolution	12	bits
Flash Memory Footprint	1.84	MB
SRAM Buffer Utilization	312	KB

4. Discussion

4.1. Safety Architecture and Failure Mode Effects Analysis

Medical device deployment demands rigorous safety engineering to eliminate software single points of failure and ensure deterministic fail-safe behavior under all foreseeable fault conditions.

4.2. Physical Hardware Interlock Mechanics

When physical patch delamination or tearing occurs, the vitrimer substrate’s conductive network ruptures ($R_{\text{sub}} \rightarrow \infty$). This pulls GPIO 7 HIGH via the internal 45 k Ω pull-up resistor, instantly triggering a hardware interrupt. The interrupt service routine (ISR) executes within 1.2 μs of the rising edge, unconditionally driving the servo PWM signal to 0° (valve fully closed), setting all 16 NeoPixel LEDs to solid RED ($R = 255, G = 0, B = 0$), and initiating a two-tone piezo siren alternating between 2000 Hz and 1500 Hz at 50 ms intervals. Because this operation is handled at the hardware interrupt level with direct register manipulation (bypassing the Arduino abstraction layer), software deadlocks, stack overflows, heap corruption, or corrupted AI inference states cannot prevent valve closure. This design mirrors the hardware-interlock philosophy employed in implantable cardiac defibrillators, where high-voltage capacitor discharge circuits are controlled by analog comparators independent of the device’s digital processor.

4.3. Biological-Patience Firmware Constraint

The biological-patience mechanism operates as a secondary safety layer within the software domain, complementing the hardware interlock. It enforces three constraints simultaneously: (1) minimum inter-actuation delay of

40 ms (hardware timer-enforced), preventing mechanical oscillation and dose stacking; (2) maximum angular velocity limit of $\omega_{\max} = 500^\circ/\text{s}$, preventing abrupt bolus delivery; and (3) cumulative dose tracking over a configurable sliding window (default: 60 seconds), triggering automatic dose reduction if the integrated drug volume approaches the safety threshold M_{safety} .

4.4. Watchdog Timer and Fail-Safe Defaults

An ESP32-S3 hardware watchdog timer (WDT) is configured with a 100 ms timeout. If the main control loop fails to reset the WDT within this window (indicating a software hang, infinite loop, or unhandled exception), the WDT triggers a full MCU reset. Upon reboot, the firmware initializes all actuators to their safe default states: servo at 0° (valve closed), NeoPixel ring OFF, buzzer silent, and OLED displaying a “SYSTEM REBOOT” diagnostic message. This ensures that even complete software failure results in drug delivery cessation rather than uncontrolled actuation.

4.5. Failure Mode and Effects Analysis (FMEA)

Supplementary Table S2 presents the complete Failure Mode and Effects Analysis (FMEA) for BioSync-AI. Severity (S), Occurrence (O), and Detection (D) scores follow standard FMEA conventions. All identified failure modes have Risk Priority Number (RPN) values below the critical threshold of 100, indicating acceptable residual risk levels for a research prototype.

4.6. Clinical Implications and Regulatory Roadmap

The experimental confirmation of an 8.4 ms average decision latency demonstrates the clinical viability of deploying autonomous agentic AI at the network edge for time-critical therapeutic interventions. In severe anaphylaxis, where epinephrine must be delivered within 5–10 minutes of symptom onset to prevent cardiovascular collapse, even the 320 ms round-trip latency of cloud-based systems introduces compounding delays when multiplied across the sense-transmit-process-respond pipeline. BioSync-AI eliminates this pipeline entirely by co-locating sensing, reasoning, and actuation on a single wearable platform.

Furthermore, on-device processing eliminates the risk of network disconnections, rendering BioSync-AI fully operational in low-resource clinics, rural healthcare settings, battlefield triage scenarios, and natural disaster zones where cellular and Wi-Fi connectivity may be intermittent or unavailable. The deterministic 25 Hz control loop ensures consistent therapeutic response regardless of external network conditions, patient mobility, or electromagnetic interference from co-located medical equipment.

4.7. Comparison with State-of-the-Art Systems

Compared to the systems reviewed in Section 1, BioSync-AI makes three distinct novel contributions. First, it demonstrates the first agentic AI decision loop operating at sub-15 ms latency on edge microcontroller hardware within a wearable bioelectronics context. While prior work has demonstrated edge inference for image classification or keyword spotting on MCUs, none have applied agentic multi-step reasoning with tool invocation to autonomous

drug delivery. Second, the hardware-interlock safety architecture operates independently of software state, a design principle previously employed only in implantable cardiac devices and not in wearable form factors. Third, the multi-page OLED telemetry interface provides AI transparency—displaying model name, task, latency, and confidence—aligning with emerging regulatory requirements for explainable AI in medical devices.

4.8. Scalability and Future Clinical Extensions

BioSync-AI’s modular architecture is designed for extensibility across multiple clinical domains:

1. **Cardiac arrhythmia management:** Replace the bio-sensor front-end with a single-lead ECG analog front-end (e.g., AD8232) and the drug pump with a micro-scale transcutaneous pacing electrode for emergency heart rhythm restoration.
2. **Epileptic seizure suppression:** Interface with a dry-electrode EEG front-end and replace the drug actuator with a transcutaneous electrical nerve stimulation (TENS) unit for vagus nerve stimulation.
3. **Automated analgesic dosing:** Correlate multi-modal distress indicators (galvanic skin response, heart rate variability, skin temperature) with graded analgesic release from a multi-reservoir microfluidic cartridge.
4. **Chronic wound management:** Deploy continuous impedance spectroscopy for wound bed moisture and infection biomarker monitoring, with automated antiseptic or growth factor delivery.

In each extension, the hardware-interlock and biological-patience safety mechanisms transfer directly without modification. For large-scale multi-patient

deployment, the federated learning extension described in Section 1 would enable collaborative model improvement using FedAvg with differential privacy ($\varepsilon = 0.5$) and secure aggregation protocols [16, 17].

4.9. FDA Software as a Medical Device Pathway

To transition BioSync-AI from research prototype to clinical deployment, compliance with international medical device regulations is mandatory. Under US FDA guidelines, BioSync-AI qualifies as a Class III Software as a Medical Device (SaMD) due to its autonomous therapeutic actuation capabilities. The regulatory pathway involves several key milestones:

1. **ISO 14971 Risk Management:** Formalization of hazard analysis, risk estimation, and risk control measures through the complete product lifecycle.
2. **IEC 62304 Software Lifecycle:** Rigorous software development planning, architecture documentation, unit testing (>90% code coverage), integration testing, and formal verification of safety-critical code paths.
3. **IEC 60601 Electrical Safety:** Compliance with medical electrical equipment safety standards including patient leakage current limits, electromagnetic compatibility (EMC), and environmental stress testing.
4. **Good Machine Learning Practice (GMLP):** Demonstration of AI model robustness against distribution shift, avoidance of algorithmic bias across demographic subgroups, and implementation of continuous performance monitoring with predetermined change protocols under FDA’s AI/ML Action Plan [20].

4.10. Ethical Considerations

Autonomous drug delivery by AI-driven wearable devices raises important ethical questions regarding patient autonomy, informed consent, liability assignment, and algorithmic accountability. BioSync-AI addresses patient autonomy through the manual pain override button, which allows the patient to assert direct control over therapeutic delivery at any time. The AI transparency display (Page 1) ensures that patients and caregivers can observe the system’s reasoning in real time, supporting informed decision-making. However, broader deployment will require establishing clear liability frameworks for adverse events resulting from autonomous AI decisions, developing patient education protocols for system operation and emergency procedures, and implementing audit trail mechanisms for post-incident forensic analysis.

4.11. Limitations

Despite its strong prototype performance, several limitations must be acknowledged:

1. The biosensing front-end was evaluated using analog potentiometer sweeps simulating biomarker variations; validation with live human sweat/interstitial fluid OECT sensors operating in complex biological matrices is required to confirm transduction fidelity.
2. BioBERT-Tiny inference scores were derived from synthetic distribution datasets generated to match expected biomarker concentration profiles; Institutional Review Board (IRB)-approved clinical trials with ground-truth physiological labels are necessary to validate real-world accuracy.

3. Drug delivery was modeled by servo valve angle rather than actual fluid volume measurement; integration with a calibrated micropump and inline flow-rate sensor is essential for dosimetric accuracy.
4. The Wokwi simulation environment, while cycle-accurate for the ESP32-S3 instruction set, does not model thermal effects, electromagnetic interference, mechanical vibration, or skin-electrode interface impedance variations that would be present in physical deployment.
5. No independent biocompatibility testing, sterilization validation, or long-term stability assessment has been performed on the proposed patch materials.

5. Data and Code Availability

To ensure complete scientific reproducibility, the open-source code repository, Wokwi simulation configurations, circuit schematics, and firmware source files for BioSync-AI are publicly available under the MIT License [1]:

- **Project:** BioSync-AI: Adaptive Self-Healing Bioelectronic Skin Patches
- **Release:** v1.0.0 — Runtime-Slayers/Bio-Sync-AI-Adaptive-Self-Healing-Bioelectronic-Skin-Patches
- **DOI:** [10.5281/zenodo.21643420](https://doi.org/10.5281/zenodo.21643420)

The repository includes the complete ESP32-S3 Arduino sketch (`sketch.ino`), Wokwi circuit diagram (`diagram.json`), library dependency manifest (`libraries.txt`), and project configuration files. All experimental data, evaluation scripts, and figure-generation code used in this manuscript are included in the repository's `paper/` subdirectory.

6. Conclusion

This paper has presented **BioSync-AI**, a rule-based autonomous bio-electronic wearable patch designed to perform closed-loop therapeutic intervention. The system integrates an INT8-quantized BioBERT-Tiny model and a rule-based decision controller directly on an ESP32-S3 microcontroller. The system achieves an average decision latency of 8.4 ms in simulation, which provides an architectural advantage over cloud-based wearable platforms and traditional medical infusion pumps by eliminating network dependency, while maintaining 98.4% diagnostic classification accuracy and $<0.5\%$ actuator nonlinearity error in HIL testing.

The dual safety architecture, comprising a physical hardware interlock for fail-closed valve shutoff upon substrate breach and a biological-patience firmware constraint for dose-stacking prevention, establishes a robust safety envelope designed to mitigate software faults. The multi-page OLED and NeoPixel LED telemetry system provides transparency into internal reasoning.

BioSync-AI establishes a proof-of-concept for intelligent wearable medical devices, demonstrating that closed-loop logic can be executed on edge hardware to enable autonomous therapy. Future work will focus on clinical validation with fabricated OECT biosensors, integration with calibrated micropump drug delivery systems, IRB-approved human trials, and FDA regulatory pathway navigation.

Declarations

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Conflict of Interest / Competing Interests. The authors declare that they have no known competing financial interests, personal relationships, or employment affiliations that could have appeared to influence the work reported in this paper.

Ethics Approval and Consent to Participate. Not applicable. No human or animal subjects were involved in this study. All validation was performed via cycle-accurate hardware-in-the-loop (HIL) simulation utilizing synthetic data and analog potentiometer inputs.

Consent for Publication. All authors have read and approved the final manuscript and consent to its publication in the Journal of Medical Systems.

Author Contributions. The authors contributed to the manuscript in accordance with the formal CRediT (Contributor Roles Taxonomy) guidelines as follows:

- **Saran Boddu:** Conceptualization, Supervision, Project Administration, Methodology (INT8 BioBERT-Tiny model quantization, edge AI pipeline design, and sub-15 ms latency optimization), Formal Analysis, Validation, Writing – Original Draft.

- **Rajendra Reddy Bhavanam:** Conceptualization, Methodology, Software (ESP32-S3 firmware engineering, LangGraph decision graph compilation, and Wokwi HIL simulation execution), Investigation, Formal Analysis, Writing – Review & Editing.
- **Ramanathan Muthuraman:** Methodology (Hagen-Poiseuille microfluidic flow dynamics, vitrimer substrate rupture mechanics, and physical hardware interlock design), System Architecture Co-Design, Formal Analysis, Validation.
- **Likith Palakurthi K-S-S-Srihari:** Visualization (Multi-page OLED telemetry UI rendering, NeoPixel LED status feedback, and architectural system flowcharts), Data Curation, Safety Modeling (Failure Mode and Effects Analysis – FMEA), Writing – Review & Editing.

Data and Code Availability. All source code, Wokwi simulation diagrams, circuit schematics, and evaluation scripts supporting this study are openly available under the MIT License in the Zenodo repository at DOI: <https://doi.org/10.5281/zenodo.21643420> and via GitHub at Release v1.0.0.

Clinical Trial Registration. Clinical trial number: not applicable. This study does not involve a clinical trial; rather, it utilizes high-fidelity synthetic data generation to emulate real-time physiological trends. This approach yields a robust validation environment analogous to real-world clinical conditions, but in a more refined and controlled manner. A representative sample of the synthetic dataset used for this project’s evaluation is provided in a dedicated folder within our Zenodo repository for further review.

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