

# VersaSens: An Extendable Multimodal Platform for Next-Generation Edge-AI Wearables

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**Abstract**—The transition of healthcare towards digitalization is closely related to the advancement of health-related technologies, including wearable sensors and edge computing. In this paper, we present VersaSens, a versatile and customizable platform concept and its real implementation as a tool to boost research in wearable sensors. The platform embodies the core attributes of the VersaSens concept: versatility, flexibility, and extendability across multiple aspects of hardware, software, and processing components. It features a modular design, consisting of sensor, processor, and co-processor modules, allowing for various configurations. To evaluate the efficiency of the platform, we tested three use cases: cough monitoring, heartbeat classification and epileptic seizure detection. In all cases, the results indicate that the platform effectively executes the applications, achieving low energy consumption. In particular, our findings indicate that the integration of a domain-specific edge-AI co-processor [i.e., HEEPocrates (Machetti et al., 2024)] equipped with several hardware accelerators further improved the overall execution time and energy consumption of the system. These results demonstrate the potential of VersaSens to effectively support a diverse range of edge-AI applications and configurations, thereby providing a robust foundation for the research and development of novel smart wearable sensor systems.

**Index Terms**—Modular platform, multimodal bio-signals, next generation edge-AI, smart wearable sensors, deep learning, HEEPocrates, heterogeneous processor.

## I. INTRODUCTION

IN 2020, the World Health Organization (WHO) introduced the global digital health strategy 2020-2025 [2], which advocates the integration of digital information and communication technologies into healthcare systems worldwide with the aim of enhancing global health outcomes. The objective of this strategy is to facilitate a transition in healthcare towards the implementation of digital solutions that are accessible, affordable, and sustainable. Furthermore, the strategy emphasizes the adoption of cutting-edge technologies such as the Internet of Things (IoT), Artificial Intelligence (AI), and smart wearables to improve medical diagnosis and treatment through data-driven approaches. Currently, despite the WHO digital health strategy, healthcare systems in most countries remain largely traditional. In contrast, AI has experienced rapid growth. To harness the benefits of AI in healthcare and bridge this gap, it is of paramount importance to conduct adequate research and development of cutting-edge infrastructure and medical instruments to enable the next-generation of smart and edge-AI wearables. For example, the development of custom hardware for smart sensors, capable of running sophisticated AI models, can facilitate a range of digital healthcare needs, including the processing of large amounts of data, the provision of virtual care [3], and the monitoring of patients remotely. Such facilities can ensure equitable access to healthcare for people of all sex, race and community worldwide. In addition, the processing results of medical data driven by AI and Machine Learning (ML) approaches on the edge, accessible to individuals, can democratize healthcare information. This empowers the user to actively participate in personalized treatment and preventive measures. Moreover, wearable edge-AI technologies have the potential to optimize medical care by moving away from a one-size-fits-all approach to personalized [4] and precision [5] medicine.

However, in contrast to software, the development of hardware is a time-consuming, less flexible, and an expensive process. While debugging software typically involves identifying and correcting errors in the code, hardware errors often necessitate significant changes, such as redoing the printed circuit board (PCB) or ordering new components. These changes can

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take weeks or even months to implement. Consequently, for the rapid advancement of research and development in the field of hardware, in particular edge-AI technologies, the implementation of flexible and modular hardware can play an essential role. This approach allows modules to be developed and upgraded independently of one another, thereby reducing the risk of disruption to the rest of the system when a module is found to have an issue or requires an upgrade.

In light of the evolution of wearable sensor technology and the importance of their rapid advancement for digital health, in addition to the considerations mentioned above, further challenges must be addressed. The design of wearable sensors must take into account the need for compactness, safety, and comfort of wear. The necessity of continuous health monitoring implies prolonged contact between the sensor and the body. Thus, comfort, robustness, and biocompatibility are requirements to ensure the long-term use of the hardware.

In addition, wearable sensors should be energy efficient while maintaining high functionality. In the literature, it is common to adopt different strategies in sleep and idle modes to reduce system consumption during low-operation instances [6], [7]. However, in accordance with the purpose and the application of the system, it is necessary to determine the optimal trade-off between energy consumption and functionality. To identify such trade-offs during the research and development of such devices, it is essential to have the flexibility to alter and assess key parameters such as the supply range and execution frequency [8]. Furthermore, integrating multiple bio-signal modalities enhances the robustness, reliability and accuracy of the derived outcomes [9].

This paper introduces VersaSens, a novel versatile and extendable platform designed to build edge-AI wearable systems in a wide range of multimodal applications. The platform addresses the aforementioned challenges by incorporating the principles of modularity, flexibility, and expandability at various levels. This approach provides a solid foundation for adapting, enhancing, and scaling hardware to keep up with advancements in AI technology. On this basis, the VersaSens platform consists of sensor and processing modules, each equipped with Flexible Flat Cable (FFC) and USB-C connectors. Communication between modules occurs through a dedicated bus that supports various standard interface protocols. The modules are compact and can be stacked horizontally, vertically, or at varying distances from each other. The platform offers the flexibility to create singular and multimodal sensors using available acoustic, bio-potential, bio-impedance, temperature, optical, and inertial sensors. Additionally, unlike any other state-of-the-art platform, VersaSens offers the possibility to be expanded with ultra-low-power AI co-processor modules. This enables efficient real-time execution of complex AI models directly at the edge. To illustrate this capability, three use cases are presented and their results are evaluated.

In summary, our main contributions can be listed as follows:

- The introduction of the novel concept of VersaSens, for the advancement in the field of edge-AI smart wearable sensors, facilitating the integration of cutting-edge deep learning (DL) models.

- The first realization of the VersaSens concept is presented. It showcases the modularity, flexibility, and expandability features of the VersaSens concept through the development of modular processor and sensor units. These features enable the creation of numerous wearable sensors tailored to specific application needs with diverse compositions, including both compact and distributed configurations. In addition, the platform supports rapid prototyping and allows for the integration of custom-designed modules.
- Enabling seamless integration of application-specific edge-AI accelerator, as well as other sensing and storage modules, within the VersaSens platform. This allows the conception of advanced multi-layer SoCs equipped with hardware accelerator units.
- Incorporating variable voltage and frequency features for co-processor to facilitate research on functionality and power consumption trade-offs.

The paper is structured as follows: Section II presents an overview of other platforms in the literature, with a comparison to VersaSens. Section III details the first version of the VersaSens platform hardware, software stack, and operating modes. Section IV illustrates three distinct VersaSens configurations and presents analysis of their usability. In Section V, we provide three case studies of cough frequency monitoring, heartbeat classification, and real-time epileptic seizure detection using a VersaSens platform configurations. Finally, Section VI offers our conclusions.

## II. RELATED WORKS

Recent advances in wearable sensor platforms have led to a significant diversification of their applications, ranging from health monitoring to educational tools [10], [11], [12], [13], [14], [15], [16], [17]. This section compares several leading platforms in the state-of-the-art targeting a multimodal concept and modular implementation. The unique contributions and technological orientations within the healthcare field are highlighted and analyzed based on the comparison shown in Table I.

### A. Research-Based Platforms

Research-based platforms have been pivotal in the advancement of the field of wearable sensor technology, offering innovative solutions that address a wide variety of scientific and medical applications. These platforms are usually designed to enhance precision, flexibility, and scalability in biomedical signal processing, enabling extensive research possibilities. Generally, there are two main types of platforms: those that target a multimodal concept, which integrates many different sensors, and those that target a unimodal concept, which focuses on a specific type of modality. For instance, in the former category, the authors in [18] introduced the Mobile Modular Multimodal Biosignal Acquisition (M3BA) platform. It provided a highly miniaturized design and integrated different sensors to acquire distinct modalities such as biopotential, biooptical, and body movement signals. Notable for its modularity, M3BA allowed

TABLE I  
COMPARISON OF LEADING PLATFORMS IN MULTIMODAL AND MODULAR WEARABLE SENSOR TECHNOLOGY

Platform	Type	Extendability	Modular Design	User-Friendly	Low Cost	Wide Sensor Support	AI Capabilities	Rapid Prototyping
M3BA	Research-based	✓	✓	✗	✗	✓	✗	✗
Amulet	Research-based	✓	✗	✗	✗	✓	✗	✗
MBioTracker	Research-based	✓	✓	✗	✗	✓	✗	✗
BioWolf	Research-based	✗	✗	✗	✗	✗	✗	✗
BITalino	Research-based	✗	✓	✓	✓	✓	✗	✓
Shimmer3	Commercial	✗	✓	✗	✗	✗	✗	✗
BioSignalsPlux <sup>®</sup>	Commercial	✗	✓	✓	✗	✓	✗	✗
BioHarness by Zephyr <sup>®</sup>	Commercial	✗	✗	✓	✗	✗	✗	✗
VersaSens	Proposed system	✓	✓	✓	✓	✓	✓	✓

flexible integration into different mechanical setups and head-and-body gears. Although M3BA was a novel highly customizable mobile architecture, the system was module-centric, i.e., the main module was the one integrating the sensors in the same PCB. Due to the latter fact, when it is desired to expand and add additional modules or sensors, the main module had to be replicated. Additionally, ensuring secure data transmission and storage is a significant concern for M3BA due to the variety of sensitive biosignals it handles, which are not addressed in its work. Note that the latter fact is mainly driven as this type of platforms and devices handle sensitive personal data, necessitating robust security measures to protect user privacy and ensure application integrity. Finally, no advanced AI co-processor is present in this platform, hindering the implementation and efficient deployment of any DL model.

In this context, the Amulet platform should also be mentioned [6]. It offered an energy-efficient, multi-application wearable platform designed for long battery life and robust application support. It included an ultra-low-power hardware architecture and a companion software framework, enabling the development of energy-efficient applications. The platform supported a variety of internal and external sensors and aimed to balance long battery life with the flexibility and programmability of a smartwatch. However, the need for strong security properties and app isolation in such a platform adds complexity to its design and usage. Furthermore, the MBioTracker platform [19] represents another significant innovation in research-based wearable systems. MBioTracker was designed for online cognitive workload monitoring and integrated multiple physiological signal acquisition channels, such as respiration cycles, heart rate, skin temperature, and pulse waveform. It featured a low-power processing platform and employed energy-sensitive biosignal processing algorithms, demonstrating the potential for extended battery life and efficient data processing. However, the complexity of the system and the need for careful calibration of its self-aware monitoring approach may present challenges to broader applicability and ease of use. Moreover, it presents the same module-centric issues and lacks AI co-processor capabilities, similar to the M3BA.

In contrast to the multimodal concept followed by the latter platforms, unimodal examples can be found. For example, the authors in [10] presented BioWolf. This platform features a nine-core processor optimized for ultra low power consumption while maintaining high accuracy and reliability in electroencephalogram (EEG) based monitoring systems. Although they achieved a highly wearable system, their main focus was

solely on brain computer interfaces, which limited the range of possible applications. In fact, the authors acknowledged this latter fact and the platform was further improved in BioWolf16 [20]. The new version offered a 16-channel, 24-bit, 4kSPS ultra-low power platform for wearable clinical-grade bio-potential parallel processing and streaming. This advancement significantly enhanced its capabilities for clinical-grade applications, maintaining ultra-low power consumption while increasing the number of channels and improving data precision and streaming capabilities. However, no further modifications were made to include more modalities or even to attach external co-processors to offload AI workloads. Unlike the platforms previously discussed, security considerations for BioWolf and BioWolf16 include ensuring the integrity and confidentiality of the EEG data, which is critical for both clinical and research purposes.

Overall, these types of platform pose a valuable potential towards modularity and flexibility; however, the complexity of their setup and integration may imply challenges for novice users. Moreover, their higher cost compared to simpler research-educational platforms might be a limiting factor. For example, BITalino is renowned for its accessibility and flexibility, particularly within research and educational contexts [11]. It provides an entry point for students and novices to explore biomedical signal processing. Although BITalino lacks the processing power and specialized capabilities of more advanced platforms, it remains a valuable tool for basic signal acquisition purposes. This platform supports various types of biosignal, making it a versatile option for a wearable proof-of-concept. However, its capacity to interface seamlessly with external co-processors is limited compared to more advanced platforms.

## B. Commercial Platforms

Commercial platforms have also made significant strides in wearable sensor technology, focusing on providing robust and reliable solutions for clinical and research applications. These platforms are designed to offer high precision, user-friendly interfaces, and extensive support for various sensor types, making them suitable for practical, real-world applications. They emphasize reliability, ease of use, and broad applicability, often providing comprehensive frameworks that facilitate data acquisition and analysis. For instance, Shimmer3 [12] is widely valued in clinical and sports science research for its precision and reliability in biophysical and kinematic data capture. This platform offers robust frameworks for biosignal processing, making it ideal for clinical research applications. However,

TABLE II  
CURRENT MODULES AND MODALITIES AVAILABLE IN VERSASENS

Module	Type	Modality	Signal Range	Resolution Bits
Main	Processor & Sensor	3-axis accelerometer	$\pm 8g$	12
		3-axis gyroscope	$\pm 2000 (^{\circ}/s)$	16
ExG	Sensor (8 channels)	EEG	$\pm 4/Gain(4, 6, 8, 12)(V)$	24
		ECG		
		EMG		
EDA	Sensor (1 channel)	ECG	$\pm 1/Gain(20, 40, 80, 160)(mV)$	18
		GSR/EDA	0 - 2 ( $M\Omega$ )	20
		RSP		
Heart	Sensor (1 channel)	ECG	$\pm 100(mV)$	18
		GSR/EDA	0 - 100 ( $M\Omega$ )	20
		RSP		
		PPG	530 ,655 ,940 (Green, Red, Infrared) ( $nm$ )	20
		SKT	0 - 70 ( $^{\circ}C$ )	16
		Acoustic sensor	27 - 27k( $Hz$ )	-
HEEPO	Co-Processor	-	-	-

while Shimmer3 offers substantial hardware flexibility, it primarily supports specific sensors designed for its ecosystem and does not explicitly support seamless interfacing with external co-processors, which limits its adaptability in some scenarios. In addition, its higher cost and technical complexity may require advanced technical skills for installation and operation. Similarly, BioSignalsPlux<sup>®</sup> [21] provides a comprehensive framework designed for versatility and ease of use in research and development settings. Supporting a wide range of sensors, the platform offers flexibility in data acquisition and analysis, making it a user-friendly option for research applications. Another example in the commercial category is BioHarness by Zephyr<sup>®</sup> [22]. This is a comprehensive wearable sensor platform that monitors various physiological parameters, including heart rate, respiration rate, posture, activity level, and skin temperature. It is widely used in both sports science and clinical research to monitor performance and health. The platform is designed to provide real-time data, which is crucial for applications that require continuous monitoring of physiological signals. However, as for the rest of the commercial available platforms, the substantial hardware flexibility in terms of the physiological parameters it can monitor, is primarily optimized for use with its own proprietary sensors.

The comparative analysis of these commercial platforms underscores their contributions to the field of wearable technology. Additionally, being commercially oriented leads to ensuring robust security measures, which is essential across all of them to protect sensitive data and maintain the integrity and confidentiality of the collected information. However, they all share common drawbacks. For instance, the reliance on proprietary sensors and ecosystems or their cost. These can potentially posing a barrier for widespread adoption in resource-constrained environments. Moreover, the complexity of the setup for some of them can also be a challenge.

As a result of the previously discussed platforms found in the literature, this work presents VersaSens, which emerges as a particularly innovative platform trying to address the limitations found in both research- and commercial-grade systems. Designed with a focus on modularity and rapid customization, which is crucial to explore various design spaces in the

integration of wearable technology. This platform allows for easy integration of a diverse array of sensors and co-processors through its modular design, facilitating efficient real-time data acquisition, processing and DL execution. In fact, the AI empowerment of VersaSens, attributable to its capacity to interface with deeply heterogeneous co-processors, positions it uniquely for applications demanding high computational power and real-time responsiveness.

### III. PLATFORM DESCRIPTION

This section outlines the VersaSens platform<sup>1</sup> and describes the first version of the realized hardware modules in Section III-A, discusses the software stack including the firmware architecture and operating system in Section III-B, and operating modes in Section III-C.

#### A. Hardware

VersaSens is a platform for the development of wearable sensors. It is modular and in its current representation consists of five individual sensor and processing modules, namely: Main, Heart, ExG, EDA, and HEEPO. The modalities included in each module, along with their respective signal ranges and resolutions, are detailed in Table II.

All sensor modules and the Main module are equipped with FFC and USB-C connectors, allowing communication through a dedicated bus called Sensor Bus (S-Bus). The co-processor module, on the other hand, communicates exclusively with the main module and is equipped only with FFC connectors. Another dedicated bus, the Processor Bus (P-Bus), facilitates communication between the processors. S-Bus supports numerous communication interfaces, including Serial Peripheral Interface (SPI), Inter-Integrated Circuit (I2C), Pulse Density Modulation (PDM), and General-Purpose Input/Output (GPIO) for digital and analog signals, as well as a 3.3V power supply and ground. Similarly, P-Bus includes SPI, I2C and GPIOs, along with 3.3V

<sup>1</sup>All information regarding the VersaSens platform can be found on its website at: <https://www.epfl.ch/labs/esl/research/smart-wearables/versasens/>

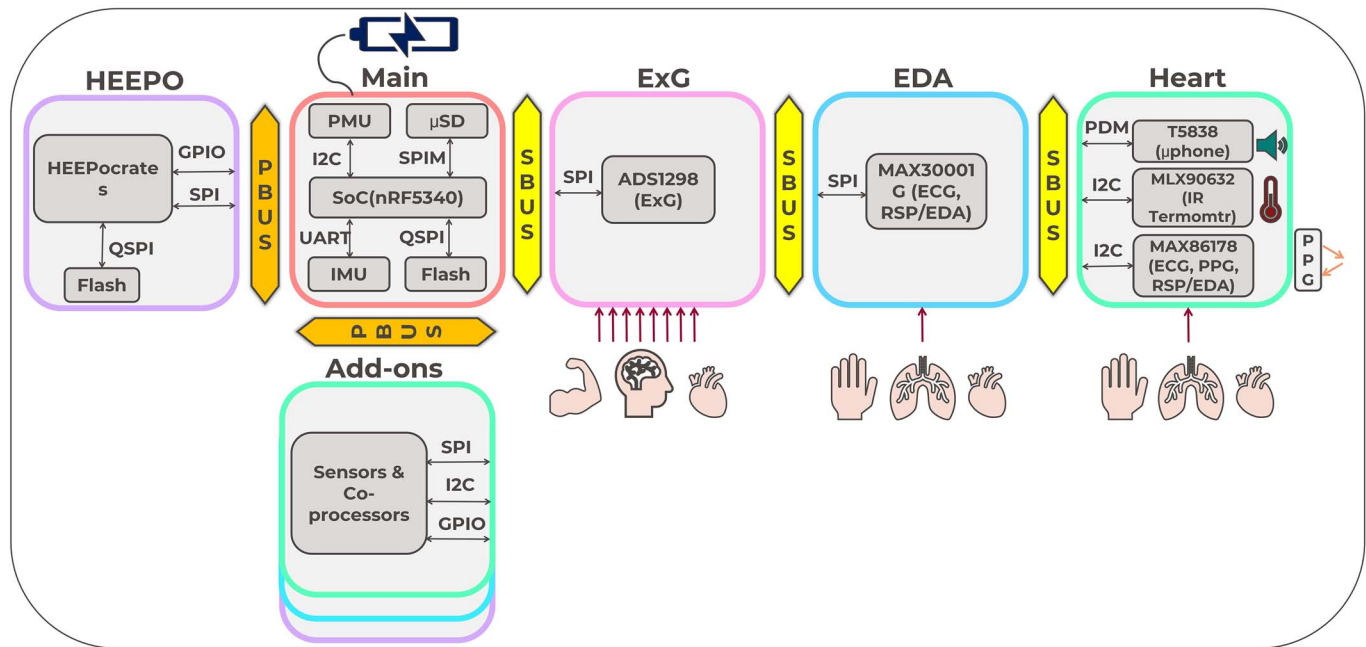


Fig. 1. VersaSens platform overview.

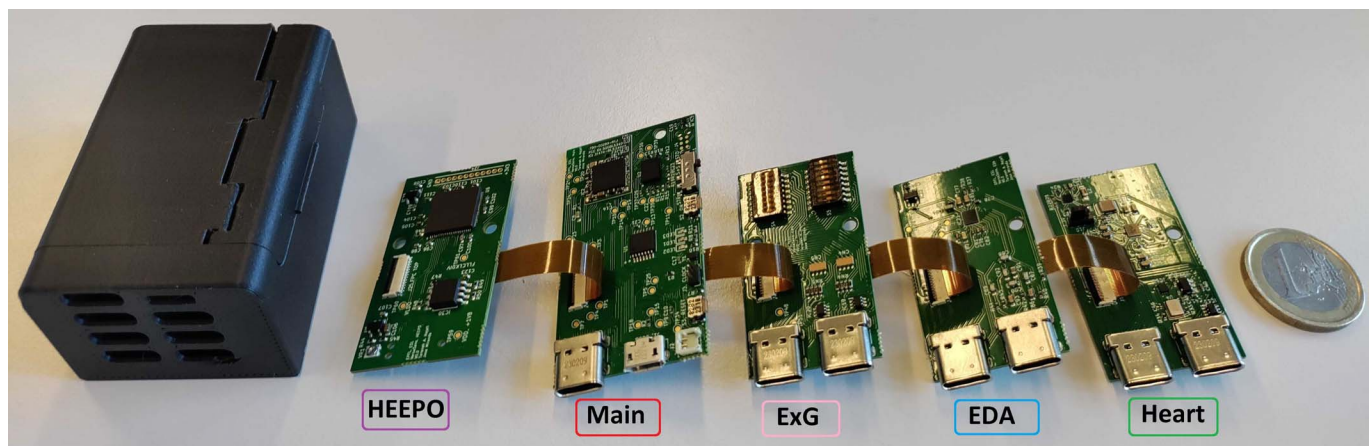


Fig. 2. VersaSens modules stacked with FFC for a compact configuration.

and ground connections. A block diagram of the platform is provided in Fig. 1.

The inclusion of buses, FFC connectors, and USB-C connectors allows modules to be arranged in various configurations. Additionally, these features allow the platform to be extendable, facilitating the integration of both off-the-shelf and custom-designed sensor or co-processor modules. The add-on modules, as illustrated in Fig. 1, can utilize any of the aforementioned interfaces on the S-Bus or P-Bus to communicate with the main module. Both busses are accessible through FFC connectors and USB-C ports.

All modules are designed on a four-layer PCB system. The Main module has a PCB dimensions of 30x55x0.8 mm<sup>3</sup>, while all the other boards have a PCB dimensions of 25x45x0.8 mm<sup>3</sup>. The physical realization of all sensor, processor and

co-processor modules is illustrated in Fig. 2 demonstrating their interconnectivity through FFC. The detail description of all modules is provided in the subsequent sections.

1) *Main Module:* The Main module serves as the central unit of the platform, housing the main System-on-Chip (SoC) based on the nRF5340 from Nordic Semiconductor®. This high-performance, low-power solution features a dual-core Arm® Cortex-M33 architecture, comprising both application and network processors. The application core has digital signal processing (DSP) instructions and a floating point unit (FPU), operating at up to 128 MHz with 1 MB of flash memory and 512 kB of RAM. The network core is optimized for ultra-low power consumption, running at a fixed frequency of 64 MHz with 256 kB of flash memory and 64 kB of RAM. The SoC supports various interfaces, including SPI, I2C, Quad SPI,

PDM, and GPIOs, in addition to a wide range of wireless protocols such as Bluetooth Low Energy (BLE), Near Field Communication (NFC), and 2.4 GHz proprietary protocols.

In the current VersaSens setup, the SoC is responsible for power management, sensor configuration, signal acquisition, data synchronization, and storage in local memory. In communications with sensors and other auxiliary components, the SoC consistently functions as the master, collecting data from the slave devices. However, in communication with the co-processor, the SoC operates as a slave, preparing data in a buffer at the required time intervals for the co-processor.

The Main module incorporates a Power Management Integrated Circuit (PMIC) utilizing the MAX77658B from Analog Devices®. This circuit is responsible for charging the battery and providing 1.8V and 3.3V power supplies from the battery. The PMIC communicates with the main SoC via I2C and GPIO interfaces.

The Main module also includes an Inertial Measurement Unit (IMU) employing the BNO086 from CEVA®, which consists of a three-axis accelerometer, gyroscope, and magnetometer. Currently, the IMU is configured to measure accelerations (X, Y, Z) and rotational angles (yaw, pitch, roll) thanks to the manufacturer's data fusion algorithms. The IMU communicates with the main SoC through a universal asynchronous receiver-transmitter (UART) interface.

For local storage, the board features an 8 G-bit flash memory utilizing the AS5F38G04SND from Alliance Memory®, and a micro Secure Digital (SD) card slot supporting various capacities. The flash memory and SD card communicate with the SoC through quad-SPI and fast SPI interfaces, respectively.

In addition, the module is equipped with reset and on-off buttons, an operating mode selector, and JTAG programmer connector pads. The on-off button controls the PMIC supply to the system. A reset signal, traveling through the S-Bus and P-Bus to all boards, can be initiated by the reset button, or the SoC.

To synchronize all sensors, the SoC provides a start signal to initiate sensor setup and acquisition. Furthermore, a 32.768kHz oscillator based on the SIT1533AI from SiTime®, provides a low-frequency clock for the sensors, distributed via the S-Bus to all peripheral modules.

2) *ExG Module*: The ExG is a sensor module that incorporates an eight-channel bio-potential analog front end (AFE) based on the ADS1298 from Texas Instruments®. This AFE can measure electrocardiogram (ECG), electromyogram (EMG), and EEG signals. It communicates with the main SoC via the SPI interface through the S-Bus. Additionally, the ExG module features two dip switches for selecting and deactivating channels. To acquire biopotential signals, the corresponding electrodes can be connected directly to the USB-C connector of the ExG module. For example, the spectrogram plot shown in Fig. 3 illustrates the EEG signals acquired by the ExG module from the location of the Fp1 electrode, according to the 10-20 system [23]. The signals were collected while a volunteer had their eyes open (exhibiting blinking) for the first half of the period, and then the eyes closed (showing Alpha waves) for the second half.

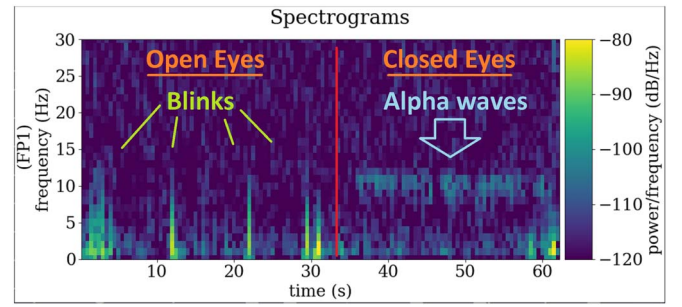


Fig. 3. EEG signal acquired from Fp1 channel during open and closed eyes.

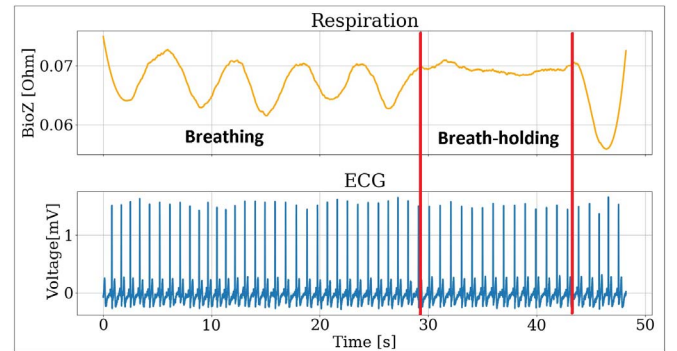


Fig. 4. Synchronized raw ECG and filtered RSP signals, acquired from the chest, using one differential channel, during breathing and breath-holding.

3) *EDA Module*: The EDA is a sensor module incorporating a bio-potential and bio-impedance AFE based on the MAX30001G. This AFE is capable of measuring electrodermal activity (EDA), galvanic skin resistance (GSR), respiration (RSP), and ECG signals using two leads. The module communicates with the main SoC via the SPI interface through the S-Bus. To acquire biopotential and bioimpedance signals, the corresponding electrodes can be directly connected to the USB-C connector of the EDA module. For instance, Synchronized ECG and RSP signals, acquired by the EDA module, are illustrated in Fig. 4. These signals were obtained from a volunteer using a single differential channel. Electrodes were positioned under the right clavicle and on the lower left abdomen to capture biopotential and bioimpedance signals during the phases of normal breathing and holding of breath.

4) *Heart Module*: The Heart module is a sensor module comprising three primary components. First, it includes a Microelectromechanical Systems (MEMS) microphone based on the T5838 from TDK®. This sensor communicates with the main SoC via the PDM interface through the S-Bus. Furthermore, the module has a contactless digital infrared thermometer based on the MLX90632 from Melexis®, which communicates with the main SoC using the I2C interface via the S-Bus.

Moreover, the Heart module incorporates an AFE for bio-impedance, bio-potential, and photoplethysmography (PPG) measurements, based on the MAX86178 from Analog Devices®. This AFE is capable of measuring ECG, RSP, or

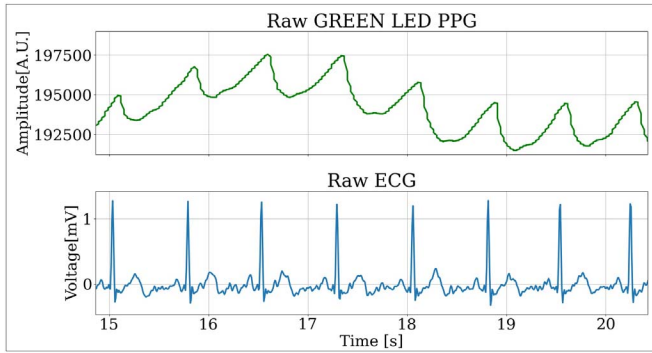


Fig. 5. Synchronized ECG and PPG signals, acquired from the chest, and finger, respectively.

EDA using two leads. It also supports up to six LEDs and four photodiodes for PPG measurements and communicates with the SoC via the I2C interface through the S-Bus.

To provide flexibility in the design and selection of LEDs and photodiodes for PPG measurements without necessitating alterations to the Heart module, an auxiliary module referred to as the PPG module was developed. This module is mounted via a stacking connector on the reverse side of the Heart module. In the current version of VersaSens, the PPG module features PCB dimensions of  $8 \times 11 \times 0.8 \text{ mm}^3$  and accommodates three LEDs (Greens, Red, Infrared), and one photodiode.

To acquire biopotential, bioimpedance signals, the corresponding electrodes can be connected directly to the USB-C connector of the Heart module. For the acquisition of biooptical signals the PPG module must be positioned in close proximity to the body. As an illustration, Fig. 5 presents the synchronized ECG and green LED PPG signals captured by the Heart module. The ECG signals were acquired using two electrodes, one positioned under the right clavicle and the other on the lower left abdomen. The PPG signals, also illustrated in the figure, were collected from the index finger.

5) *HEEPO Module*: The HEEPO is a co-processor module that incorporates the HEEPocrates SoC [1], specifically designed for ultra-low-power healthcare applications based on the X-HEEP platform [24]. HEEPocrates integrates both a Coarse-Grained Reconfigurable Array (CGRA) accelerator [25] and an In-Memory Computing (IMC) accelerator [26], both recognized for their efficiency in reducing overall energy consumption in healthcare applications. HEEPocrates operates within a high-frequency, low-voltage range, achieving 170 MHz at 0.8V and 470 MHz at 1.2V. The SoC features the CV32E20 core, eight SRAM banks, a fully connected bus, and a wide array of peripherals, including SPI, I2C, UART, and GPIOs.

On the HEEPO module, the voltage of HEEPocrates can be adjusted for various applications via an adjustable Low Dropout Regulator (LDO) based on the TLV75801PDBV from Texas Instruments®. This LDO provides a voltage range from 0.6V to 1.2V, adjustable through a potentiometer. Additionally, an external clock generator with a frequency of 32.768 kHz feeds the internal Frequency Locked Loop (FLL) of the SoC, facilitating the generation of the system clock, which can be configured by

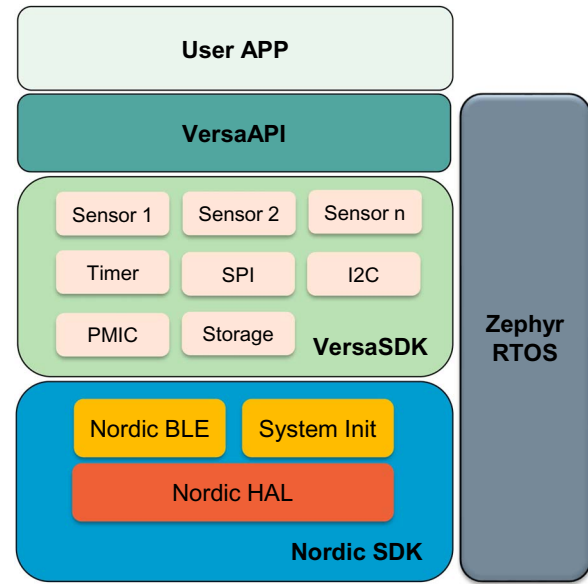


Fig. 6. Software stack of the VersaSens platform, showcasing its modular and layered architecture.

the main SoC. These features collectively offer significant flexibility in optimizing voltage and frequency parameters, thereby enhancing power efficiency across different operational states, including data acquisition and idle modes.

HEEPocrates interfaces with the main SoC via SPI interface through the P-Bus, operating as the SPI master. It receives the necessary signals collected by the main SoC at specific time intervals, facilitating higher-level processing tasks, including complex machine and deep learning training and inference. This configuration, coupled with the high-performance attributes of HEEPocrates, enables it to function effectively as a co-processor, thereby enhancing the AI capabilities of the VersaSens system.

## B. Software Stack

VersaSens, in addition to its hardware expandability features a flexible and easy-to-extend software stack architecture, Fig. 6. The firmware design allows researchers and developers to seamlessly interface with different peripherals. Moreover, the upper layers of the software stack enable the integration and execution in real-time of advanced deep learning models through and by the attached heterogeneous co-processor modules, facilitating complex data analysis and real-time decision-making.

The firmware and operational framework of the VersaSens platform are designed to emphasize its core attributes of flexibility, modularity, and efficient performance, essential for deploying effective wearable sensor platforms across various applications. Specifically, VersaSens utilizes a robust firmware architecture designed to accommodate a modular approach, enabling seamless integration and interchangeability of sensor modules. This architecture facilitates the plug-and-play functionality of sensors, where adding or swapping sensors can be done without disrupting the overall system operations.

This structured approach ensures that VersaSens is highly adaptable and capable of supporting a wide range of bio-signal processing applications. The main layers in the architecture are described as follows:

- **User APP.** This is where end-user applications are developed. This layer interacts directly with the second one, the *VersaAPI*, to utilize the underlying functionalities provided by the firmware.
- **VersaAPI.** This specific layer serves as a crucial interface, exposing the necessary functionalities to the *User APP* layer. It provides a set of APIs to interact with sensors, handle data processing, and manage system resources.
- **VersaSDK.** This is a key part of the architecture. It includes development tools and libraries specific to VersaSens, enabling developers to build applications and firmware optimized for the platform. This layer also implements various peripherals and low-level functionalities, including analog and digital interfaces with sensors and co-processors. In addition, power supply orchestration for the attached modules and flash data storage and retrieval are also managed in this layer.
- **Nordic SDK.** This last layer represents the hardware abstraction layer for the SoC of the Main Module. It includes libraries, drivers, and tools necessary for developing applications on Nordic System on Chip (SoC). Key components within this layer include, in particular, Bluetooth management and System Init functionalities. Specifically, for the first VersaSens realization presented in this work, this layer includes Nordic SDK and HAL related functions, provided by Nordic Semiconductor.
- **Zephyr RTOS.** This cross-cutting layer is a real-time operating system that provides foundational services for task scheduling, interrupt handling, and resource management. This layer deals with the entire firmware architecture and ensures robust and efficient system performance.

Moreover, recognizing the importance of security, especially in handling sensitive health data, the current software stack also employs stringent encryption protocols for data at rest and in transit. It supports secure, over-the-air firmware updates, allowing for seamless enhancements to its functionalities and security features without compromising user data or device integrity.

### C. Operating Modes

VersaSens is designed to operate in three distinct modes: idle, storage, and storage-stream. These modes are selectable via a selector located on the Main board. In idle mode, the main SoC minimizes power consumption by shutting down the supply to peripheral modules and entering sleep mode, with operations limited to battery charging. When storing mode is selected, the SoC wakes up, powers peripheral modules, sends a start signal to all sensor modules, and begins collecting sensor data without real-time transmission. The collected signals are stored locally on one of the available onboard storage devices. The data throughput is contingent upon the number of sensor modalities and the acquisition frequency, which can vary

depending on the application. For example, employing all the modalities presented in the current version of VersaSens at common acquisition frequencies results in a data throughput of 21,364 bytes per second. At this rate, it would take over 13 hours of continuous data recording to fill the 8 G-bit flash memory available on the main board.

In storage-stream mode, the system not only collects and stores data locally but also enables real-time data transmission via a BLE communication network. Although this mode increases power consumption, it facilitates real-time monitoring and immediate data access. These operating modes offer flexibility in resource usage, particularly in power management, allowing the user to switch to a less active mode when certain features are not needed. The battery life duration depends on the selected operating mode, the number and types of sensor modalities, and can vary depending on the application. For example, utilizing all the presented modalities in the current version of VersaSens and operating the sensor in storage-stream mode, a 420mAh battery can last up to 10 hours, resulting in a total average power consumption of approximately 42mA.

## IV. SENSOR CONFIGURATIONS AND USABILITY ANALYSIS

The platform was designed to ensure that the sensors are light, compact, and easy to use. Various sensor compositions can be configured from the VersaSens platform, with different battery size, depending on the application of interest. Thanks to the FFC connectors and the dedicated buses, modules can be stacked horizontally, vertically, or in a combination of both within single or separate enclosures. In addition, USB-C connectors allow modules to be placed at a distance from each other in separate enclosures. Finally, the BLE capability of the platform allows real-time communication with other devices (e.g., smartphones, tablets, laptops, or even other VersaSens units). The aforementioned features offer flexibility and ease in the usage of the platform and provide an adequate tool for prototyping new generations of wearable sensors. Although numerous configurations are possible, this section describes three examples of configurations: compact, shoulder-distributed, and wrist configurations. The open-source repository of VersaSens can be found at <https://github.com/esl-epfl/VersaSens>. It contains all the files and information required to replicate the described VersaSens platform. In particular, it includes the PCBs layout, SoC software, and 3D models for the enclosures of all three configurations.

1) *Compact Configuration:* In the proposed compact configuration, illustrated in Fig. 7, an enclosure with dimensions of 40x60x30 mm<sup>3</sup> can accommodate all modules and a 750 mAh battery, weighing a total of 50 grams. After being interconnected via FFC, all modules can be easily inserted into the enclosure. The enclosure can be made of biocompatible polymers (e.g., Polylactic acid or Polyamide 12) and coated with skin-safe silicon rubber (e.g., Dragonskin™), ensuring optimal safety and comfort during daily use and clinical trials. The compact configuration can be worn on various parts of the body, including the chest, arm, shoulder, and neck, by using straps or medical adhesive patches (e.g., 3M 1577 or 3M 1522).



Fig. 7. Compact configuration.



Fig. 8. Distributed shoulder configuration.

2) *Distributed Configuration:* In the proposed shoulder distributed configuration, shown in Fig. 8, three separate cases are designed to accommodate the Main and ExG modules in the red enclosure placed on the back of the neck, the Heart module in the green enclosure positioned on the left side of the chest, and the EDA module and the battery in the blue enclosure located on the right side of the chest. In this configuration, the Main and ExG modules are interconnected via FFC due to their shared enclosure, while the Heart and EDA modules, which are placed at a distance, are connected to the Main and ExG modules via USB-C cables. Furthermore, the ExG module is connected via USB-C to a headband embedded with up to eight electrodes to collect cortical brain activity. The dimensions are  $34 \times 60 \times 18 \text{ mm}^3$  for the red casing and  $27 \times 50 \times 13 \text{ mm}^3$  for both the green and blue casing. All cases are secured with a U-shaped skin-safe silicone rubber (Dragonskin™) with increased tackiness to minimize movement artifacts for various sensors. as an alternative implementation option for rapid prototyping and testing, silicone can be replaced by adhesive patches.

3) *Wrist Configuration:* In the proposed wrist configuration, shown in Fig. 9, a unique enclosure accommodates both vertical and horizontal modules arrangements. The Main and HEEPO modules are vertically stacked in the upper section of the wrist within the red compartment of the case. The ExG module, intended for measuring EMG signals from the arm, is housed in the pink compartment behind the Main module, along with the battery. The Heart module, intended for PPG measurements from the wrist, is positioned on the inner side of the wrist in the green compartment. In this configuration, the Main and Heart modules are interconnected via FFC, while the Heart and



Fig. 9. Wrist configuration.

ExG modules are connected by a USB-C cable. The enclosure is shaped as a bracelet and can be adjusted to fit various wrist sizes or placed on other body parts, such as the upper arm or ankle.

## V. EXPERIMENTAL SETUP AND RESULTS

This section presents the deployment of three different health-related use cases on our platform with a specific configuration. First, a cough-frequency monitoring application [27] to detect and identify cough events in real-time by relying on the joint usage of two AI models. Second, a heartbeat classifier is evaluated, relying on a machine learning pipeline to accurately identify and classify heartbeats [28]. Finally, a seizure detection model is evaluated based on a complex deep learning model designed to detect seizure events with high precision and sensitivity [29], [30].

As already mentioned, the physiological acquisition is orchestrated by the Main module of VersaSense. For the initial application, algorithmic computations are also conducted within this Main module. For the subsequent two applications, the processing workloads are entirely performed by the co-processor SoC, i.e. the HEEPO module porting HEEPOcrates in this case.

Regarding the VersaSense multi-board system configuration, the necessary modules per application were stacked vertically and enclosed in a casing along with a battery. The cough frequency monitoring case used the Main and Heart modules, while the other two cases required the Main, HEEPO, and ExG modules. For these applications, high-tack skin-safe silicone allows the frame to be placed directly on the chest and neck, as illustrated in Figs. 10(a) and 10(b). In the heartbeat monitoring scenario, the electrodes are in contact with the skin on each side of the apparatus. For the seizure detection scenario, electrodes are mounted on a headband. Specifically, a 1-lead ECG is utilized for the heartbeat classification application, while a bipolar montage (F7, T7, F8, and T8) is employed for the seizure detection use case.



Fig. 10. Sensor configurations for the health-related use cases reported: (a) Cough frequency monitoring and heartbeat classifier configurations, which relies on machine learning algorithms to detect cough events and classify heartbeats respectively, and (b) Seizure detection configuration, which uses a complex deep learning model to detect seizure events.

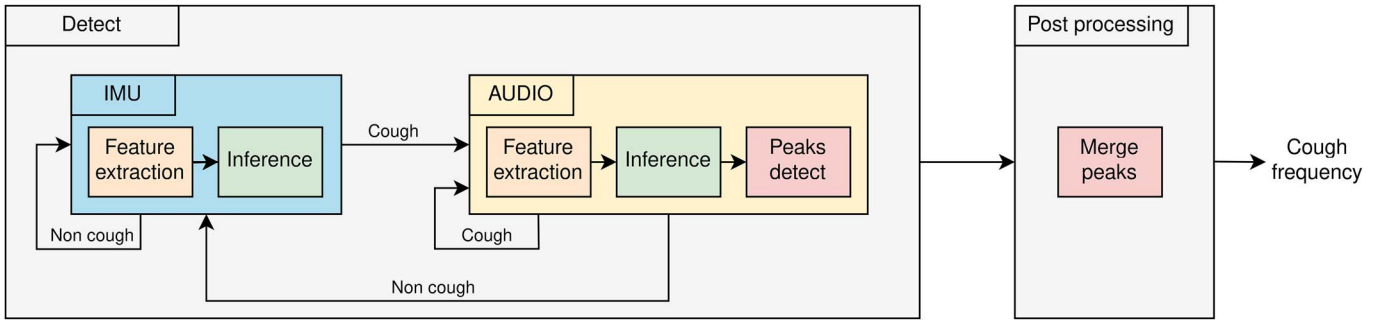


Fig. 11. Cough frequency monitoring application flow.

### A. Cough Frequency Monitoring

The first use case focuses on a cough-frequency monitoring application, leveraging machine learning capabilities on two distinct modalities, specifically audio and kinematic signals captured from a microphone and an inertial measurement unit (IMU). Both sensors are placed on the chest. Two distinct XGB (eXtreme Gradient Boosting) models are used, one per modality, to exploit the different information carried by each signal. Both are trained to detect cough events from their input data.

The training and testing were performed on a multimodal dataset for cough detection [27]. Data were collected from 20 healthy subjects (10 males, 10 females; age  $26.5 \pm 6.5$  years) during sitting and walking activities while being exposed to different environmental noises (silent, traffic, music, and bystander cough), and while performing different sounds (coughing, laughing, deep breathing, and throat clearing). This provides a wide variety of data to allow the final models to be robust for deployment in real-life scenarios.

Fig. 11 shows the main phases of the algorithm, namely the detection and post-processing phases, and their flow. The detection phase is based on the cooperation of the two classifiers. In particular, the kinematic-based one will serve as a trigger for the acoustic-based one, executed only when a cough event is

TABLE III  
ENERGY CONSUMPTION OF THE MAIN PROCESSOR FOR ONE CLASSIFICATION WINDOW OR IMU-BASED MODEL (0.5s) AND AUDIO-BASED MODEL (0.8s) FOR COUGH FREQUENCY MONITORING

Parameter		Processing	Deep Sleep
Duration	IMU	11 ms	489 ms
	Audio	114 ms	686 ms
Power consumption	IMU	27.7 mW	9.05 $\mu$ W
	Audio	30.3 mW	
Voltage		3.3 V	3.3 V
Frequency		128 MHz	32 KHz
Energy consumption	IMU	0.30 mJ	4.42 $\mu$ J
	Audio	3.45 mJ	6.2 $\mu$ J
Total energy		IMU	<b>0.31 mJ</b>
		Audio	<b>3.51 mJ</b>

identified. The switch from one model to the other will solely depends on the output of the current classification. For both models, feature extraction and inference are executed. Different sets of features are extracted from the audio signal from both the time and frequency domains, yielding intense computations. In contrast, for the IMU signals only time domain features are computed. After the inference phase, a post-processing routine is implemented. This accumulates information about the

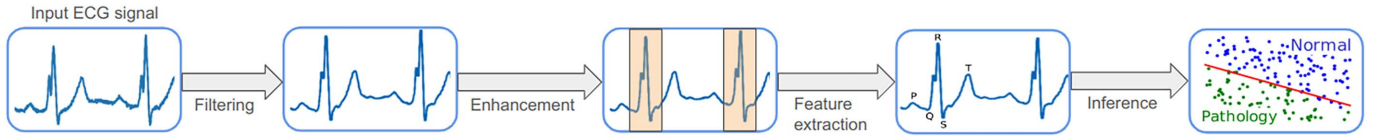


Fig. 12. HBC application phases.

identified cough positions to provide the final frequency estimation over a selected time frame. This application is a version of the algorithm presented in [27], which was originally achieving 91% of sensitivity, 92% of specificity, and 80% of precision.

The processing of the classifiers of the application is executed on the processor of the main module, running at 128 MHz. In both cases, the processor is active only during execution and enters deep sleep mode for the remaining of the window (0.5s and 0.8s for IMU and audio models, respectively). Table III reports average power and energy consumption of feature extraction and inference phases, measured during processing and deep sleep. The computations required by the IMU-based model can be terminated in 11ms over its window of 0.5s, allowing the processor to stay in deep sleep mode for 489ms. Given the average power consumption of 27.7 mW and  $9.05 \mu\text{W}$  during processing and sleep phases, the resulting energy consumption is 0.30 mJ and  $4.42 \mu\text{J}$ , respectively. Analogous behavior occurs for the audio-based classifier, which presents 114ms of execution time and 686ms of sleep time, yielding 3.45 mJ and  $6.2 \mu\text{J}$  of consumed energy. In both cases, the limited duty cycle and the energy-efficient sleep mode of the processor allow us to keep the total energy consumption at low values (0.31 mJ and 3.51 mJ for IMU and audio models, respectively). As for the peak identification and post-processing module, their measurements are not reported due to their negligible impact on the total energy, given their low computational complexity and the small amount of data they process.

### B. Heart Beat Classifier

As a second use case, we employed a comprehensive approach to heartbeat classification (HBC) based on advanced signal processing and machine learning techniques [28], Fig. 12. The algorithm pipeline leverages a modular design to optimize both performance and energy efficiency on ultra low power platforms. Specifically, ECG samples are captured during 12 seconds and then, the systems process them. The data processing is divided into four phases: filtering, enhancement, feature extraction, and inference. Once the ECG signal is acquired, it is filtered to remove unwanted noise using the morphological filter (MF), a technique that extracts the signal baseline based on the shape of the original signal and subsequently subtracts it. Initially utilized in image processing, this method has been adapted for use on single- or multi-lead ECGs in embedded systems. [31]. Then, the Relative Energy (Rel-En) [32] technique is used to extract the energy of specific windows of analysis to amplify the R peaks. Subsequently, the ECG delineation method is employed to extract features. A crucial part of this process is R peak detection, accomplished using the

TABLE IV  
ENERGY CONSUMPTION OF CO-PROCESSOR FOR ONE  
CLASSIFICATION WINDOW (12s) FOR HBC

Parameter	Processing	Deep Sleep
Duration	22 ms	11978 ms
Power Consumption	8.68 mW	0.29 mW
Voltage	830 mV	830 mV
Frequency	170 MHz	32 KHz
Energy Consumption	0.19 mJ	3.47 mJ
<b>Total Energy</b>		<b>3.66 mJ</b>

REWARD [32] algorithm. And the remaining fiducial points are delineated with a low-complexity method [33]. Finally, a neuro-fuzzy classifier [34] with 97% accuracy is employed to detect the abnormal beats.

To train and test the heartbeat classification model, we used the MIT-BIH Arrhythmia Database (MITDB) [35]. It contains 48 half-hour excerpts of two-channel ambulatory ECG recordings from 47 subjects. The dataset includes a wide variety of arrhythmias and provides a robust foundation for developing and validating the classifier.

The processing part of the application is executed on the HEEPocrates co-processor. Given that in this case, the described algorithms does not present a high complexity, no hardware accelerator available in HEEPocrates were really needed or employed. Furthermore, an optimal setting for voltage and frequency was selected based on previous research results [36]. Specifically, the co-processor runs at 170 MHz with a voltage of 830 mV while processing. For the 12-second window duration, the co-processor executes the application and enters deep sleep mode for the remainder of the time. The latter mode is achieved by power-gating the modules in the system and reducing the system frequency to the lowest feasible level, 32 KHz, to minimize both static and dynamic power consumption. The average power and energy consumption, and the corresponding voltage and frequency parameters for both processing and deep sleep conditions are outlined in Table IV.

The results show how during the processing phase, which lasts 22 milliseconds, the average power consumption is 8.68 mW, resulting in an energy consumption of 0.19 mJ. This brief duration of high activity ensures that computational tasks are completed quickly and efficiently, minimizing the time spent in the higher-power-consuming state. Once classification is complete, the co-processor transitions into a deep sleep state for the remaining time of the 12-second window (1978 ms), dramatically reducing power consumption to 0.29 mW. Despite the longer duration in this state, the energy consumption is kept low at 3.47 mJ, mainly due to the reduced power requirements. Summing up the energy consumption for both states, the

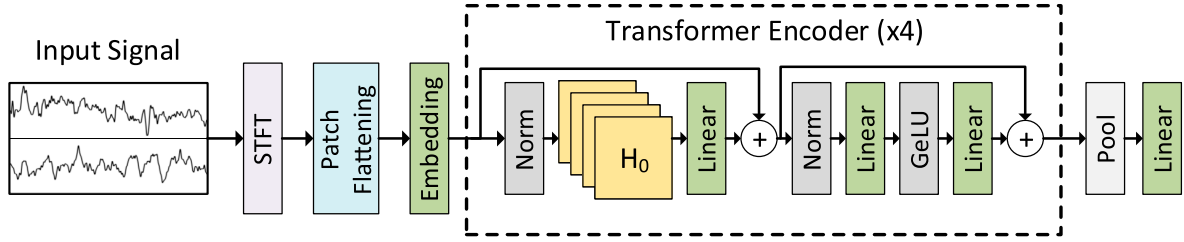


Fig. 13. Transformer model used for seizure detection.

total energy expenditure for the 12-second window amounts to 3.66 mJ. This demonstrates a highly efficient energy profile as most of the time is spent in a low-power state. The power-gating strategy and the possibility of selecting optimal voltage and frequency settings in the VersaSens platform play crucial roles in achieving this efficiency. Thus, in this case, by minimizing both static and dynamic power consumption, the co-processor is able to maintain prolonged operation without frequent recharging or battery replacement, which is critical for wearable health monitoring devices.

### C. Seizure Detection With Transformer

For this use case, a modified 4-layer VisionTransformer [37] specifically adapted for epileptic seizure detection [29], [30] serves as the core model. The transformation of each 12-seconds EEG segment through the Short-time Fourier Transform (STFT) extracts time-frequency features from each EEG channel, which are then treated as input images for the transformer encoder. A fully connected layer in the decoder compresses the output of the encoder to the necessary class dimensions. The preprocessing steps and the architecture of the model, key to understanding epilepsy detection, are illustrated in Fig. 13.

To train and test the model, we used the publicly available Temple University Hospital EEG Seizure Corpus (TUSZ)-v2.0.0 [38], which includes recordings from 675 individuals totaling 1476 hours. The dataset exhibits heterogeneity in sampling frequency. Thus, to achieve consistency, we resampled all recordings to 256 Hz, following the recommended practices [39].

As for the previous application, the Transformer architecture is executed on the HEEPocrates co-processor. While 16-bit fixed-point arithmetic is used for linear operations within the transformer, non-linear functions such as Softmax, Normalization, and GELU activation utilize a 32-bit floating-point unit. Moreover, we selected an optimal setting for the voltage and frequency as described in [36]. Specifically, the chosen configuration operates the co-processor at the highest frequency supported at the lowest voltage, i.e. 160 MHz with a voltage of 830 mV while processing. Similar to the HBC, once the classification is complete, the system transitions to the deep sleep mode until the next classification.

Finally, the performance of the model is evaluated using the AUC (Area Under the Curve) metric, which is recognized for its efficacy in binary classification tasks such as seizure

TABLE V  
ENERGY CONSUMPTION OF CO-PROCESSOR FOR ONE CLASSIFICATION WINDOW (12S) WITH AND WITHOUT CGRA

Parameter	With CGRA	Without CGRA	Deep Sleep
Processing time	53 ms	79 ms	11947 ms
Power Consumption	8.86 mW	8.83 mW	0.29 mW
Voltage	830 mV	830 mV	830 mV
Frequency	160 MHz	160 MHz	32 KHz
Energy Consumption	0.47 mJ	0.70 mJ	3.46 mJ
<b>Total Energy</b>	<b>3.93 mJ</b>	<b>4.16 mJ</b>	

detection [40]. In our work, an AUC value of 0.84 is achieved using the transformer model and the previously mentioned four electrodes, indicating the ability of the model to distinguish between seizure and non-seizure classes. The processing time, average power, and energy consumption for the transformer model are detailed in Table V. The preprocessing steps (STFT, patch flattening and embedding) are not taken into account for this use case. Additionally, to show the potential of having such a deeply heterogeneous SoC in VersaSens when dealing with this type of complex applications, a comparison between processing some parts of the transformer on the CGRA or on the CPU is also shown. For both scenarios and to get a fair comparison, we set the same voltage and frequency settings.

Results presented in Table V verify that using the CGRA implies a reduction of energy consumed during the processing period. Furthermore, a speedup of up to 1.5 in the processing time is achieved, giving a minimum execution time of 53ms suitable for a real-time system, since it is lower than the 12s of the acquiring data window.

## VI. CONCLUSION

This paper has introduced VersaSens, an innovative and new versatile wearable multi-sensing platform concept to advance research in edge-AI based wearable technologies. VersaSens addresses key challenges in the field by offering a tool to promote the development and enhancement of the next generation wearable sensor systems. The architecture design and physical realization of the platform, as detailed in this paper, exemplifies its core attributes of versatility, flexibility, and extendability with various hardware, software, and processing components.

To demonstrate the platform's capabilities, three edge-AI use cases of medical wearables have been tested with notable results. First, in the cough-frequency monitoring case, VersaSens was able to process two modalities at different frequency

within their respective short windows to reach the desired outcome. The processing was fast enough to allow an efficient switch to idle mode, thus achieving optimized energy consumption. Second, in the heartbeats classification, the system efficiently processed ECG data while achieving a very low energy consumption of 3.66 mJ for a 12-second classification window. In the last case of seizure detection using transformers, the integration of hardware accelerators seamlessly (a key feature of VersaSens extendability) significantly reduced energy consumption and processing time in comparison to the latest SoC designs. Thus, a total energy reduction is obtained from 4.16 mJ to 3.93 mJ (approximately 8% less), and, more importantly in the context of real-time operation of the next-generation of edge-AI wearables, a much lower execution time (33% less) is achieved (from 79 ms to 53 ms).

Finally, the presented VersaSens platform concept can be modified to meet various requirements. For instance, the Main module can incorporate different SoCs, sensor modules can integrate various types of AFEs or custom-designed AFEs, and the co-processor unit can utilize alternative SoCs with advanced hardware accelerators. Additionally, multiple co-processors can concurrently manage different applications on physiological signals in real-time. The software and operating modes of the system are also customizable. Furthermore, several VersaSens sensors can collaborate via a wireless network, enabling the execution of more complex deep learning models, such as federated learning models. This extendability, combined with the platform's modular architecture and advanced edge-AI processing capabilities, ensures that VersaSens can support a wide range of wearable applications in digital health, wellness, and complex multi-modal edge-AI medical applications. For future research, we will use the current version of the VersaSens platform in a series of studies on medical and wearable systems in multiple applications. These studies will involve comprehensive experiments to evaluate the usability of the platform and to assess its capabilities for continuous real-time training and inference.

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