

AI and Smart Sensors Usher in a New Era in Patient Care

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Smart sensors and AI are transforming healthcare by enabling precise diagnostics, continuous monitoring, personalized treatments, and minimally invasive procedures. These advances enhance patient outcomes, reduce risks, and improve accessibility. Using cardiac care as an example, we highlight emerging innovations driving the rapid evolution toward Medicine 3.0.

Medicine 3.0 is not far away! Reports on the use of smart watches providing health warnings, leading to early detection of cardiac problems and saving lives, are already heard every now and then. With the ongoing advances in sensing and machine learning (ML), we envision advanced smart devices becoming common, affordable, and accessible for the general population. Imagine an intelligent

Band-Aid—a Band-Aid that continuously monitors your wellness by integrating a neural network (NN) and alerts you on the need for medical intervention well in advance of illness! Technologies enabling such devices are maturing as we speak! This article describes advances in medical sensors and achievements in artificial intelligence (AI)-integrated sensors. The potential for using a unique NN paradigm called *weightless NNs* (WNNs) in creating tiny ML models suitable for medical sensor integration is described. Recent advancements, including a WNN arrhythmia detector fabricated on a thin plastic film

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substrate, achieving 88% accuracy in detecting arrhythmia, are described.

SMART SENSORS AND AI

Smart sensors and AI technologies have significantly influenced health care in recent years. These technologies are enhancing diagnostics, treatment precision, remote monitoring, and personalized medicine, improving patient outcomes and streamlining health-care operations. Smart sensors embedded in diagnostic tools allow for rapid and precise disease detection. AI-powered imaging systems analyze medical scans with high accuracy,

allows continuous remote patient monitoring. Wearable devices track vital signs such as heart rate (HR), oxygen levels, and glucose levels, transmitting real-time data to health-care providers. AI analyzes these data to detect anomalies and alert medical professionals, ensuring timely interventions and reducing hospital admissions. AI-assisted robotic surgery enhances precision and reduces risks during medical procedures. Smart sensors embedded in robotic surgical systems provide real-time feedback, improving surgeon accuracy and reducing complications. These tech-

health. Inexpensive solutions in this domain are predicted to emerge, making such sensors pervasive and bringing health equity to the masses. Significant progress has been made in recent years in sensors and computing to make such connected health feasible. We describe some of these exciting developments and present the kind of technology advancements that are necessary to make Medicine 3.0 a mature reality. We use cardiac health care as an example.

State of the art of cardiac sensors

The field of cardiac health sensors has seen remarkable advancements in recent years, driven by the integration of cutting-edge technologies aimed at improving the monitoring, diagnosis, and treatment of cardiovascular conditions. As of 2025, a diverse range of cardiac sensors is available, encompassing both electrical and nonelectrical modalities, with increasing incorporation of AI to enhance performance and clinical utility.

WEARABLE BIOSENSORS CONTINUOUSLY MONITOR BIOMARKERS, PROVIDING REAL-TIME INSIGHTS INTO PATIENT HEALTH AND ENABLING EARLY INTERVENTION.

detecting anomalies such as tumors, fractures, and neurological disorders earlier than traditional methods. Wearable biosensors continuously monitor biomarkers, providing real-time insights into patient health and enabling early intervention. AI-driven algorithms process vast amounts of patient data, including genetic information and medical history, to generate personalized treatment recommendations. Smart drug delivery systems, equipped with biosensors, ensure precise medication dosages tailored to individual patient needs, optimizing therapeutic outcomes and reducing side effects.

The integration of smart sensors with AI-powered telemedicine platforms

nologies enable minimally invasive procedures, leading to faster patient recovery and shorter hospital stays. In rehabilitation, AI-powered smart sensors track patient progress and provide personalized feedback. Prosthetic limbs integrated with AI analyze muscle movements, adapting to user needs and improving mobility. These advancements significantly enhance the quality of life for individuals with disabilities.

Medicine 3.0 is arriving very fast! Inexpensive intelligence integrated with sensors is helping to meet the primary goals of Medicine 3.0,¹ which include evidence-based guidelines, preventative measures for chronic illnesses, and highly personalized

Electrical activity sensors. Conventional electrocardiographic (ECG) monitoring continues to evolve. Single-lead and multilead Holter monitors are widely used for clinical and ambulatory ECG monitoring. In parallel, mobile-based ECG devices—available in both single and multiple-lead configurations—offer accessible and portable solutions for personal health tracking outside clinical settings.

Nonelectrical activity sensors. Beyond electrical sensing, a variety of nonelectrical modalities have emerged. Optical sensors, such as photoplethysmogram (PPG) devices—including both LED-based and laser-based PPG—measure blood volume changes. Video

cardiography and oscillometric blood pressure monitors also capture arterial pulsations for cardiac assessment. An example of ultrasound-based sensing is the Pulsify Patch, which uses miniaturized ultrasound technology for continuous cardiac monitoring (<https://pulsify-medical.com/>).

Impulse and motion-based sensors. Cardiac impulse sensors have expanded to include gyro-cardiography, vibro-cardiography, and seismocardiography, all of which detect subtle mechanical vibrations generated by heartbeats. Additionally, sonar- and radar-based heart motion sensors provide noncontact options for monitoring cardiac activity. Wearable mechano-acoustic devices further enable continuous and noninvasive monitoring of heart sounds, using soft flexible materials to ensure comfort and high signal sensitivity.

Multimodal wearables. Advanced wearable devices, such as Empatica's Embrace2 and E4, monitor a variety of physiological parameters, including HR variability (HRV), electrodermal activity, and skin temperature (ST) (www.empatica.com). These multimodal systems support holistic health monitoring and are particularly valuable in managing stress, epilepsy, and cardiovascular conditions.

The role of AI in next-generation sensors. The integration of AI into cardiac sensing systems marks a transformative leap in sensor capabilities. AI enhances sensing accuracy through noise reduction, motion artifact filtering, and individualized calibration. Moreover, ML algorithms enable predictive analytics by identifying early warning signs in physiological data. AI-driven insights support early

detection of arrhythmias, sudden cardiac events, and decompensation in chronic heart failure. In comparison to traditional signal processing-based techniques, AI techniques are considered to yield additional shielding of noise resulting from vibration, moisture, and other environmental factors.

Popular consumer devices demonstrate the growing clinical potential of AI-enhanced wearables. The Apple Watch, for example, assists in the detection and management of atrial fibrillation, while the Google Pixel Watch 3 introduces a "Loss of Pulse Detection" feature capable of identify-

Recent advances in cardiac sensing/actuating

The world's smallest pacemaker is smaller than a grain of rice and can be implanted with a syringe. Remarkably, the device is fully bioresorbable, meaning that it naturally dissolves in the body once it is no longer needed—eliminating the need for surgical removal.²⁴ The researchers from Northwestern University who invented the tiny pacemakers also paired the tiny pacemaker with a wearable patch on the chest. The wearable chest patch is designed to emit pulses of near-infrared light, which will control the pacemaker in a wireless fashion.

THE INTEGRATION OF SMART SENSORS WITH AI-POWERED TELEMEDICINE PLATFORMS ALLOWS CONTINUOUS REMOTE PATIENT MONITORING.

ing cardiac arrest by detecting anomalies in blood flow. In critical situations, these devices can autonomously alert users and emergency services, offering life-saving intervention windows. The state of the art in cardiac sensing is rapidly advancing toward smart AI-integrated systems that offer noninvasive, continuous, and personalized monitoring. These technologies not only improve diagnostic accuracy and patient engagement but also pave the way for proactive and data-driven cardiovascular care. As sensing modalities diversify and AI continues to mature, the next generation of cardiac health monitoring will be defined by its adaptability, intelligence, and seamless integration into everyday life.

Leadless pacemakers, introduced several years ago, represent a major advancement in cardiac pacing technology. Unlike traditional systems that require transvenous leads and a subcutaneous pulse generator, leadless pacemakers are fully self-contained devices implanted directly into the heart via catheter insertion through the femoral vein. This design significantly reduces complications associated with leads, such as infection, lead fracture, or dislodgement, and is especially beneficial for patients with limited vascular access or elevated infection risk.

Initially, leadless pacemakers were restricted to single-chamber (ventricular) pacing. However, recent developments have led to the introduction of

dual-chamber leadless pacemakers, which support synchronized pacing of both the atria and ventricles. This advancement extends the applicability of leadless systems to a broader patient population, offering improved hemodynamic performance and greater clinical flexibility. As a result, leadless pacemakers are increasingly favored for their safety, efficacy, and minimal invasiveness, particularly in outpatient and elderly patient populations.²⁵

Connected AI for cardiac health care

More than 4 million people worldwide have an implanted pacemaker or other cardiac rhythm management, and an additional 700,000 patients receive the devices each year. In the United States, nearly 225,000 permanent pacemakers are implanted annually,²⁰ and there are indications of trends showing an increase in the number of pacemaker installations (<https://www.indexbox.io/blog/pacemaker-united-states-market-overview-2024/>). The functionality of implantable cardiac devices (ICDs), such as a pacemaker or a defibrillator, has been traditionally limited to monitoring signals from the heart and delivering therapy

based on predefined criteria or algorithms. However, device manufacturers have recently started incorporating advanced features to make pacemakers smarter and more connected. The modern ICDs have low-energy Bluetooth connectivity through which the devices are connected to the patient's cell phone. This cell phone can then be connected to the doctor's cell phone or to the hospital network infrastructure. This setup is depicted in Figure 1. The development of the next generation of smart sensors and AI-enabled pacemakers opens a new frontier in patient care where the patient is “connected” to the doctor at all times. With low-energy wireless connectivity, the ICDs can be programmed to automatically activate alerts to the cardiologist or to the hospital via the connected smartphone or network when an emergency occurs (Figure 1). In the future, wireless connectivity may also enable the cardiologist to remotely adjust the settings of the ICD to address the emergency or to recommend other corrective measures.

By connecting patients and physicians, remote smart cardiac monitoring provides many clinical and economic benefits. These include faster time to treatment if the physician

detects a problem with a patient with an implanted cardiac device based on data transmitted from ICD; less time spent at a doctor's office or clinic for regular checks of the ICD; reduced time spent in the hospital if the physician quickly detects and treats a medical problem; and a potential increase in patient survival rates.

Wired and wireless systems have their own advantages and disadvantages. Wired systems offer high signal fidelity, whereas they restrict patient movement and are often obtrusive and inconvenient. Wireless heart health monitoring allows patients to move freely without being tethered to equipment, and hence, is suitable for ambulatory and home-based long-term monitoring. **Wireless systems** are best suited for long-term, continuous, and remote heart health monitoring—ideal for wearable health tech and chronic condition management. Wireless systems may pose some security risk in that malicious attacks could occur. **Wired systems** are optimal in clinical environments where accuracy, reliability, and uninterrupted power are critical. The choice between the two depends on the use case—clinical diagnostics versus daily monitoring, mobility versus precision, cost versus convenience, and security considerations.

THE ROLE OF SMART SENSORS AND AI IN THE TREATMENT OF CARDIAC DISEASES

The integration of smart sensors and AI in cardiac care can improve patient outcomes by improving diagnostics, treatment, and patient monitoring in multiple ways/

Early detection and risk assessment. Smart sensors embedded in wearable

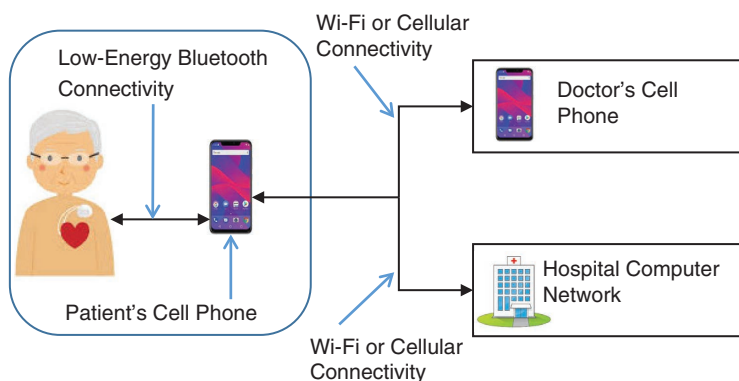


FIGURE 1. The connectivity of smart ICDs.

devices continuously monitor vital parameters such as HR, blood pressure, oxygen levels, and electrocardiogram patterns. AI algorithms analyze these data to detect irregularities, identify early signs of cardiac distress, and predict potential heart conditions before symptoms become severe. By leveraging predictive analytics, AI can assess an individual's risk of developing heart disease based on real-time data and historical health records.

AI-enhanced diagnostics. AI-driven diagnostic tools improve the accuracy and efficiency of detecting heart conditions. ML algorithms analyze medical imaging data, ECG readings, and echocardiograms to detect abnormalities such as arrhythmias, arterial blockages, and valve disorders. These automated analyses reduce human error and enhance the speed of diagnosis, allowing for timely medical intervention.

Personalized treatment plans. AI and smart sensors enable the development of personalized treatment strategies tailored to individual patient needs. By analyzing data from wearable sensors and medical records, AI can recommend lifestyle modifications, optimize medication dosages, and predict treatment outcomes. Smart drug delivery systems ensure the precise administration of medication, improving adherence and reducing side effects.

AI-driven cardiac surgery. AI-powered robotic systems assist in performing complex cardiac procedures with greater precision and efficiency. Smart sensors provide real-time feedback during surgeries such as coronary artery bypass grafting and valve replacements, enhancing surgical accuracy and reducing complications. Minimally invasive

robotic-assisted surgeries lead to faster recovery times and improved patient outcomes.

Remote patient monitoring and telemedicine. Wearable smart sensors facilitate the continuous remote monitoring of patients with chronic heart conditions. These devices transmit real-time health data to health-care providers, allowing for proactive interventions and reducing hospital readmissions. AI-powered telemedicine platforms enable remote consultations, ensuring that patients receive timely medical attention regardless of their location.

high-fidelity, continuous, and mobile sensing of biometrics.² Multimodal chest e-tattoos encompassing multiple sensors, including electrocardiogram, seismocardiogram (SCG), PPG, and ST sensors, are emerging. These collectively address electrical, mechanical, optical, and thermal sensing modes. The electrocardiogram and SCG are sampled at rates of 250 Hz to capture relevant high-frequency signals. In addition to detecting HR and HRV from the ECG signal, a pivotal feature of this multimodal chest e-tattoo is its cross-sensor synchronization scheme, enabling precise simultaneous signal



**AI-DRIVEN INSIGHTS SUPPORT EARLY
DETECTION OF ARRHYTHMIAS, SUDDEN
CARDIAC EVENTS, AND DECOMPENSATION
IN CHRONIC HEART FAILURE.**



Predictive analytics for preventive care. AI-driven predictive analytics help identify high-risk patients before they experience a cardiac event. By integrating data from electronic health records, wearable devices, and genetic tests, AI can recommend preventive measures such as dietary adjustments, exercise routines, and routine screenings to mitigate the risk of heart disease.

The e-tattoo

Ongoing research targets ultrathin, lightweight, and multifunctional wearable patches called *e-tattoos*, which can conform to soft and curvilinear skin surfaces without creating mechanical perception but can perform

sampling across all modalities. This capability facilitates the extraction of accurate cross-modality timing information, including critical cardiac time intervals such as the preejection period (PEP) and left ventricular ejection time (VET).

The PEP is a time interval in the cardiac cycle that reflects the time between the electrical activation of the ventricle and the beginning of ventricular ejection (mechanical systole). It essentially represents the period of left ventricular contraction with the cardiac valves closed, where the heart is preparing to pump blood. The VET is the duration it takes for a ventricle to eject blood into the aorta or pulmonary artery, measured from the time the valve opens

until it closes. A longer than normal VET can indicate conditions like heart failure. These parameters exhibit high correlations with hemodynamic metrics like stroke volume (SV) and cardiac output (Cardiac Output = SV × HR). It is essential to note that the electronics are insulated to ensure that they do not directly contact the skin, with only the medical dressing and biocompatible graphite electrode in contact with the skin. A version of the e-tattoo without the PPG sensor (Figure 2) has already undergone human subject testing, with approval from the University of Texas Austin Institutional Review Board (IRB), demonstrating accurate ECG and SCG sensing without any malfunctions or safety concerns.^{3,4} The IRB has also approved human subject testing of the new e-tattoo incorporating the PPG

sensor, and developments of the e-tattoo with the PPG sensor are ongoing.

ML FOR HEALTH PATCHES

Medical patches monitor the patient and generate a lot of data. These data can either be transmitted to a remote processing station (computer or phone) or processed on the patch itself. Transmitting the continuously generated data using Bluetooth or similar technology consumes energy. Processing the data locally near the sensor means that the ML models must be low-power and low-area to be integrated into the sensor.

The types of ML that are popular today are convolutional NNs (CNNs), transformers, etc. They are, in general, computation intensive and energy hungry. But health patches would need ML that does not drain the battery

quickly and that does not generate thermals and heat the patch.

The low power, energy, and area requirements of near-sensor ML put research such as Tiny classifiers⁵ and WNNs^{6,7,8} to great importance. Iordanou et al.⁵ demonstrated tiny classifier circuits in the range of only hundreds of gates as accelerators for the classification of tabular data. Susskind et al.^{6,7,8} presented WNNs for edge inference. WNNs are a type of artificial NN that does not rely on traditional weighted connections between neurons. Figure 3(a) illustrates a traditional neuron (also known as a McCulloch-Pitts neuron), which relies on the multiply accumulate operation, where the neuron multiplies each input (for example, x1, x2...) with a coefficient or weight (for example, w1, w2, ...). In contrast, the weightless neuron, represented

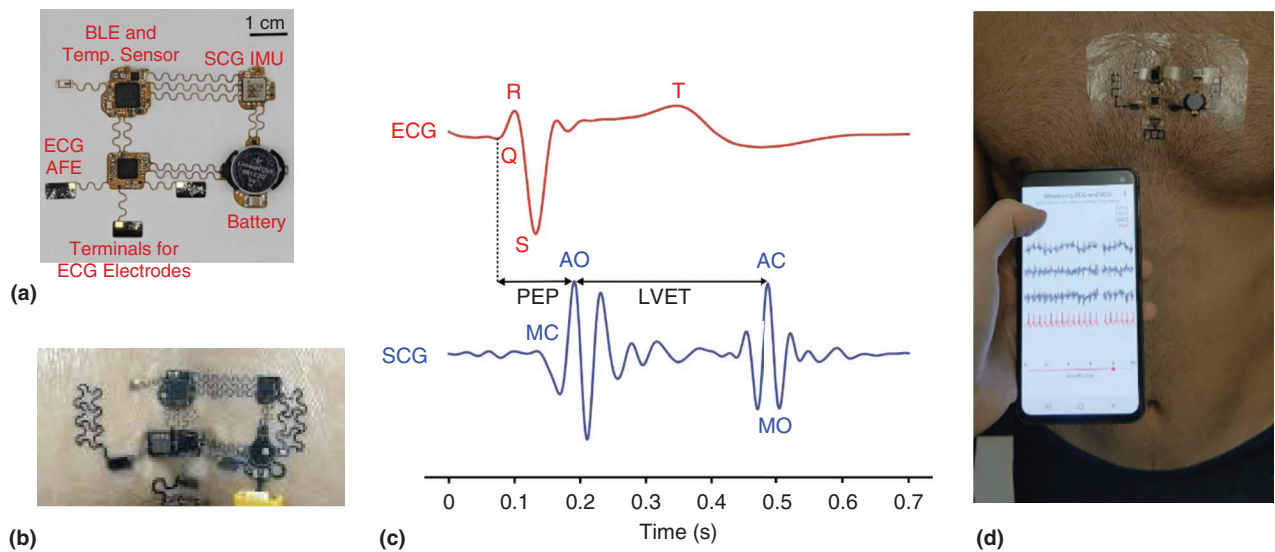


FIGURE 2. (a) An overview of chest-conformable multimodal e-tattoo design containing sensors and blue tooth communication. (b) A chest conformable e-tattoo that can adhere to curvilinear surfaces. (c) A synchronized ECG and SCG provide complementary information on cardiac activities, including the QRS complex and T-wave in ECG, and aortic valve opening (AO), aortic valve closing (AC), mitral valve closing (MC), and mitral valve opening (MO) in SCG. PEP is from the Q wave to the AO peak, and left ventricular ejection time (LVET) is from the AO peak to the AC peak. (d) A synchronously ECG and SCG measured by the e-tattoo can be used for the estimation of cardiac output and blood pressure. (Source: Adapted from [4].)

in Figure 3(b), uses a memory-based architecture, such as random-access memory (RAM) nodes or lookup tables (LUTs), to store and retrieve patterns directly.

In Figure 3(b), a RAM neuron with two inputs is illustrated. This neuron performs no multiplications; however, it uses four memory cells to store four bits. While small, this neuron can express any one of the 16 possible logic functions of two variables, also illustrated in Figure 3(b). A LUT with six input variables will contain 64 bits and can store any one of 2^{2^6} (that is, 2^{64}) functions, demonstrating its high expressiveness. WNNs rely on interconnected LUTs, often each LUT with a small number of inputs (for example, two to six). The expressiveness of LUTs is utilized, and during training, the most suitable function each neuron should contain is learned. This unique design allows WNNs to perform inferences with high speed and efficiency, making them particularly suitable for real-time applications such as image recognition, pattern classification, and cybersecurity. They offer faster training times and lower computational complexity than traditional deep NNs.

Traditional deep NN approaches, such as CNNs and transformer-based networks, deliver great accuracy,^{9,10,11,12} but their resource consumption and energy consumption are outside the range for medical sensor integration and continuous wearable monitoring. For example, on a human activity recognition (HAR) dataset, as Table 1 demonstrates, other NNs (rows one to four) consume 8–52 mJ, while a differentiable weightless neural network (DWN) consumes only 56–104 nJ.¹³ The e-tattoo currently houses an edge-grade microcontroller, and the DWN model is small enough to be integrated within the microcontroller.

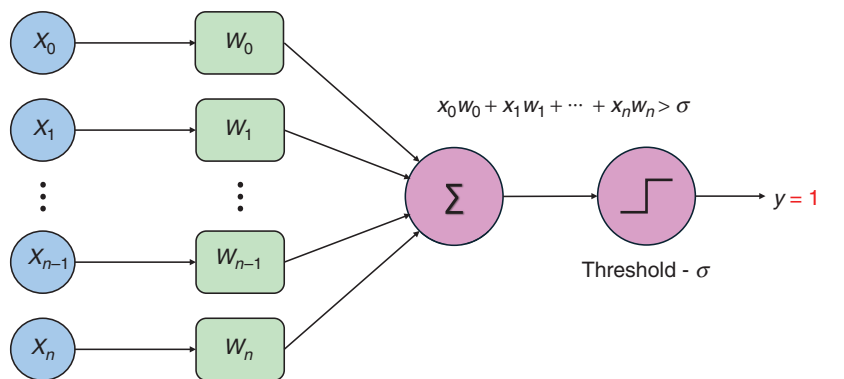
ML models and circuits consuming nanojoules as opposed to millijoules

will continue to be relevant for the continuous monitoring of patients. Such models and circuits for additional health-care tasks need to be developed if the vision of the intelligent Band-Aid has to become a practical reality.

Flexible microchips for sustainable and affordable health care

Recently, plastic substrate-based integrated circuits (ICs) have emerged as a

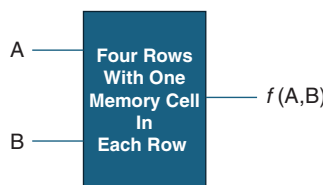
viable and sustainable alternative for silicon-based ICs, using metal-oxide thin-film-transistor technology now available as a foundry service.¹⁴ Researchers have demonstrated the feasibility of implementing microprocessors and ML on flexible substrates.^{15,16,17} Plastic ICs offer several advantages over traditional silicon-based ICs, making them a promising technology for health applications. Their flexibility



(a)

RAM Neuron With 2 Inputs
4 Locations

2^{2^n} i.e. 16 Distinct Functions



(b)

Function ID	Function	Output Values $f(A,B)$ for Inputs (A,B)			
		00	01	10	11
0	0	0	0	0	0
1	A AND B	0	0	0	1
2	AB'	0	0	1	0
3	A	0	0	1	1
4	A'B	0	1	0	0
5	B	0	1	0	1
6	A XOR B	0	1	1	0
7	A OR B	0	1	1	1
8	A NOR B	1	0	0	0
9	A XNOR B	1	0	0	1
10	B'	1	0	1	0
11	(A'B)'	1	0	1	1
12	A'	1	1	0	0
13	(AB)'	1	1	0	1
14	A NAND B	1	1	1	0
15	1	1	1	1	1

FIGURE 3. (a) The traditional McCulloch-Pitts neuron performs multiplication of inputs with the weights and then accumulates the products. (b) A RAM neuron with two inputs and the 16 functions that can be represented by this neuron.

TABLE 1. Accuracy, model size, compute operations, and energy of four deep NNs and two WNNs.

Model	Accuracy	Model size (KiB)	Floating point operations	Energy per inference
TSLANet	96.06%	—	69M	52 mJ
Channel Equalization HAR	97.35%	1,600	44M	33 mJ
CNN	96.27%	5,100	35M	26 mJ
HARMamba	97.65%	1,300	11M	8 mJ
DWN-small	96.34%	19	0	56 nJ
DWN-large	96.67%	39	0	104 nJ

KiB: kibibyte; M: million.

and lightweight nature enable the development of bendable and stretchable electronics, ideal for wearable devices, flexible displays, and biomedical sensors. Additionally, plastic ICs are more cost-effective to manufacture as they can be produced using low-temperature printing techniques on large-area substrates, reducing production costs compared to traditional semiconductor fabrication. Their durability and resistance to mechanical stress make them suitable for rugged environments where conventional ICs may

fail. Furthermore, plastic ICs contribute to the advancement of sustainable electronics as they can be developed using recyclable materials, reducing electronic waste. It is also reported that the water consumption during the foundry process is smaller for plastic ICs than for traditional ICs. The many outlined benefits position plastic ICs as a key technology for the future of flexible and energy-efficient electronics.

An arrhythmia detection chip that uses ML and detects arrhythmia with an accuracy of 88% was recently implemented on the flexible substrate by Pillai et al.¹⁸ with an implementation that uses approximately 3,000 gates. As shown in Figure 4, inexpensive health strips with such plastic ICs can be envisioned. The combination of low gate count (complexity and density) possible by WNN methodology and the relatively slower timescales (speed) of many medical applications allows one to leverage the flexible technology. Such a flexible “plastic” chip would be particularly suitable for integration with the flexible/conformal e-tattoo platform. While the process is not

suitable for all applications, the flexible thin-film transistor chip process has a low capital cost and impact compared to traditional fabrication.

While the previous discussion utilizes cardiac health monitoring as an example, similar techniques can be used for many health-care applications. The e-tattoo and similar advanced sensors are emerging for many applications, including dehydration, blood pressure, brain activity, etc.^{21,22,23}

Ethical considerations. The use of AI in health care presents several challenges that must be addressed for its effective and ethical implementation. Ensuring the accuracy, security, and ethical use of AI-driven health-care solutions will be crucial for their widespread adoption. One major concern is data privacy and security as AI systems rely on vast amounts of sensitive patient information, making them vulnerable to cyberthreats and unauthorized access. Potential solutions include federated learning, differential privacy, homomorphic encryption, secure multiparty computation (SMPC), etc. Federated learning is a decentralized ML approach where data remain on local devices (for example, patients’ devices and hospitals), and only the model updates are shared. Differential privacy approaches utilize mathematical techniques that add noise to the data, making it difficult to determine individual data points from the aggregate results, and thus, allow the analysis of data while protecting the privacy of individuals within those data. Homomorphic encryption is a form of encryption that allows computations on encrypted data without decrypting it first, enabling AI models to make predictions or updates while data remain encrypted, providing strong confidentiality during processing. SMPC is a

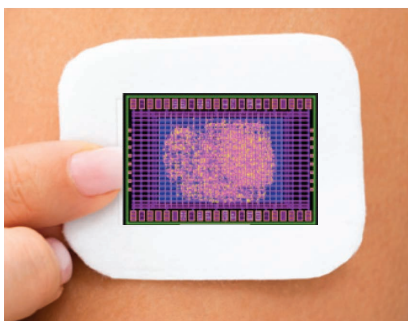


FIGURE 4. Envisioning an inexpensive intelligent health strip with machine intelligence integrated near sensors.

cryptographic protocol where multiple parties compute a function over their inputs without revealing them to each other, enabling collaborative health-care research across institutions while maintaining data secrecy.

Security is another major concern for wirelessly connected medical devices such as pacemakers. The possibility of an enemy hacking into your pacemaker may become a reasonable possibility rather than science fiction. Wirelessly connected devices such as pacemakers should be equipped with appropriate multistep authentication techniques.


Additionally, AI models require high-quality unbiased data to function accurately, yet disparities in health-care data can lead to biased algorithms that may disadvantage certain populations. Regulatory and ethical concerns also pose significant hurdles as AI-driven medical decisions must comply with stringent health-care regulations while maintaining transparency and accountability. Furthermore, integrating AI into existing health-care systems requires substantial infrastructure upgrades and training for medical professionals to effectively use AI-driven tools. Finally, while AI can enhance diagnostics and treatment planning, it should complement rather than replace human expertise, ensuring that clinical decisions remain patient centered and guided by medical professionals. Many possibilities for effective personalized medicine using AI are discussed in recent literature.¹⁹ The hope is that ethical and technological hurdles on the path can be overcome.

Smart sensors and AI are revolutionizing cardiac disease treatment by enhancing early detection, improving diagnostics, enabling

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personalized care, and supporting remote monitoring. As these technologies continue to advance, they hold the potential to improve the quality of life for millions of patients worldwide. The integration of AI and noninvasive sensors promises to further enhance the management and treatment of many diseases. More advances on tiny ML models and hardware consuming nanojoules per inference and research on sensing effectively from the human body need to happen. 

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