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Review

Self-powered sensing systems with learning capability

Avinash Alagumalai,[2,18] Wan Shou,[3,4,18,*] Omid Mahian,[1,5,6,*] Mortaza Aghbashlo,[7] Meisam Tabatabaei,[8,9,10] Somchai Wongwises,[11,12] Yong Liu,[13] Justin Zhan,[14] Antonio Torralba,[3] Jun Chen,[15] ZhongLin Wang,[16,*] and Wojciech Matusik[3,17]

SUMMARY

Self-powered sensing systems augmented with machine learning (ML) represent a path toward the large-scale deployment of the internet of things (IoT). With autonomous energy-harvesting techniques, intelligent systems can continuously generate data and process them to make informed decisions. The development of self-powered intelligent sensing systems will revolutionize the design and fabrication of sensors and pave the way for intelligent robots, digital health, and sustainable energy. However, challenges remain regarding stable power harvesting, seamless integration of ML, privacy, and ethical implications. In this review, we first present three self-powering principles for sensors and systems, including triboelectric, piezoelectric, and pyroelectric mechanisms. Then, we discuss the recent progress in applied ML techniques on self-powered sensors followed by a new paradigm of self-powered sensing systems with learning capability and their applications in different sectors. Finally, we share our outlook of potential research needs and challenges presented in ML-enabled self-powered sensing systems and conclude with a road map for future directions.

INTRODUCTION

Over time, technological advances made sensors vital, allowing us to communicate more efficiently and interactively with the world. Sensors are ubiquitously used in our society, including healthcare,[1,2] wearable,[3] personal electronics,[4] automobiles,[5] buildings,[6] food monitoring,[7] robotics,[8] and environmental monitoring.[9] Sensors are electronic devices that detect or measure physical/chemical/biological quantities and record, indicate, or react to them in a certain way. In a nutshell, a sensor takes our real-world senses or changes and converts them into readable/visible/audible information for practical applications.

Sensors have existed for a long time. The first device we might define as a sensor was invented way back in 1883 by Warren Johnson. The patented work by Johnson more or less measured the temperature of a room. Twelve years later, his invention appeared in a pneumatic device regulating heating systems. He referred to it as an "electric tele-thermoscope[10]," which we now call a thermostat. The term "smart sensor[11]" refers to a group of extremely powerful devices. Smart sensors are those that can sense more than just a few simple physical properties, as well as perform digital data conversion, and connect to cloud-based devices. They are capable of self-evaluation and self-calibration. Notably, industry 4.0 is built on the foundation of smart digital technologies, machine learning (ML), and big data.

Context & scale

The large-scale internet of things appears to be still on the way, and progress toward that vision is slow. One explanation for this is that the batteries are incompatible with this massive-scale internet of things. The use of energy-harvesting techniques is one of the promising alternatives to batteries. On the other hand, introducing self-powered systems will pave the way for a myriad of challenges, including the grand challenge of fairly small power generation in most energy-harvesting modalities. It is necessary to envision an active operating condition for the electronics, ideally taking advantage of the relatively low power produced by most energy-harvesting systems. Lowering the power consumption of active operating electronic systems is an excellent approach in this context. Besides, this challenge requests the development of novel electronic devices with low active processing power in the future.

This review presents the significant advantages of combining machine learning and self-powered sensors/systems in terms of energy scavenging, output performance, and power management. We explore the new paradigm of self-powered sensor/system, focusing on how machine

In recent days, researchers have been working to advance technology to allow the production of energy-autonomous (self-powered) wireless sensors. The term ''self-powered sensor,'' first introduced by Wang,[12–15] can be interpreted in two ways. The first is that it generates an electric signal without external power when triggered by mechanical force. The second interpretation is that it can power itself from ambient energy. Thus, without the need for batteries, self-powered technology is becoming increasingly important for wireless sensing and the emergence of the internet of things (IoT). To achieve the trillion-node IoT mission, self-powered batteryless technology is inevitable. The self-powered wireless sensors will pave the way for the future massive-scale IoT deployment. The gigantic prospect of IoT comes with a huge amount of new types of data. Batteryless sensors will indeed drive the next data revolution by enabling billions of never before monitored physical assets to transfer actionable data. According to a recent survey, the battery-free electronics market could grow from under \$8 billion to more than \$120 billion by 2041.[16]

learning would aid in applications from healthcare to intelligent systems. Although combining machine learning with self-powered systems is proving to have a lot of exciting new applications and advantages, as it shifts from the research facility to real-world implementation, technical, ethical, and security issues must be tackled. In this context, the technical and ethical implications of machine learning systems in real-world applications are also discussed.

A self-powered sensor system is fabricated with components for energy harvesting/storage, sensing, interaction, monitoring, and communication (Figure 1). Self-powered sensors can harvest energy from the surrounding environment. However, energy harvesting remains challenging; for example, solar energy is strongly dependent on climatic conditions, making it less viable and reliable for self-powered sensors. Mechanical[17] and fluid energy[18] may be viable energy sources. The viability of utilizing the waste heat from industry[19] and automobiles[20] to produce power can be scrutinized. Developing advanced waste energy recovery systems[21] can also lower energy consumption and associated environmental impacts. However, a limited amount of power can be harvested (approximately tens of microwatts per square centimeter) in most energy-harvesting modules, such as solar,[22] thermoelectric[23]/pyroelectric generation,[24] and radiofrequency.[25] Nevertheless, batteryless technology is becoming a feasible solution to low-power electronic systems.

The exponential growth of sensors will significantly impact the big data market in several ways. One way it allows us to measure things we have never been able to measure before. One of the issues with sensor networks is real-time data analytics with the explosion of data generated by sensors. Therefore, statistical analysis tools are necessary. To date, the use of statistical tools to explore the data is gaining increased attention. The most significant advances that we see today in data science are mainly due to two things. The first is ML techniques.[33] Notably, deep learning has been around for many years, but they were not that effective early on due to the limited computational power to run such algorithms.[34] In the past decades, the increased computational power has unlocked the power of learning techniques, and together with better access to the data, various breakthroughs have been achieved. The second is the ability of computers to do different kinds of tasks, *viz.*, image recognition[35] and speech/voice recognition.[36,37] Therefore, ML is making a big difference in various fields, including biomedicine,[38] drug discovery,[39] modern education,[40] cybersecurity,[41] bioinformatics,[42] material science,[43] quantum matter research,[44] psychological research,[45] ecology,[46] and so on. It is anticipated that systems with learning capability will be universally available in daily lives in the near future, and humans will be able to interact with them naturally and seamlessly as never before. Above all, these unique systems would be intelligent to better serve human beings.

Here, we present the recent progress in applied ML techniques on self-powered sensors and systems based on triboelectric, piezoelectric, and pyroelectric principles in

[1]School of Chemical Engineering and Technology, Xi'an Jiaotong University, Xi'an, Shaanxi 710049, China

[2]Department of Mechanical Engineering, GMR Institute of Technology, Rajam, Andhra Pradesh 532127, India

[3]Computer Science and Artificial Intelligence Laboratory, Electrical Engineering and Computer Science, Massachusetts Institute of Technology, Cambridge, MA 02139, USA

[4]Department of Mechanical Engineering, University of Arkansas, Fayetteville, AR 72701, USA

[5]Department of Chemical Engineering, Imperial College London, London SW7 2AZ, UK

[6]Department of Mechanical Engineering, Center for Nanotechnology in Renewable Energies, Ferdowsi University of Mashhad, Mashhad, Iran

[7]Department of Mechanical Engineering of Agricultural Machinery, Faculty of Agricultural Engineering and Technology, College of Agriculture and Natural Resources, University of Tehran, Karaj, Iran

[8]Higher Institution Centre of Excellence (HICoE), Institute of Tropical Aquaculture and Fisheries (AKUATROP), Universiti Malaysia Terengganu, 21030 Kuala Nerus, Terengganu, Malaysia

[9]Henan Province Engineering Research Center for Forest Biomass Value-added Products, School of Forestry, Henan Agricultural University, Zhengzhou, Henan 450002, China

[10]Biofuel Research Team (BRTeam), Terengganu, Malaysia

[11]Fluid Mechanics, Thermal Engineering and Multiphase Flow Research Lab. (FUTURE), Department of Mechanical Engineering, Faculty of Engineering, King Mongkut's University of Technology Thonburi, Bangmod, Bangkok 10140, Thailand

[12]National Science and Technology Development Agency (NSTDA), Khlong Luang, Pathum Thani 12120, Thailand

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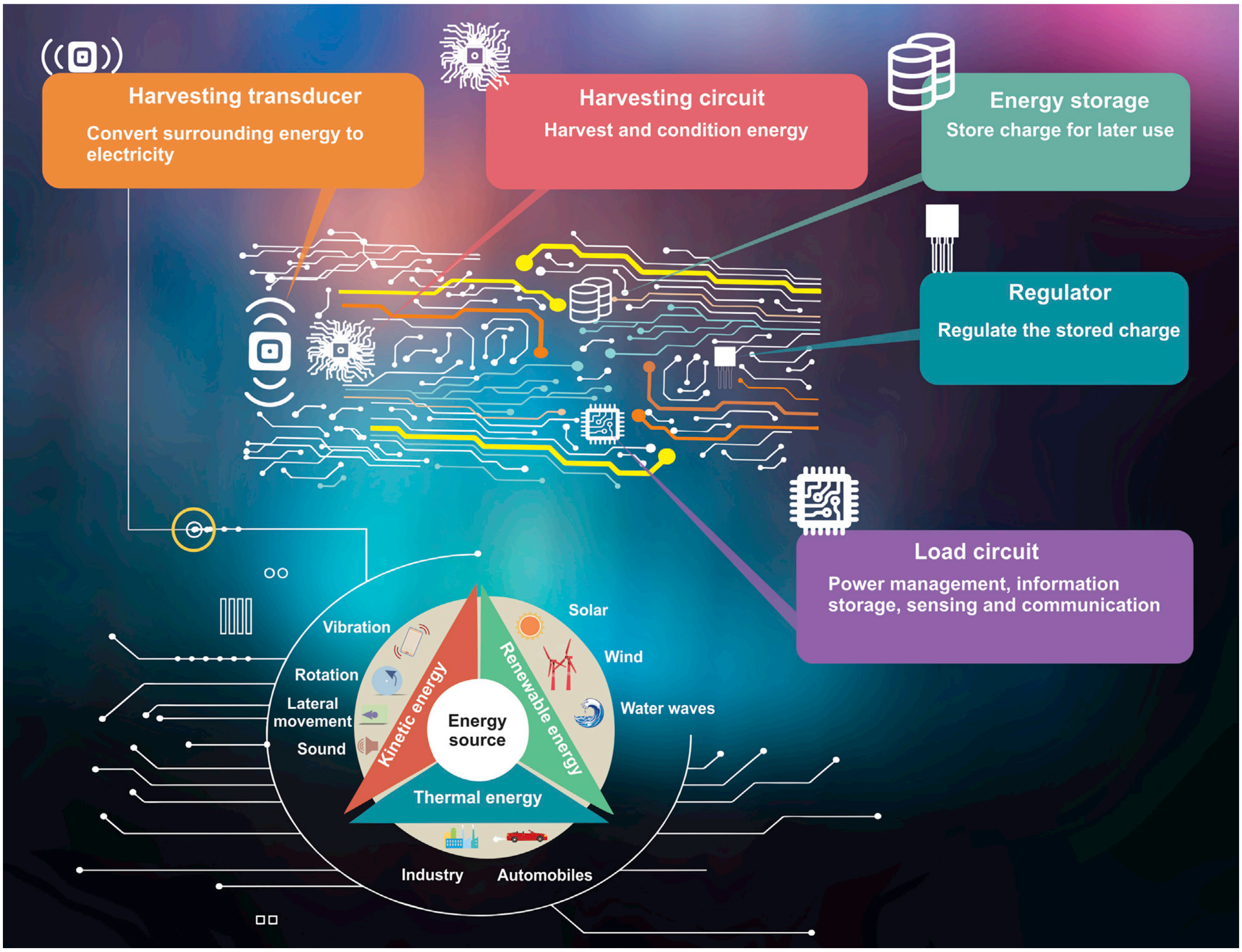

Figure 1. Anatomy of an integrated self-powered system on a chip
The primary five modules of this integrated system include harvesting transducer, harvesting circuit, energy storage, regulator, and load circuit. Solar,[26] wind,[27,28] water waves,[29] heat,[30] and kinetic energy[31,32] are some of the potential energy sources for self-powered operation.

different application fields. We also discuss the technical challenges and ethical implications and provide our outlook on this emerging field.

SELF-POWERING PRINCIPLES AND PROGRESS

Self-powered sensors and systems based on displacement current[13,24,47] (Figure 2) have recently gained considerable attention for their ability to convert biomechanical or thermal energy to electricity for use in different applications. Each of these displacement current-dominated energy-harvesting devices has its own merits and practical limitations, as summarized in Figure 3.

In 2006, Wang and Song[13] demonstrated the first nanoscale mechanical to electrical energy conservation using zinc oxide (ZnO) nanowire array-based piezoelectric nanogenerator (with 17%–30% efficiency). According to their study,[13] the basic principle for producing piezoelectric discharge energy is derived from how the piezoelectric and semiconducting properties of ZnO are connected. In the past decade, the majority of research focused on piezoelectric nanostructures (particularly ZnO[48,49]) due to their easy fabrication using low-temperature methods, whereas many ferroelectrics require high-temperature methods. In addition to

[13]School of Textile Science and Engineering, Tiangong University, Tianjin, China
[14]Computer Science and Computer Engineering, University of Arkansas, Fayetteville, AR 72701, USA
[15]Department of Bioengineering, University of California, Los Angeles, Los Angeles, CA 90095, USA
[16]School of Materials Science and Engineering, Georgia Institute of Technology, Atlanta, GA 30332-0245, USA
[17]Department of Mechanical Engineering, Massachusetts Institute of Technology, Cambridge, MA 02139, USA
[18]These authors contributed equally
*Correspondence: wshou@uark.edu (W.S.), omid.mahian@xjtu.edu.cn (O.M.), zhong.wang@mse.gatech.edu (Z.W.)
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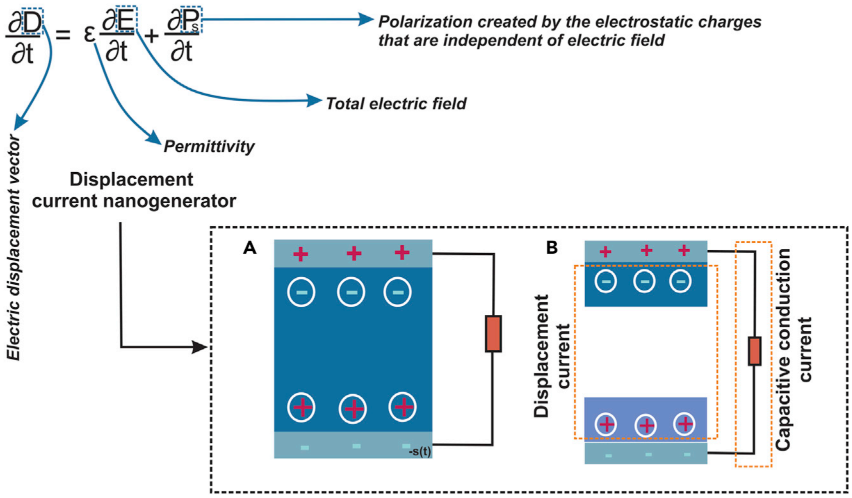

Figure 2. Self-powering principles

Schematic illustrating the displacement current-dominated energy-harvesting devices (nanogenerators) based on (A) piezoelectric/pyroelectric principle and (B) triboelectric/electrostatic/electret effects.

the evaluation of nanorod arrays grown on rigid substrates, these devices can benefit from the usage of flexible substrates, as first demonstrated by Choi and co-workers in 2009.[50] Their investigations showed that ZnO nanorods could be produced in aligned arrays on plastic substrates, thus allowing the devices to be strained by bending the substrate instead of just absorbing energy from direct compression/vibrations. Besides, devices were also produced by growing ZnO nanorods on "paper substrate[51]" for potential fabrication of large-area flexible devices. Alongside ZnO-based piezoelectric energy harvesters, non-ZnO-based piezoelectric devices based on lead zirconate titanate,[52,53] $ZnSnO_3$ nanostructures,[54,55] barium titanate,[56,57] potassium sodium niobate,[58] and polyvinylidene fluoride[59] are gaining interests. Recently, two or more filler materials based on electrospun nanofibers have been exploited to improve the piezoelectric and electromagnetic wave absorption properties.[60,61]

Triboelectric nanogenerators (TENGs) convert mechanical energy from the surrounding environment into electricity, which can be used to operate small devices like sensors. These nanogenerators are based on the convolution of contact electrification and electrostatic induction, which was first demonstrated by the Wang group.[47] The friction between the two sheets resulted in equal but opposite charges on each side. TENGs operate in four modes[62]: (1) contact-separation mode (contact charging and electrostatic induction in tandem), (2) lateral-sliding mode (sliding in the lateral direction between the two surfaces), (3) single-electrode mode (two electrodes form a closed circuit for the flow of electrons), and (4) free-standing mode (energy harvesting from a moving object without an attached electrode). These nanogenerators offer a higher output performance than piezoelectric nanogenerators, and they can be employed as flexible devices at lower frequencies (<4 Hz).[63] Developing high voltage TENGs is one of the primary objectives in this field. Many investigations on TENG as a high voltage source have previously been performed.[64,65] However, TENGs cannot currently be used in industrial or commercial applications due to the unpredictable magnitudes and frequencies of input sources,[66] durability[67]/stability issues,[68] and inefficient power management.[69]

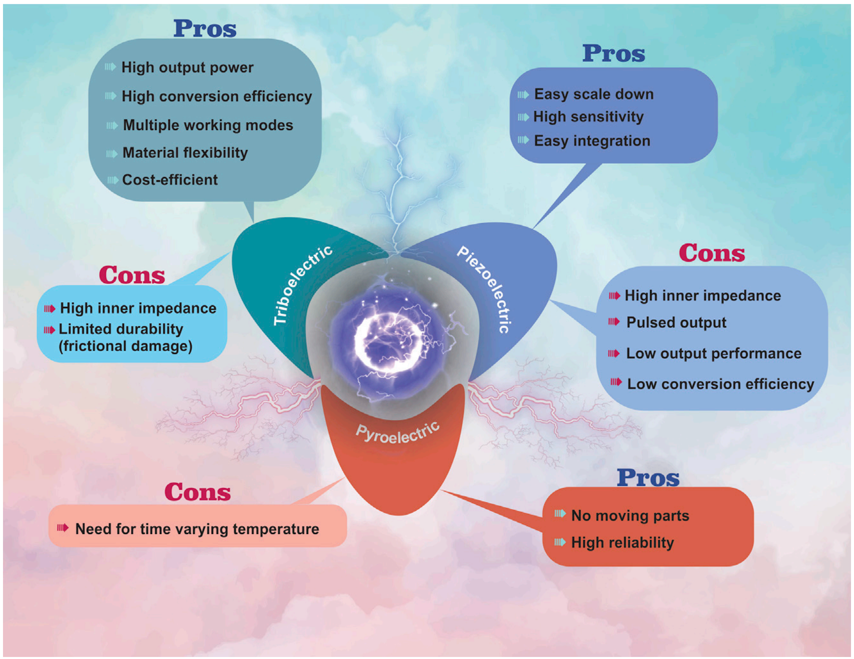

Figure 3. A comparison of merits and limitations of energy-harvesting devices based on triboelectric, piezoelectric, and pyroelectric principles

In thermoelectric power generation, the Seebeck effect uses a temperature difference between two ends of the device to drive charge carrier diffusion, whereas the pyroelectric effect is intimately linked to changes in a material's polarization due to temperature changes.[70] It should be emphasized that devices based on the Seebeck effect have a reduced energy conversion efficiency due to the low efficiency of the Seebeck effect in thermal energy conversion, which is mainly caused by time-dependent temperature changes with spatial homogeneity into electrical energy.[71] In 2012, Zhang's group[24] exhibited the pyroelectric effect of ZnO nanowire arrays for the first time by linking the pyroelectric and semiconducting capabilities of ZnO to create a polarization electric field and charge separation utilizing the time-dependent change in temperature. A typical pyroelectric nanogenerator comprises three layers: (1) the top metal layer is patterned to effectively accept heat energy and also serves as a top electrode, (2) the middle layer transforms thermal energy to electric energy by changing its internal polarization, and (3) the bottom metal layer serves as a bottom electrode. Unlike piezoelectric and TENGs, pyroelectric nanogenerators would not suffer mechanical deformation; hence, they are more reliable in practical applications. Pyroelectric nanogenerators possess a lot of potential in wearable technologies. A wearable pyroelectric nanogenerator that harvests energy from breathing could be utilized as a self-powered sensor to track human health.[72,73] The dielectric breaking strength of the materials determines the energy density of pyroelectric nanogenerators. In this context, the usage of ferroelectric materials such as lead zirconate titanate, barium titanate, polyvinylidene fluoride, and poly(vinylidenefluoride-co-trifluoroethylene), and ceramic materials like ZnO are beneficial.[74] However, compared with polymer-based pyroelectric nanogenerators, high power output is offered by ceramic-based pyroelectric nanogenerators.[75] Overall, the important historical milestones in self-powered sensors and systems based on piezoelectric, triboelectric, and pyroelectric principles are summarized in Figure 4.

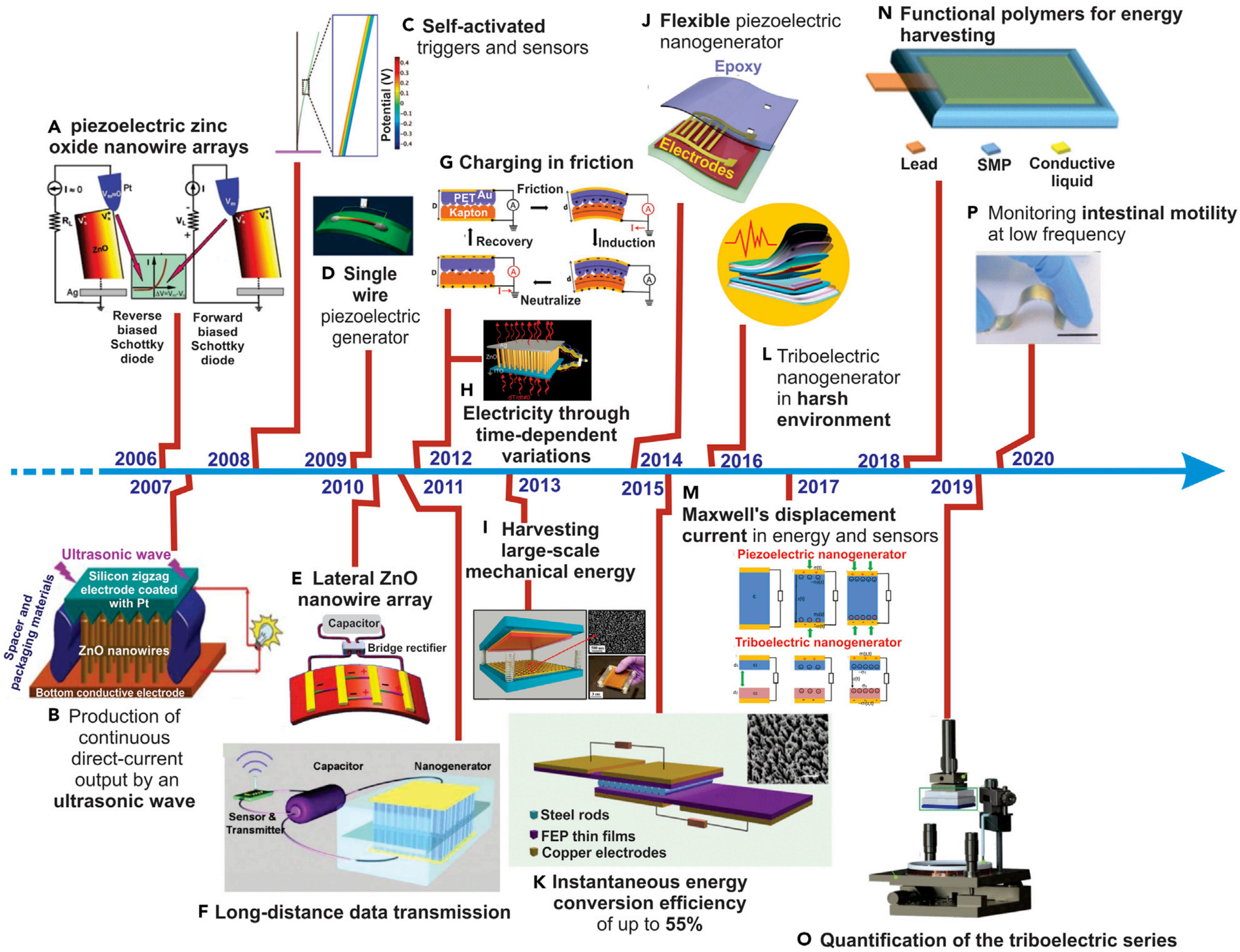

Figure 4. Historical milestones in the self-powered sensors/systems based on piezoelectric, triboelectric, and pyroelectric principles

(A) Wang and Song,[13] with permission from *Science*, LN: 5257090180791.
(B) Wang et al.,[76] with permission from *Science*, LN: 5257090612378.
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(M) Wang,[85] with permission from Elsevier, LN: 5257110035065.
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MACHINE LEARNING IN SENSORS AND SYSTEMS

Machine learning in triboelectric sensors and systems

Self-powered triboelectric sensors and systems have recently been used in a variety of fields, including wearable devices,[89–91] healthcare,[92–97] smart technologies,[98–100] industrial automation,[101] and environmental monitoring,[102,103] which has prompted their integration with emerging areas such as ML and the IoT. However, to achieve

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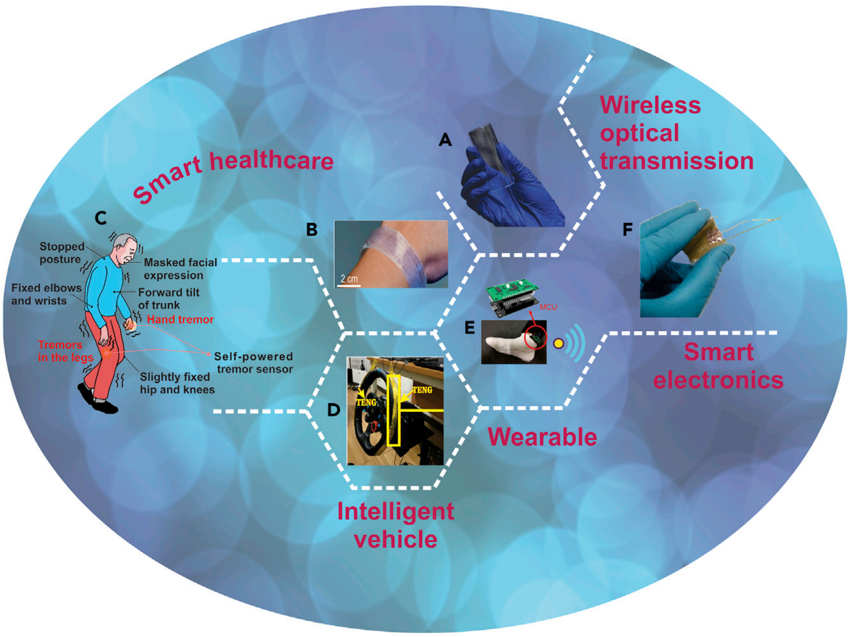

Figure 5. Representative real-time applications of triboelectric sensors with ML techniques

(A) Self-powered wireless optical transmission for wireless pressure detection.[104] Used with permission from Elsevier, LN: 5257131196824.

(B) 3D-printed elastomeric metal-core triboelectric wristband.[105] Used with permission from Elsevier, LN: 5257131451505.

(C) Tremor sensor targeting Parkinson's disease.[106] Used with permission from Elsevier, LN: 5257140161996.

(D) Intelligent driver assistance system.[107] Used with permission from Elsevier, LN: 5257140423436.

(E) Smart socks.[108] Adapted[108], copyright © 2020, Springer Nature.

(F) TENG-based writing pad.[109] Used with permission from John Wiley and Sons, LN: 5257660311252.

such integration, the current overcrowding of radiofrequency signals must be resolved. Also, it is possible to expand IoT applications by combining optical wireless communications and TENGs.[104] Some of the real-time applications of triboelectric sensors with ML techniques are illustrated in Figure 5.

A recent study shows that TENGs can be used not only as a mechanical trigger but also as a power source, enabling the development of a simple optical wireless communications transmitter with no additional power or complicated circuits.[104] Image processing techniques may aid in the decoding of the associated data, so that the functionality of wireless access, pressure sensing, and security authentication can be well understood. Furthermore, different features such as the typical on-off feature, intensity feature, and biometric feature can be demonstrated.[104]

In the case of biomedical applications (e.g., health monitoring of patients), integrating tremor sensors with ML can help diagnose a patient's health issues and monitor real-time health.[109,110] According to the researchers, a catechol-chitosan-diatom hydrogel-frequency TENG can be used for energy harnessing and powering a wearable self-powered tremor sensor for Parkinson's disease prediction using ML.[106] As a suitable platform for long-term health analysis of individuals, deep learning integrated triboelectric sensor coupled with an image sensor can be used to construct smart toilets with more than 90% prediction accuracy.[111]

In applications like controlling human organs, self-powered 3D-printed devices outperform shape-adaptive membrane-based devices.[105] The self-powered 3D-printed stretchable devices show three distinct advantages: (1) self-powering functionality, (2) form-fitting design, and (3) real-time monitoring capability. Stretchability, reliability, efficiency, and compatibility with ML algorithms are just a few of the main benefits of these devices. Therefore, 3D-printed stretchable TENG devices are good candidates for organ preservation. By using a perfusion system to locate swollen organs, improved organ protection can be achieved. The 3D-printed TENGs' utility and sensitivity can be demonstrated through applications such as organ mechanosensing and human motion sensing. By combining a 3D-printed wearable TENG interface with supervised ML algorithms, researchers recently created a high-accuracy real-time "silent voice[105]" (a silent speech interface system that allows people to communicate in the absence of sound). Their inventions include image-based facial expression tracking and speech in the nonexistence of the user's sound output. The most popular silent speech interfaces are continuous sound security control and facial expressions. Notably, the ability to 3D print elastomeric metal-core TENG fibers has far-reaching implications in this field. Advanced image and data processing methods are needed for the mentioned interface methods. However, advanced processing techniques could require a lot of computing power. The power requirements for imaging systems, on the other hand, restrict the system's portability.

ML algorithms can be used in a variety of fields other than biomedicine and healthcare. Recently, a new TENG-based method for detecting driver steering behavior was developed.[107] The TNEG-based approach has a faster average reaction time than other possible methods for detecting driver steering behavior, such as a driving simulator or a camera. TENG-based ML methods are said to aid in developing intelligent driver assistance systems with a detection accuracy of more than 85%.[107] Merging triboelectric and photonics technology can provide a cost-efficient solution for secure communication with nearly 95% accuracy when paired with deep learning.[112]

A textured TENG could be used to detect people's handwriting with high accuracy. Such textured TENG has many potential applications, including personal handwriting recognition, authentication, safety, and private data protection. Advanced data processing methods can be used to get essential information and minimize data dimensionality for multilanguage recognition. Furthermore, combining the advanced data processing methods with the statistical learning classifier might help identify multilanguage handwriting with greater than 90% accuracy.[113] Sign language is critical for bridging the communication gap between speech-/hearing-impaired persons and others. Recently, deep learning-assisted sign language identification and communication systems are evolving to allow remote and bidirectional communication with more than 85% accuracy.[114]

The pre-trained neural network is an excellent approach in the race to digitize data[115] and sensor applications in the IoT era.[116] A high recognition rate could be achieved in data digitization by improving the reference points and spacing lines. Moreover, the issues associated with optical character recognition can be resolved when character recognition based on TENG is the light-free touch type.[115] There is also a possibility of creating memristive neural networks using self-powered electronics.[117] Artificial neural network (ANN) models can be used to develop music-playing versatile flags, flexible patches for the high-fidelity recording of music, or discrete devices that can expose the identity of people attempting to gain access to a computer.[118]

In the environment application, one of the significant environmental problems faced by scientists and hydrologists is improving awareness of suspended sediment dynamics. Thus, the effect of suspended sediment transport on water quality, biogeochemistry, and landforms is critical. Combining TENG with a deep learning method makes it easy to identify sand particle parameters,[119] shedding light on developing new methods for real-time sediment monitoring.

It is noticed that the high amount of energy that is required to acquire and interpret subtle sensory data is a major obstacle for intelligent systems.[120] Thus, developing an artificial sensory memory system would advance intelligent and bioinspired electronic devices. Other applications, such as neuromorphic systems, human-machine interaction, and massive neural networks, pose exciting opportunities. Additional spatiotemporal cross-correlations for associative learning and memory are likely to be implemented to incorporate more mechanoplastic neurons.[121] Active mechanoplastic neuromorphic systems are crucial for progressing beyond von Neumann's architecture in terms of flexibility and diversity toward modern human-machine interfaces. ML techniques can be applied to develop various smart electronics based on TENG. To name a few, ML models were used to create high-accuracy TENG-based smart electronics for voice recognition[122] and self-powered stretchable IoT-based triboelectric systems to detect toxic gas leaks in chemical plants (D. Hasan et al., 2019, IEEE, abstract).

Machine learning applied to piezoelectric sensors and systems

The knowledge of approximate data associated with internal parameters is needed to model, simulate, and optimize piezoelectric sensors and transducers. Consequently, the material constants determined by electrical impedance tests can significantly impact the characteristics of lossy piezoelectric materials. In such a case, intelligent evolutionary algorithms like genetic algorithm[123] can improve parameter estimation of piezoelectric sensors and systems, reasonably enhancing their performance. Such techniques can also be used for a variety of piezoelectric or composite materials.[123] One may also use statistical learning approaches like data mining to estimate the governing properties of piezoelectric materials with high Curie temperatures.[124] Rather than a heuristic approach, a statistical learning-based computational strategy would be a mechanistic approach. Generally, integrating the statistical learning approach in the field of piezoelectric will help material discovery and materials design.

ML combined with piezoelectric transducers improves the system's performance and efficiency when it comes to applications like damage deduction of structural components. In ML, supervised learning algorithms, such as support vector machines (SVMs),[125] can be used to evaluate the results of damage deduction. Supervised learning can ensure accuracy during the cross-validation set to yield better efficiency. Moreover, higher scores (>90%) can be expected with a small dataset.[125] A further improvement in the results is possible by considering the external variables such as temperature, loading conditions, etc. In addition to applications like damage deduction of structural components, piezoelectric transducers and ML can also be used to monitor the health of wooden structures.[126–128] If "artificial intelligence installed on things" and online learning are used, energy-saving is ensured.[126] Indeed, supervised learning algorithms can be implemented in different applications with different kernel functions for better accuracy and precision.[129]

Experimental determination of the operating frequency of a piezoelectric transducer is difficult. It is even more challenging to determine the resonance frequency of the transducer theoretically. Mega-fuzzification methods are suggested to determine the frequency of the piezoelectric transducer, which can provide better estimation even when the data size is large.[130] Intelligent techniques such as deep neural networks and genetic algorithms, in addition to mega-fuzzification methods, can optimize the resonant frequency of piezoelectric devices. A well-trained deep neural network can predict results with greater than 90% accuracy. On the other hand, genetic algorithms can reduce the operating frequency and increase the energy conversion performance.[131] When comparing the accuracy of classification, simple ML techniques show a clear advantage over deep neural networks.[132]

Besides converting mechanical stress to electricity, piezoelectric materials also show great promise in actuator applications such as ultra-precise motion control systems. However, the high nonlinear features seen in the dynamics of piezoelectric actuators are the biggest challenges to utilizing their potential effectively. Employing piezoelectric actuators in conjunction with ML algorithms allows for more accurate control.[133] In the presence of disturbances and noise, the tracking differentiators of a nonlinear proportional integral derivative controller may aid in the production of high-quality differential signals. Incorporating a learning controller into such a scenario can cut the tracking error in half.[133]

In the field of self-powered piezoelectric nanosystems, using the univariate procedure to study the piezoelectric characteristics does not provide good predictions due to the absence of interaction between different variables. Thus, ANN is thought to be more capable of making accurate predictions. A recent study demonstrated that the ANN could accurately model the physical and chemical properties of electrospun nanogenerators.[134]

Machine learning in pyroelectric sensor technology

Pyroelectric sensor technology has recently gained popularity. Combined with ML, this technology would play a significant role in intelligent systems to open up new possibilities and provide solutions that are both effective and useful in various applications (Figure 6). Integrating different ML algorithms in building intelligent systems is becoming more popular as ML techniques are applied in various industrial sectors; for example, a combination of ML and pyroelectric infrared sensors was used to detect movement direction.[135] Although instant movement detection remains a challenge, learning algorithms are helpful in this situation. When we compare the recognition accuracy of different ML algorithms like decision tree, decision table, naive Bayes, Bayes net, k-nearest neighbor (kNN) algorithm, multilayer perceptron, and SVM with different kernels, Bayes net is found to be good in the classification of walking directions and distances. For classifying walking speeds, direction, and distance, a multilayer perceptron works well. However, in most analyses, the kNN algorithm and SVM outperform the others. In general, the kNN algorithm is a better option because SVM's quadratic and cubic kernels need more computing load and memory resources. On the other hand, SVM works better with a smaller feature set.[136]

The sensing capability of distributed infrared sensors is limited in movement deduction because they can only recognize the path-dependent activity. Incorporating a mask array can account for visibility modulation, and stereo sensing mechanisms can be used to increase the sensing area.[140] In human movement detection studies, exploring the applicability of open-source software platforms will also aid in deploying a variety of real-time applications, including smart technologies. However, real-time applications necessitate the incorporation of safety and security systems.

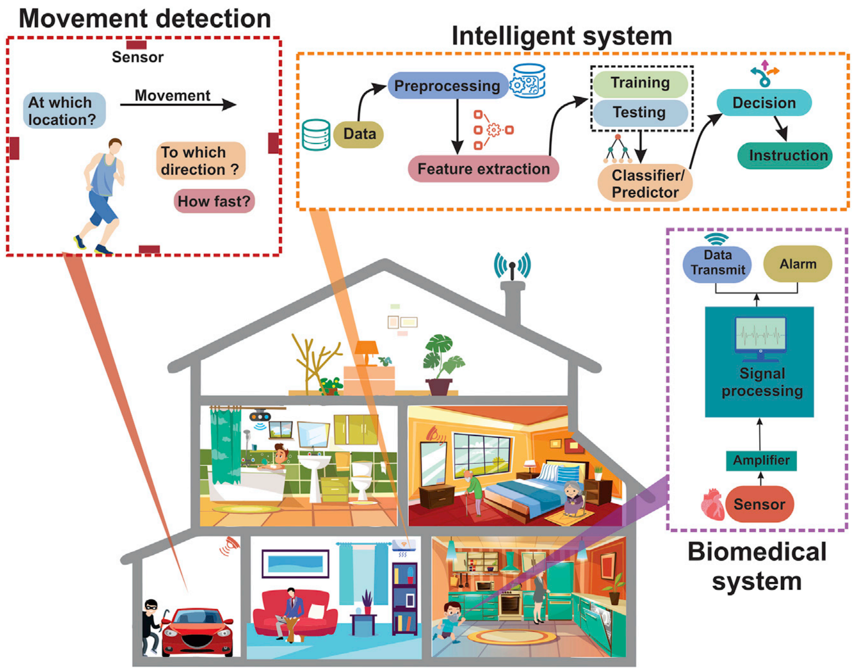

Figure 6. Some applications of pyroelectric sensor technology

From left, real-time motion detection and in-house monitoring,[136,137] intelligent electronics,[138] and biomedical systems to predict respiratory failure.[139]

Valuable information about the position of people and their movement in an indoor environment can also be extracted using multiple pyroelectric infrared sensors. Therefore, a pyroelectric infrared sensor array can be used to create a human tracking system. The human tracking devices can be arranged in a square grid, 3.64 m apart across the ceiling and 2.6 m above floor.[137] Such human tracking systems have massive demand in many fields, including biomedicine, healthcare, and the energy sector. Interestingly, the combination of pyroelectric infrared sensor modules and ubiquitous IoT allows for accurate human movement monitoring. The use of feature vector-based classification is a viable way to improve performance using less computing power.[141] Although the computing power requirements can be solved with multiple sensor modules, achieving significant accuracy with just one sensor module is highly appreciated.

Intelligent home technologies are becoming increasingly common these days. In the case of a voice-controlled intelligent fan device, ML algorithms can recognize the voice command. However, when there is no voice command, the infrared pyroelectric sensor can be incorporated with the device to sense the temperature of the people and regulate the fan speed.[138] Intelligent home systems offer high accuracy, better efficiency, and reasonable practicality in the modern age.

Wearable smart pyroelectric transducer-based devices are becoming more and more important in the medical field for monitoring and treating critical patients. The time it takes for medical experts to get the data they need will be significantly reduced if an ML algorithm and a patient tracking scheme are integrated.[139] The use of such high-precision devices would substantially reduce the labor-intensive hours spent on critical care units. If an emergent patient requires noninvasive care, the device's automatic alarming system will notify the patient if apnea occurs. Unsupervised ML methods such as principal component analysis (PCA) can be used to

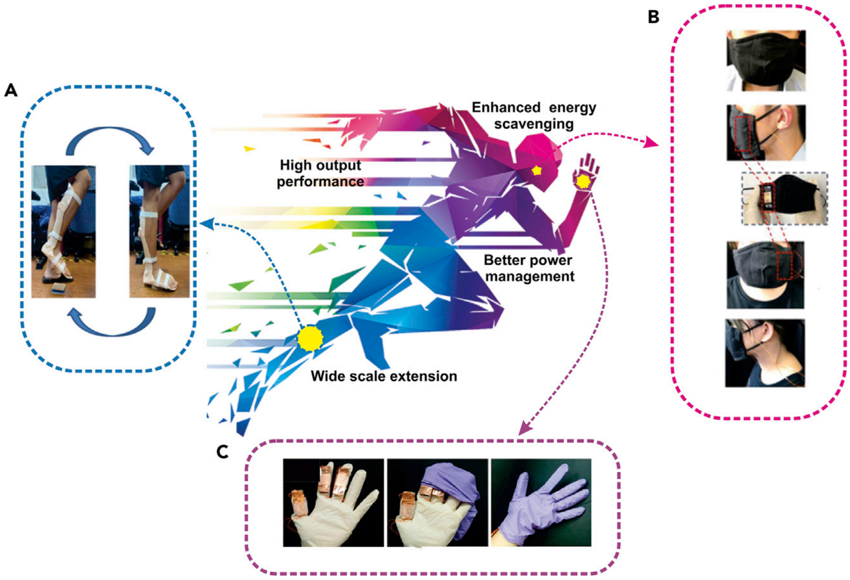

Figure 7. Some real-world applications of hybrid sensors with ML techniques to detect biomechanical energy emitted by human motions

(A) Hybrid sensor under the leg-rehabilitation device,[148] adapted from Lu et al.,[148] copyright © 2021, MDPI.

(B) Hybrid sensor for on-skin triggered biomechanical motion.[149] Used with permission from IOP Publishing, LN:1194679-1.

(C) hybrid sensor for multifunctional pressure sensing and human gesture identification,[150] Used with permission from Elsevier, LN:5260241225331.

build an intelligent multi-walker identification and tracking device.[142] The PCA is nothing but the use of binary principal components to extract the content pattern from high-dimensional data. Integrating binary PCA and pyroelectric sensor data would help build a robust and intelligent real-time multi-walker system.

Extracting required functionality, like any other ML application, is crucial to the success of pyroelectric sensor-based technology. The most challenging part is deciding on the correct feature set. The accuracy can suffer as different features are used directly to train model.[143] Studies are, therefore, needed on characterizing appropriate features using pyroelectric infrared transducers. In general, organic materials have potential applications in biomedical monitoring, tactile sensing, and artificial e-skin applications.[144]

Machine learning in hybrid sensor technology

Hybrid nanogenerators integrate different nanogenerators into a single system that can use several energy sources independently/simultaneously, maximizing the use of any accessible ambient energy.[145,146] The hybrid mode of operation is primarily concerned with power optimization and device compactness.[147] Being introduced as health monitoring sensors, they can detect even minimal biomechanical energy emitted by human motions (Figure 7). Recently, some progress in using ML techniques in hybrid nanogenerators has been demonstrated.[148–151]

The use of triboelectric and piezoelectric energy-harvesting devices has been demonstrated to detect and monitor human motions. In recent works, a triboelectric-piezoelectric multifunctional sensor was used to analyze different actions in a leg-rehabilitation device,[148] human gesture recognition,[150] and in the context of mask vibrations recognition.[149] The deep learning long short-term memory model was used for data analysis in all three cases. Practically, the importance of the vanishing gradient problem limits the use of recurrent neural networks. The long short-term memory approach can be used to solve the data training problems that have been observed in recurrent neural networks.[149] It was noted that the recognition rate of biomechanical motion-level classification using the deep learning model corresponded to 81.8%, whereas the human gestures classification rate corresponded to 82.3%. High classification accuracy was achieved by combining a piezoelectric-triboelectric hybrid sensor and a long-short-term memory model to identify data related to facial muscle. The developed integration could result in an 88% classification accuracy,[149] revealing a promising future of self-powered sensors in intelligent medical systems.

Nowadays, cyberattacks are becoming a global threat. A promising security layer system against password vulnerabilities is urgently needed. Keystroke dynamics-based authentication offers higher cybersecurity than most password-based authentication.[151] In recent work, an electromagnetic-triboelectric hybrid nanogenerator for biometric keystroke dynamics-based authentication and identification coupled with ML is reported. The hybrid sensor-based authentication system combined with ANN achieved an accuracy of 99%.[151]

A summary of various ML algorithms used in triboelectric, piezoelectric, pyroelectric, and hybrid sensor systems is provided in Figure 8. Most ML models have a classification/prediction accuracy of over 90%, and SVM is found to be the most promising ML technique for data categorization.

A NEW PARADIGM OF SELF-POWERED SENSOR/SYSTEM WITH LEARNING CAPABILITY

Because of the wide use of internet-related technologies, huge volumes of data are now accessible for analysis. However, humans lack the intellectual ability to comprehend such large quantities of data. Data science techniques may thus be used to process large quantities of data and make prudent decisions. ML is one such data analysis technique that employs statistical tools to explore the data without explicitly being programmed. By combining ML and self-powered sensors/systems, significant advantages in terms of energy harnessing, power management, information extraction, and decision-making can be envisaged, paving the way for the large-scale utilization of self-powered systems ranging from agriculture to various personal smart technologies. We have identified five sectors and some prominent technologies based on ML in self-powered sensors/systems (Figure 9).

Agriculture

The development of ML-enabled self-powered devices in the field of agriculture allows monitoring of critical parameters like climatic conditions, soil pH, nutrient content in the soil,[152] and so on to improve the crop yield. Furthermore, monitoring such parameters would prevent overfertilization or overwatering in advance. Overfertilization can reduce osmotic potential, leading to decreased photosynthesis.[153] This issue can also promote algal growth in waterways, degrading water quality.[154] Overwatering, on the other hand, is a big concern in locations with limited water supplies. In aquaponics[155] (a type of aquaculture that can be utilized to produce food closer to urban areas), self-powered sensors/systems can be used to optimize the growth of both fish and plants by monitoring and adjusting factors like oxygen depletion and pH swings. Recently, unmanned aerial vehicles (UAVs) or drones are becoming increasingly important and have numerous applications in digital farming, including

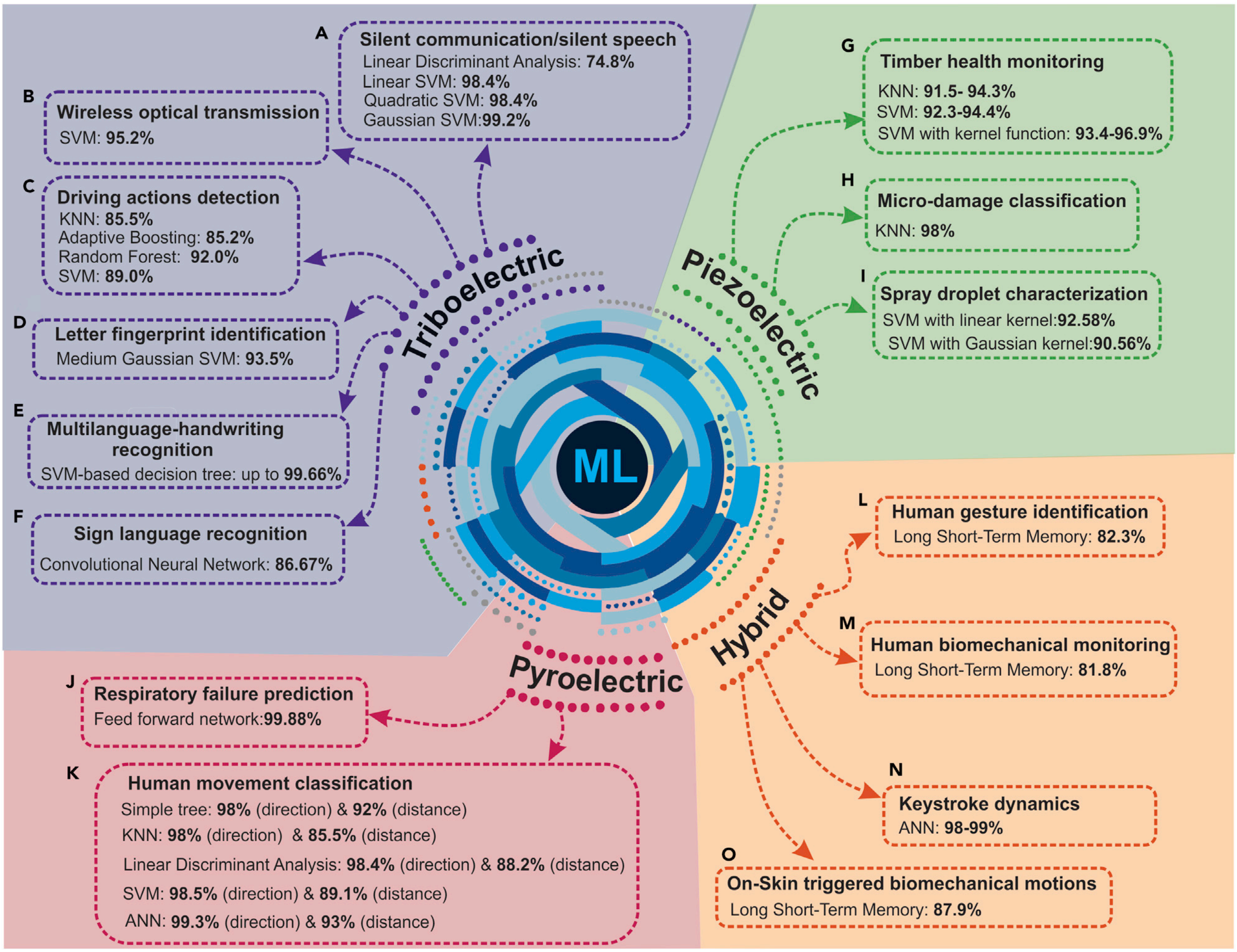

Figure 8. A summary of ML algorithms used in triboelectric, piezoelectric, pyroelectric, and hybrid sensing systems with their classification rate/prediction accuracy

(A) Tong et al.[105]
(B) Ding et al.[104]
(C) Zhang et al.[107]
(D) Ji et al.[122]
(E) Zhang et al.[113]
(F) Wen et al.[114]
(G) Oiwa et al.[126]
(H) Tripathi et al.[132]
(I) Gargari et al.[129]
(J) Hassan et al.[139]
(K) Gami.[141]
(L) Syu et al.[150]
(M) Lu et al.[148]
(N) Maharjan et al.[151]
(O) Shu Fang et al.[149]

high-throughput phenotyping (HTP), plant breeding programs, and weed/insect/disease/injury stressors control.[171–173] However, the charging of UAVs relies heavily on manual operation, which is not only tedious and stressful for human operators but also inefficient and costly for long-duration flight missions. The short endurance of UAVs due to the battery constraint (~30 min) also limits the practical application in large farm sites. Particularly, when heavier sensing equipment is attached to the

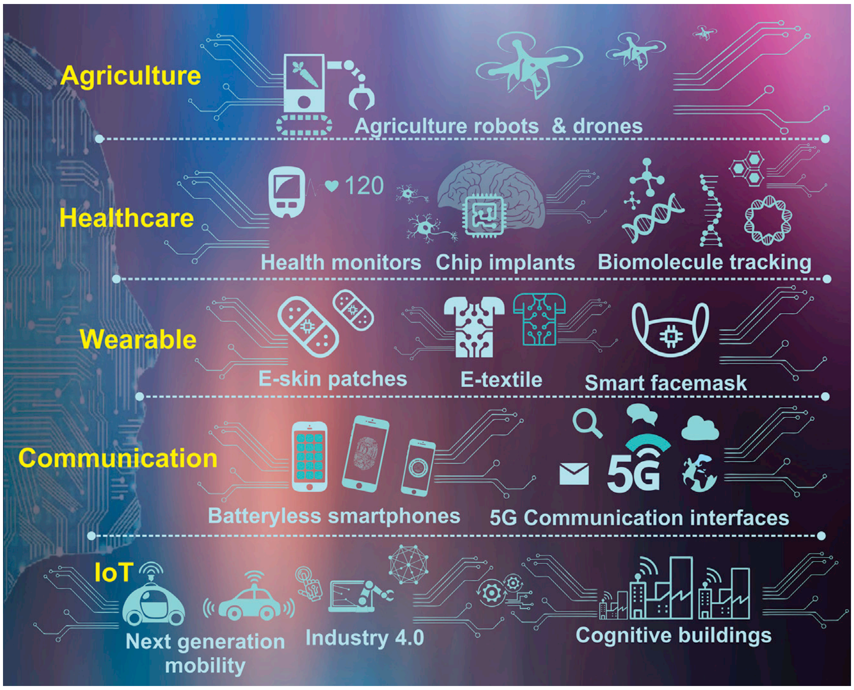

Figure 9. Future perspective of ML in self-powered technology
From the top, five major sectors such as agriculture,[152–156] healthcare,[108,147,157–159] wearables,[160–165] communication,[166,167] and IoT[168–170] in which self-powered sensors and ML will play a huge role, particularly in healthcare and wearables, technologies including implantable self-powered wireless chips to cure neurological conditions, self-powered nanosensors to explore the biological world, biomimetic self-powered electronic skin to monitor health, and self-powered facemasks activated by breathing will make a breakthrough in the coming years.

platform, battery consumption is exponentially accelerated. Thus, developing energy-autonomous UAVs combined with ML techniques could address numerous challenges in smart agriculture.

Healthcare

In the healthcare sector, self-powered sensors capture data from human bodies and environments, allowing continuous monitoring and generating huge amounts of data for analysis.[157] Self-powered sensors can benefit from ML technologies to expand their capabilities. In piezoelectric and TENGs, classification, regression, and probability algorithms can be used to tackle design, fabrication, analysis, and application problems.[158] For implantable sensors or electronics, biocompatibility is a critical factor. Therefore, the implanted self-powered devices should be made of biocompatible materials. In addition, the nanogenerator's structure should be optimized to reduce output attenuation after packaging and implanting.[159] In this sector, hybrid nanogenerators are suggested for a variety of healthcare settings to power noninvasive sensors, enabling continuous patient monitoring without infringing on the user's motion or comfort.[147] Once combined with ML techniques, new opportunities will be created in health diagnostics and disease prevention.

Wearable electronics

Wearable electronics have advanced tremendously in the past decade, owing to their inherent flexibility and portability. Wearable sensors monitor physiological signals and allow for continuous and real-time sensing.[160,161] High-performance wearable bio-electronics should have exceptional sensitivity[174] and long-term stability.[175,176] In 2019, the market for wearable technology was approximately $70 billion.[177] Furthermore, the COVID-19 pandemic has put a greater emphasis on wearable sensors, including real-time disease monitoring,[162] wearables for contact tracing,[178] and isolation patient monitoring.[179] In wearable technology, e-textiles provide a framework for deploying sensors and actuators in applications that are unobtrusive and ubiquitous.[163,180] By convolving E-textile with advanced algorithmic techniques, textile designers will be able to build more sophisticated systems.[163,164] Likewise, the deployability of e-skin systems has increased recently, establishing the groundwork for their scalability.[165] However, constraints like resilience, mechanics, information processing, and transport pose a challenge to providing efficient tactile skins to robots or prosthetic devices.[165] Upscaling e-skin system necessities processing of vast amount of variable tactile input with complex spatial relationships between sensing locations.[181]

Communications

Self-powered wireless sensing devices are becoming increasingly important in developing remote monitoring systems as fifth-generation (5G) communication is advancing.[182] However, adopting 5G networks comes with a slew of challenges, including limited communication range and high power requirements.[182] In 5G, ML would aid in precise learning about the working environment and offer a wide range of services.[166] Moreover, deep learning has shown that it can improve communication reliability while also reducing the computational complexity of 5G and future networks.[167]

IoT

The ML-enabled smart homes and related applications have been demonstrated to be an efficient paradigm for capturing a richness of sensory data.[168] Although current developments have shown successful implementation of intelligent technology for individual event recognition in smart home applications,[169,170] system-level integration of sensor, power supply, and ML technologies has not been fully explored. Self-powered systems with learning capability will correlate with more intelligent things in the network, thereby recognizing complex events and making appropriate decisions to serve human beings better.

The emergence of bioinspired sensors

Recently, bioinspired sensors have demonstrated immense applications. Bioinspired sensors have excellent electrical power harvesting abilities and multifunctional sensing capabilities. To cite a few examples of bioinspired sensors, Calathea Zebrine leaf has uniform conical structures that allow for fabrication and use of artificial superhydrophilic surfaces[183] for applications including robotic tactile sensing[184] and ionic skin[185]; self-cleaning capability of lotus leaves allows for fabrication of superhydrophobic interfaces[186]; superhydrophobic and adhesive nature[187] of rose petal allow for the fabrication of biomimetic polymer films for harvesting mechanical energy[188,189]; large number of air-filled chambers in water hyacinth petiole allow for the development of porous triboelectric materials[190]; electrical signal generation ability of living aloe vera plant indicates its potential use in biomechanical energy-harvesting applications[191,192]; superior specular transmittance (maximum of 91% for visible light) of moth's eye allows for the development of anti-reflective energy harvesters[193]; electrostatic field obstacle detection mechanism of cockroaches allows for the development of sensor devices for identifying non-contact motions[194]; butterfly wing architecture instigates the fabrication of devices for sensing[195] and energy applications[196]; treefrog's toe pads show superior frictional properties for high self-powered operation[197]; high electric potential generation ability of electric eel opens up new opportunities for the development of devices for underwater sensing[198,199]; and muscle-fiber-inspired piezoelectric textile having interfacial-adherent linkage for personalized wearable healthcare devices.[200] Applying ML techniques in bioinspired/biomimetic sensors will open up new possibilities for intelligent systems, security, and information protection.

CHALLENGES AND OUTLOOK

The large-scale IoT appears to be still on the way, and progress toward that vision is slow. One explanation for the slow progress of large-scale IoT is that the batteries are incompatible with the massive sale of IoT deployment. It is estimated that nearly 1 billion batteries need to be replaced every day for potential large-scale IoT deployment. The use of energy-harvesting techniques is one of the promising alternatives to batteries. On the other hand, introducing self-powered systems will pave the way for a myriad of challenges, including the grand challenge of relatively small power generation in most energy-harvesting modalities. It is necessary to envision an active operating condition for the electronics, ideally taking advantage of the relatively low power produced by most energy-harvesting systems. Lowering the power consumption of active operating electronic systems is a compelling approach that opens up new possibilities for building electronic devices with low active processing power in the future. We foresee the following major research issues, and problems should be addressed to completely enable the large-scale development of self-powered sensing systems based on piezoelectric, triboelectric, and pyroelectric principles:

- When exploring the vast unexplored space in the field of ML systems based on piezoelectric sensors, we will find that traditional trial-and-error methods face numerous challenges. Therefore, informatics-based techniques are considered promising due to their ability to learn from available data. It is suggested that to design advanced piezoelectric materials, better encoding processes should be considered, as well as a combination of theory and data-driven approaches should be envisaged.[201] Future piezoelectric sensor and actuator research should focus on extracting better functionality from multi-sensor/actuator systems.[202] ML, in particular, plays a critical role in determining measurement accuracy. To demonstrate higher potency, various algorithms with different iteration levels must be evaluated.
- The surface charge generated by contact electrification needs to be greatly raised to harvest adequate energy for powering many of the typical electronic gadgets that we use in our everyday lives. As a result, there is still a pressing need to develop more efficient methods for increasing, decreasing, or controlling charge generation via contact electrification.[203] In the future, TENG-based human-machine interfaces will certainly give insight into the harmonious cohabitation of humans and machines, as well as immersive and efficient interactions in different scenarios.[204] The self-powered triboelectric sensors can be combined with ML to construct wearable real-time health tracking and disease prediction devices, allowing for early detection of diseases and avoiding intensive care.[95,205,206] If more than one such self-powered sensor is deployed, it is easy to achieve multi-target monitoring as well. However, the reproducibility of ML in healthcare research is still challenging.[207] On the other hand, the grand challenges lie in adopting, regulating, integrating, standardizing, and updating these technologies over time.
- As ML expands in various applications, the selected applications like human motion detections that use pyroelectric sensors and systems face some challenges. One grand challenge is that accuracy varies depending on the size of the dataset.[135]

Figure 10. Roadmap to foster the market uptake of self-powered intelligent systems

- Hybrid nanogenerators provide significant advantages in terms of energy scavenging and output performance.[208] However, toward the use of hybrid nanogenerator-based sensors on a broad scale, a list of challenges needs to be addressed. First, it is inevitable to enhance hybrid generators' power and their synergic outputs through integration.[209] Second, the sensitivity of hybrid sensing systems needs to be enhanced. The confluence of ML techniques and hybrid sensors can optimize the device's performance and allow for the accurate detection of more minute senses. Furthermore, ML techniques can be used to address the poor linearity of nanogenerators' output. Hybrid sensing systems with excellent linearity can offer better sensing capabilities and broaden applications.

Overall, to overcome some technical challenges of self-powered sensors/systems, we envisage a roadmap to foster the market uptake of self-powered intelligent systems (Figure 10).

Materials

High-performance and low-cost materials for self-powered sensors and potentially biocompatible/biodegradable materials need to be explored. The term "transient electronics[210,211]" has recently gained popularity, and it is expected that research in this area will revolutionize the electronic industry and bring viable answers to e-waste problems by physically degrading devices in specific environments, including water,[212] moisture,[213] light,[214] or heat.[215,216] However, the transiency of such devices must be thoroughly evaluated. For example, implantable bioresorbable devices would have an impact on the human body and may cause side effects.[217]

Manufacturing

Currently, active component density in sensing systems is very low compared with human skin.[218] Sensor repeatability and reliability might be problematic when manufacturing scales up. Furthermore, manufacturing and assembling multimodal sensors in a compacted form at scale is nontrivial. New processing techniques should be explored to fabricate human skin-like self-powered sensors with high density and low impedance.

Multimodal sensing

Future sensing devices should be multimodal to understand heterogeneous data for situation awareness, better human-machine interface, and improve prediction accuracy.[219] Conventional wearable electronics are sensitive to both strain and temperature, making them suboptimal for use as artificial multimodal receptors.[220] Decoupled multimodal sensing is one of the recommended ways for achieving multimodal sensing on an e-skin by using the same sensory unit to differentiate physical variables without signal interference.[221]

Energy management

Novel ML algorithms for self-powered sensors and innovative ML for energy management in self-powered sensory systems need to be explored. More detailed information can be retrieved by matching a specific functional system with the right ML model.[222] There is also a need to develop a model that demonstrates the potential for intelligent energy management on both micro and macro scales by integrating ML and big data.

Machine learning

Although ML allows for fast analysis, prediction, and processing in the field of self-powered sensors, it requires a large dataset, which can often be biased and could not deliver the right quality. Data acquisition issues can come from both quantity and quality. The time needed for algorithms to evolve and learn is longer to complete their tasks with an acceptable level of relevance and accuracy. ML often necessitates a large number of resources to function, needing more computing power when used on a commercial scale. New configurations of ML-embedded self-powered sensors (or sensing systems) and powering ML units (computing) need to be considered. The functionality and/or structuralism of biological systems,[219,223–225] such as neuroplasticity and neuro-biological architectures, would provide design principles that can intrinsically address unmet needs in current artificial intelligent systems. Although massive data and more dimensions of data improve prediction accuracy, handling massive raw data is difficult. Edge computing nodes should be considered in the future.[226]

Evidently, algorithms are optimized for efficiency rather than humanity. We must ensure that algorithms represent human values and principles as they govern the future. It is also necessary to ensure that these algorithms are transparent and accountable so that privacy is respected and human autonomy is maintained. We here present five grand ethical and security implications of ML systems in real-world applications (Figure 11). Despite the challenges of ML-based sensing systems, it paves the way to discover new patterns and trends from diverse datasets, providing new products and services. It is believed that with the evolution of adaptive ML techniques, the challenges mentioned above can be sorted out.

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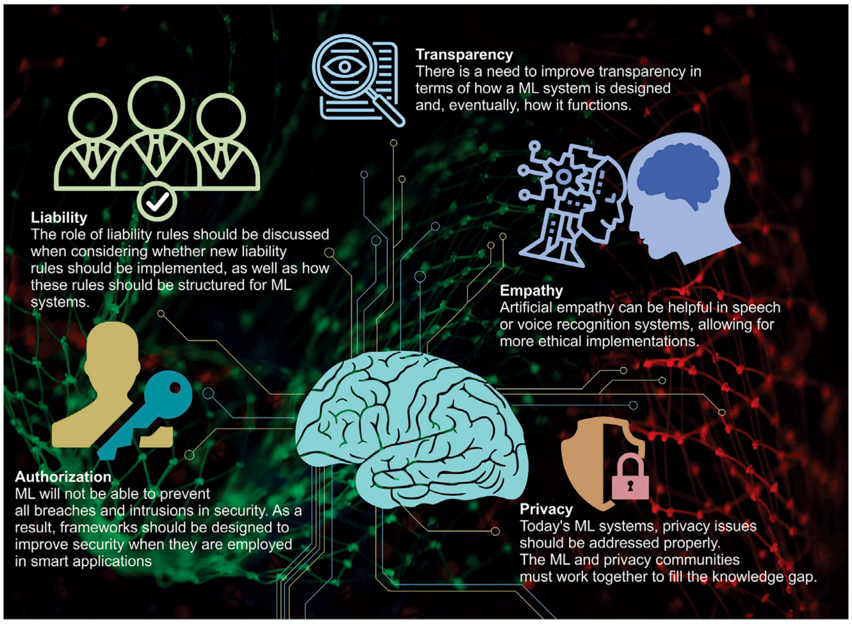

Figure 11. Ethical and security challenges to be tackled for ML systems in real-world applications

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DECLARATION OF INTERESTS

The authors declare no competing interests.

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