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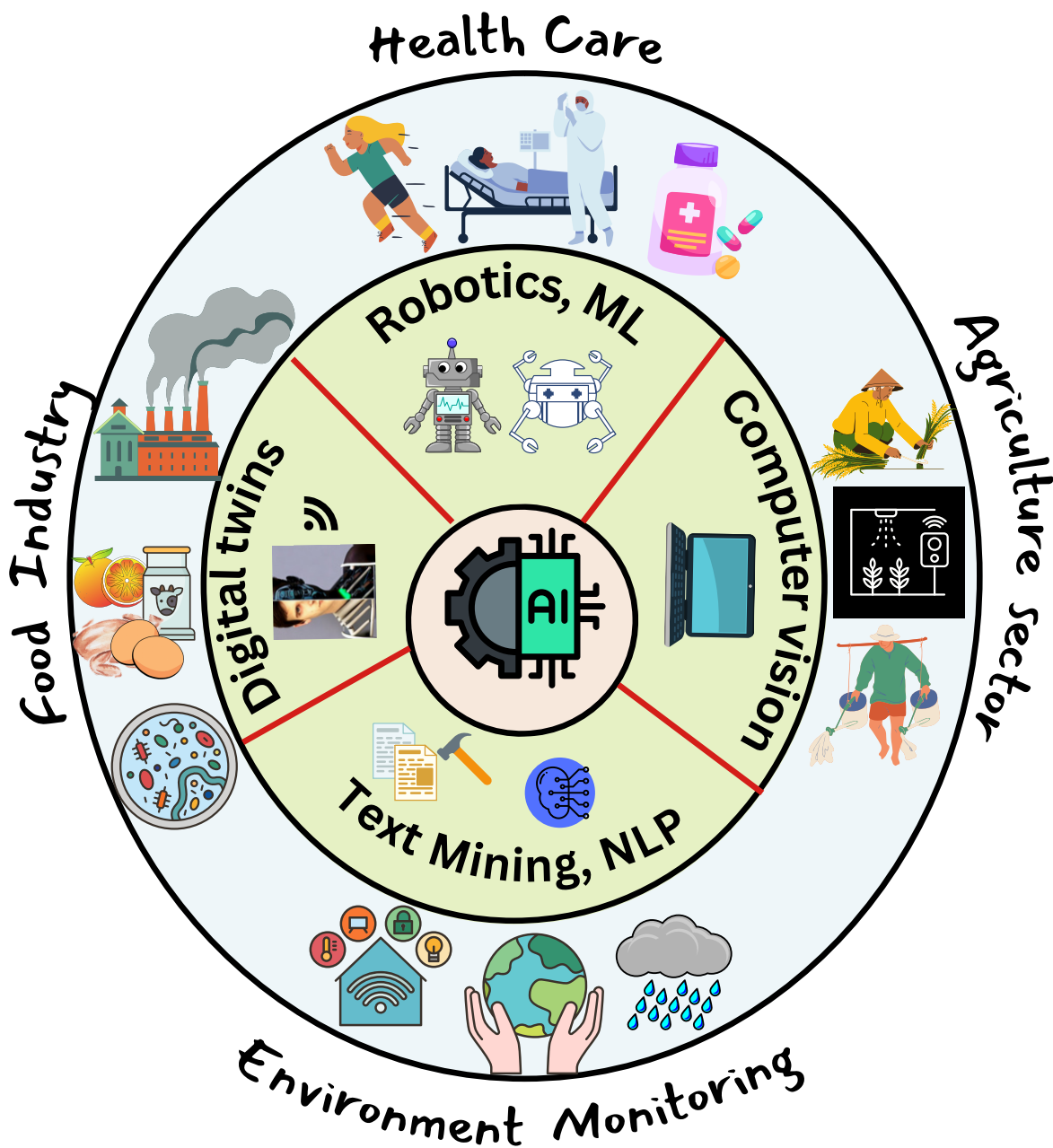


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Graphical Abstract

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Highlights

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- Elaboration of the symbiotic relationship between machine learning and sensing technology.
- Uncertainty quantification in multiphysics models guided sensors enabled by AI
- Widespread integration of AI technique in devices for computer vision, e-skin, e-tongue and e-nose.
- Generative AI enables the exploration of appropriate substrate pair for a selected enzyme.

A topical review on AI-interlinked biodomain sensors for multi-purpose applications

Rubi Thapa^a, Sachin Poudel^b, Katarzyna Krukiewicz^{c,d} and Anil Kunwar^{b,*}

^a*Padhmashree International College, Institute of Science and Technology, Tribhuvan University, 44600 Kathmandu, Nepal*

^b*Faculty of Mechanical Engineering, Silesian University of Technology, Konarskiego 18A, 44-100 Gliwice, Poland*

^c*Department of Physical Chemistry and Technology of Polymers, Silesian University of Technology, M. Strzody 9, 44-100, Gliwice, Poland*

^d*Centre for Organic and Nanohybrid Electronics, Silesian University of Technology, S. Konarskiego 22B, 44-100 Gliwice, Poland*

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ABSTRACT

Based on their construction or working principles, biosensors, biomimetic sensors, and bioapplicable sensors may have been understood differently, but everyone acknowledges their commonality of sensing in fields that require knowledge of biochemical science and engineering. In the era of big data and industry 4.0, the amalgamation of artificial intelligence (AI) technology and the Internet of Things (IoT) with the applied science of sensing is seen as a way forward to achieve unprecedented growth in the design and development of novel and robust biochemistry-related sensors. The integration of AI with sensing technology makes it possible to produce sensors that can rapidly detect targets while maintaining high sensitivity, accuracy, and precision, all at a cost-effective price point. This work reviews recent literature on the applications of AI tools to accelerate the advancement of intelligent biosensors. Also, it projects how novel AI tools such as digital twins, machine vision, robotics, natural language processing, and text mining will transform the design and broaden the applicability of biosensors, bio-inspired sensors, and bioapplicable sensors.

1. Introduction

Nature serves as an abundant source of inspiration for technological innovations, particularly in the field of biomimetics, which harnesses nature's principles to generate new ideas [1]. Sensors, defined as devices that detect and measure physical or chemical properties, play a crucial role in technological advancements. Within this realm, biomimetic sensors have made significant strides, imitating natural systems to enhance sensing capabilities. Biosensors, a specific category of biomimetic sensors, combine biological components such as microorganisms, tissues, enzymes, and synthetic catalysts with physiochemical transducers, enabling advanced bioanalytical measurements [2]. These biosensors have a wide range of applications in biomedicine, environmental monitoring, and food safety. Additionally, bio-applicable sensors are gaining prominence, encompassing various types of sensors used in biomedicine, healthcare, and biological research. By interfacing with biological systems, these sensors provide valuable insights into monitoring physiological parameters, diagnosing diseases, and advancing personalized medicine and tissue engineering. The collective contributions of biomimetic sensors, biosensors, and bio-applicable sensors drive innovation in bio-related fields.

Biomimetic sensors, utilize materials, structures, and functions inspired by nature to achieve high levels of sensitivity, selectivity, and adaptability. Drawing inspiration from nature and borrowing its concepts through biomimicry enables the creation of innovative technical systems and

processes [3]. The potential of biomimetics is believed to be boundless, with significant scientific, sociological, and economic implications that can enhance the quality of life [4, 5]. The concept of biomimetic technologies emerged from the transfer of ideas from the biological sciences to engineering, benefiting from millions of years of evolutionary design carried out by natural selection in living organisms [6]. The rapid development of computing has led to the emergence of important fields in artificial intelligence (AI), machine learning (ML), system accumulation, and hardware design. These interdisciplinary approaches contribute to the advancement of biomimetic technologies in various areas such as evolvable electronic circuits, computer-assisted creation, material manufacturing technologies, and robotics [7]. Bio-inspired approaches have historically played a significant role in the development of crucial inventions, particularly in engineering design and technology. Figure 1 demonstrates the arts guiding the biomimetic sensor design, with the human olfactory system serving as the de facto source of inspiration. The researchers have created artificial nose-type sensing systems that mimic the pattern recognition capabilities of the olfactory system. These systems aim to enhance the specificity and sensitivity of odor detection by analyzing and identifying smells chemically similar to the olfactory system [8, 9]. Section 6.2 provides a detailed description of an artificial olfactory system. The research fields of biomechanics, bioengineering, bionics, robotics, and biomimetics originated in the mid-twentieth century and have since become widely explored areas. Over the past few decades, data science and machine learning have experienced significant growth, leading to their recognition as the fourth pillar of science.

*Corresponding author

✉ anil.kunwar@polsl.pl (A.K.)

ORCID(S): 0000-0002-8973-331X (R. Thapa); 0000-0003-1427-5550 (S.P.); 0000-0003-0503-0906 (K.K.); 0000-0003-4295-5772 (A.K.)

Biosensors, which are analytical devices that combine the precision and specificity of biology with physicochemical transducers, facilitate advanced bioanalytical measurements in user-friendly formats [10]. These sensors integrate biological, such as microorganisms, tissues, enzymes, and synthetic catalysts, with a range of physicochemical transducers including optical, electrochemical, thermometric, piezoelectric, magnetic, or micromechanical technologies [2]. However, conventional biosensors have limitations in terms of sensitivity, selectivity, and stability. To address the sensitivity limitation, Miller et al. [11] enhanced biosensors by introducing extracellular components that hinder the escape of target molecules. In terms of selectivity, conventional biosensors struggle to distinguish between various target analytes. Hasib et al. [12] demonstrated a surface plasmon resonance (SPR) biosensor with exceptional sensitivity, detection accuracy, and quality factor using the Kretschmann configuration. Additionally, Wann et al. [13] outlined the primary obstacles and forthcoming outlooks for novel and enhanced biosensor technology. To overcome the limitations

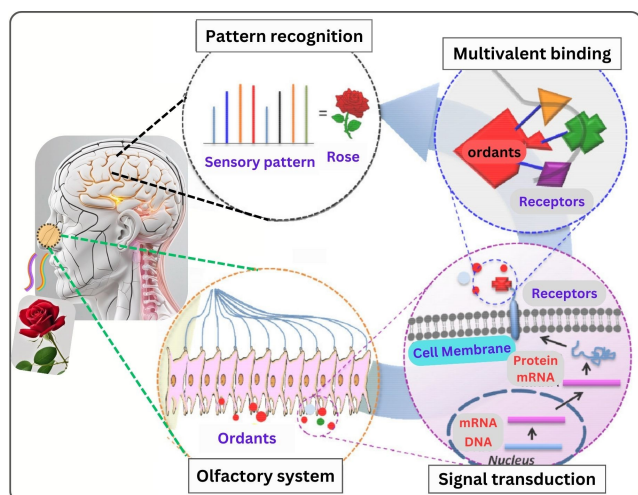


Figure 1: Schematic illustration for bio-inspired design of sensors[14]. The image showing the human olfactory system has served as a valuable inspiration for designing biosensors, where arrays of olfactory receptors at the molecular level can accurately detect specific target molecules. Reproduced with permission from [14].

faced by conventional biosensors, the integration of AI technology and Internet of Things (IoT) is expected to accelerate the advancement of intelligent biosensors. AI has played a significant role in the development of biosensors, utilizing tools such as Biorobotics, machine learning, digital twins, computer automation, natural language processing, text mining, and image and speech recognition. Overall, biomimetics and AI-driven advancements have the potential to revolutionize biosensor technology, enhancing sensitivity, selectivity, and stability, while paving the way for next-generation biosensors that are rapid, precise, and cost-effective. Biosensors have witnessed remarkable growth across various fields, benefiting from numerous technological advancements that have provided us with the necessary tools and resources

for manufacturing sophisticated biosensor devices. Modern biosensors have undergone significant improvements in terms of sensitivity, selectivity, and the ability to perform multiplexing. These advancements have led to the development of biosensor solutions that address a wide range of challenges, including disease monitoring, food safety and processing, environmental monitoring, modern agriculture, and many other domains [15, 16].

In addition to biomimetic sensors and biosensors, a third category of sensors called bio-applicable sensors plays a crucial role in various bio-related fields. Bio-applicable sensors are simple mechanical or other types of sensors that find applications in areas such as biomedicine, healthcare, and biological research. These sensors are designed to interface with biological systems, providing valuable data and insights for monitoring physiological parameters, diagnosing diseases, and studying biological processes. With their ability to detect and measure physical and chemical signals in a biocompatible manner, bio-applicable sensors contribute to advancements in personalized medicine, wearable devices, implantable sensors, and tissue engineering. These sensors offer great potential for improving healthcare outcomes and understanding the intricacies of biological systems, opening up new avenues for research and development in the field of bioengineering.

Our comprehensive review article aims to explore the synergistic relationship between material science, artificial intelligence (AI), and machine learning (ML) in the context of biomimetic sensors, biosensors, and bio-applicable sensors. It is first necessary to introduce the concepts of sensing and biodomain sensors, and thus Sec. 2 is devoted in summarizing the recent studies and work that outline the basic models and design of biomimetic (Sec. 2.1) as well as biosensors (Sec. 2.2). In the era of big data, the AI tools and techniques have been influencing the design, manufacture and application of sensors. At the meantime, there is an understanding that the explainability of AI renders an application more reliable, and this is possible by incorporating theoretical models with the AI methods. Thus, Sec. 3 is a synopsis of previous works that have focused on both the multiphysical mathematical models and AI methods, directly or indirectly related to biodomain sensor applications. At the forefront of ushering in a new era, 4 delves into AI-guided sensor design, encompassing the holistic development of sensors in various fields, particularly in the biochemical domain, and explores the symbiotic relationship between sensing technologies and artificial intelligence. Section 5 navigates the integration landscape of AI tools with biosensors, leveraging insights from notable review papers and works. It encompasses diverse aspects: from the amalgamation of artificial intelligence and robotics in biosensors (5.1) to the synergy between machine learning and sensing technology (5.2), exploring the potential applications of digital twins and real-time data in sensing technology (5.3), utilizing computer vision for enhanced automation in biosensors (5.4), and innovating interactive biosensors through techniques such as text mining and NLP

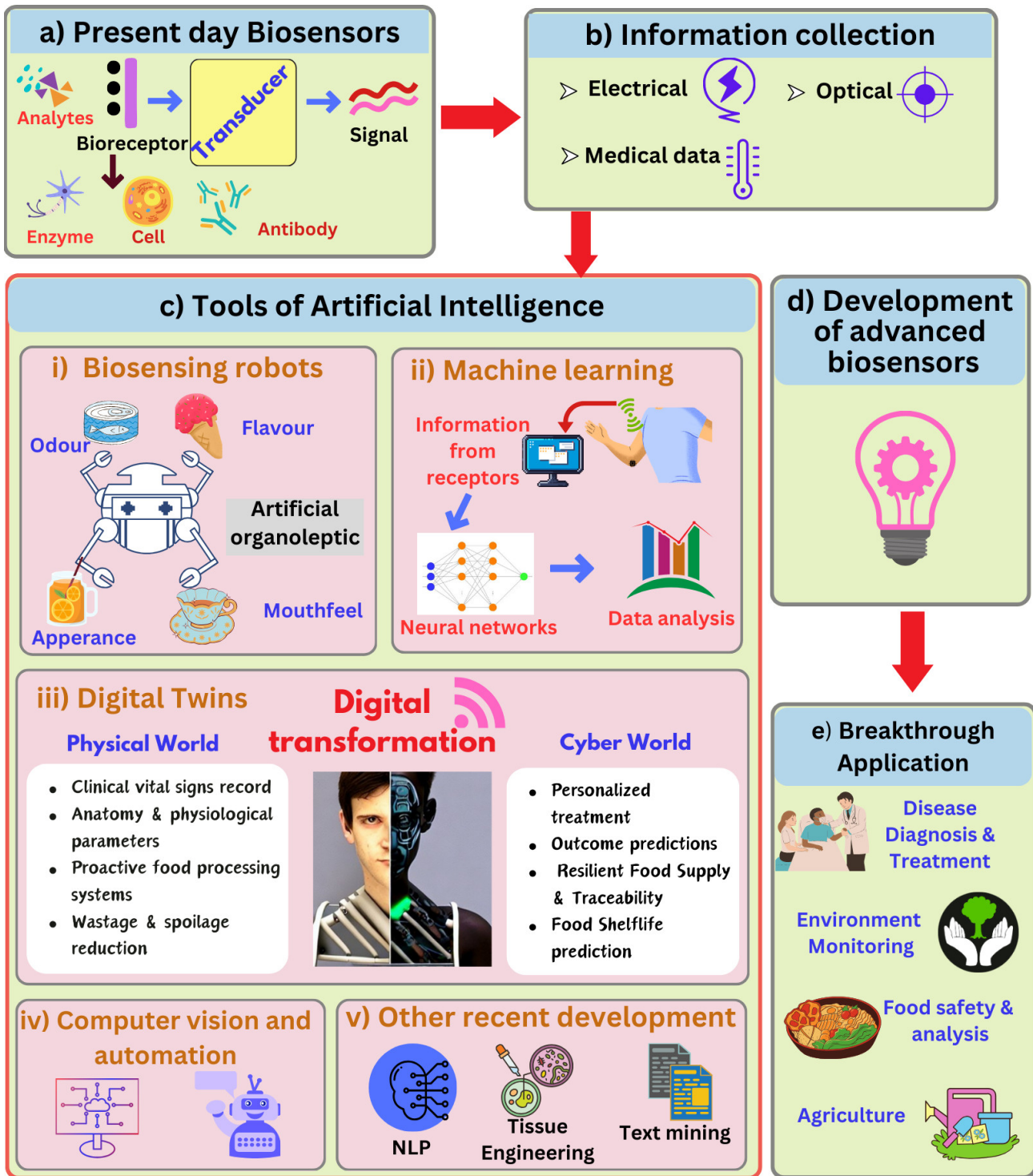


Figure 2: Schematic illustration of a) workflow mechanism in a biosensor revealing how a receptor interacts with a biological element to further induce the transducer to generate an electric signal is generated by the transducer, and b) categorical types of collected information c) applied artificial intelligence for sensing d) how continual usage of data-driven methods can enhance the design of improved biosensors and e) potential advanced applications of the highly improved and sensitive sensors.

(5.5). It is followed by Sec. 6 which traverses through notable insights gleaned from existing scholarly publications and research, elucidating the realm of data-driven sensing technology applications across various biosensors, biomimetic sensors, and bioapplicable sensors. It spans from

exploring tactile and vision applications of biomimetic sensors (6.1) to simulating biomimetic olfaction and gustation systems (6.2). Additionally, it delves into critical domains such as food processing, awareness, quality, and safety (6.3),

disease diagnoses and health monitoring (6.4), environmental monitoring (6.5), and agricultural applications (6.6). After highlighting the challenges intrinsic to the integration of artificial intelligence within the biodomain sensors (e.g. biosensors, biomimetic sensors, and other sensors), Sec. 7 then outlines the way or roadmap for future advancements or directions in the realm of these AI-interlinked sensors.

2. Biomimetic sensors and biosensors: basic models and design

The world is undoubtedly moving towards Industry 4.0, also known as the fourth industrial revolution, characterized by the convergence of information communication and industrial technologies [17]. This revolution aims to integrate the digital and physical realms by leveraging cutting-edge technologies such as cyber-physical systems (CPSs), IoT, artificial intelligence, big data, cloud computing, additive manufacturing (AM), and automation [18, 19, 20]. In the era of Industry 4.0, there exists a substantial demand for both biomimetic sensors and biosensors in scientific and technological applications. With advancements in materials science and biotechnology, biomimetic sensors and biosensors are expected to gain further traction in the era of Industry 4.0 and beyond. Their integration into larger systems opens up new possibilities for improved efficiency and precision. The growing popularity of biomimetic sensors and biosensors can be attributed to their numerous advantages, surpassing those offered by conventional sensors and analytical methods.

2.1. How the biological phenomena are inspiring the sensor design

The natural world has evolved and refined a vast array of sensors for tasks such as navigation, prey, and object detection, and spatial orientation, offering valuable hints for engineers to gather new ideas for developing novel sensor technology and enhancing current technology [21]. Drawing on concepts from biology has been proven to stimulate creativity and promote innovation in a wide range of forthcoming technologies [6, 22]. Biomimetic material design involves studying the design principles of natural structures to gain a fundamental understanding of them, and then using biological building blocks such as DNA/RNA, peptides/proteins, lipids, and sugars, to develop practical applications that mimic hierarchically organized functional structures [23, 24]. To create biomimetic sensors, there are several approaches to imitate biological systems such as functional design, morphological design, the use of biological principles, strategies, and manufacturing either individually or in combination. The concept of biomimicry is broad-ranging and encompasses many different approaches. Such sensors are developed through systematic procedures, including observing natural systems and using databases for inspiration [25]. Using biological inspiration for sensor design has the potential to not only enhance existing sensor models but also encourage the development of novel ones [26, 25]. For instance, The development of vision sensors

has been inspired by the structure and function of the human eye. Steffen et al [27] discuss the application of biomimetic approaches to recreate essential attributes found in the human eye, such as high-resolution imaging, wide dynamic range, and low power consumption. The authors emphasize the utilization of diverse sensor designs and architectures that closely mimic the structural principles of the human eye.

2.2. Biological components in sensor design and manufacture

The use of biological components is crucial in the design and manufacturing of biosensors. In a common setup (shown in Figure 2(a)), the three major components of a biosensor are a bioreceptor, a transducer, and a signal processing system [28]. A bioreceptor, also known as a biological recognition element, interacts with the substance being measured i.e. analytes (enzyme, antibody, nucleic acid, cells, aptamers, tissue, microorganism, organelle, cell receptor), emerging options involve biomimetic materials such as biomimetic catalysts, molecularly imprinted polymers, and combinatorial ligands [29]. A bioreceptor typically consists of a biological component that has been immobilized and can recognize and respond to a specific target analyte [30]. The sensitivity of the entire device is determined by the biological receptor generating a physicochemical signal that is then monitored by the transducer [31]. A transducer is a substance or material with the ability to convert energy from one form to another [32]. It detects and measures changes resulting from the interaction between the biological receptor and the target analyte and converts the biochemical signal produced by this interaction into a quantifiable signal (refer Figure 2(a)-(b)), which could be in the form of piezoelectric, optical, or electrochemical signals, among others [33].

Nature and biology guide in many ways how overall sensing and measurements are designed. While the biosensors themselves include biological components, the bioinspired sensors are inspired by natural/biological phenomena, and the bioapplicable sensors are developed to work together with biological systems. By imitating the structure and function of biological systems, bioinspired sensors have the potential to provide better sensitivity, selectivity, and robustness compared to conventional biosensors. As biosensors, biomimicking sensors, and bioapplicable sensors are important tools in studying nature through quantitative means, it is very much fundamental to advance the sensing techniques by utilizing artificial intelligence. The concept of AI-guided sensor design will be explained in the following section (Sec. 4).

3. Multi-physical theoretical models meeting data-driven methods

The knowledge of the working principles of biodomain and environmentally applicable sensors makes it possible to design routes and mechanisms not only for their performance improvement but also for broadening their application areas. The correct information on the fundamental physical models

governing the working mechanism of a sensor is required for the process integration with data-driven methods or equipment. The integration of AI techniques into the design and operation of multiphysical equation-driven sensor technology holds promise for enabling uncertainty quantification within biodomain areas. It is noteworthy to highlight that the integration of multiphysical theoretical insights with the machine learning technique makes the latter explainable. On the other hand, the explainable AI (XAI) enables the uncertainty quantification in physics governed sensors via statistical optimization techniques. The details about the quantification of uncertainties are presented in Sec. 7. The nature of the materials used in the sensor design, and the expected field of applications require different mathematical models in the sensing action. For example, Michaelis-Menten Equation [34, 35] for substrate-enzyme kinetics is utilized in the design of biosensors, whereas piezoelectric equations govern the working mechanisms of flexible bio-applicable sensors [36]. While the stimuli in sensors will be obtained in terms of variables associated with mechanical or chemical fields, the measurement mostly takes place after conversion into the variable of electrical field. Thus, multiphysical models are mostly employed with sensing activities. This section will present a summarized literature review of the basic physical equations utilized in the design of bio- and environmental-domain sensors. Wherever applicable, the progress made toward the implementation of AI-related tools in the corresponding sensors will also be discussed. It is to be noted that the integration of physics-based equations with AI can greatly help render the latter explainable.

Kinetics at substrate-enzyme interface: The Michaelis-Menten model is a fundamental approach in enzyme kinetics, portraying the reaction velocity (V) in relation to substrate concentration. As depicted in the top image of Fig. 3 (a), it characterizes reversible binding of a substrate (S) to an enzyme (E) forming an enzyme-substrate complex (ES), which then undergoes irreversible reactions to generate a product (P) and regenerate free enzyme (E). The Michaelis-Menten equation states that the product formation rate V depends hyperbolically on $[S]$, and is depicted mathematically as follows:

$$V = \frac{V_{max} \times [S]}{(K_M + [S])} \quad (1)$$

where, $[S]$ is understood as the substrate concentration and V_{max} is the maximum velocity at saturating substrate concentrations. In Eq. 1, K_M is the Michaelis constant, defined as the substrate concentration at which V attains half the value of V_{max} . In amperometric enzyme-based biosensors (refer Fig. 3 (b)), the current density (J) values [37] could be taken as a quantitative indicator for reaction rate (V). Fig. 3 (b) illustrates the method of calculating the K_M for the specific enzyme-substrate pair [37]. In the figure, $J_{max} \approx 100 \mu A/cm^2$, and from the curves it can be observed that the $J \approx 50 \mu A/cm^2$ is attained for glucose (substrate) concentration of 16 ± 2 mM. Thus, the K_M for this biosensor system is 16 ± 2 mM. It is to be noted that Eq. 1 is

established by assuming that the enzyme concentration ($[E]$) is in excess; and thus does not influence the rate of reaction. If $[E]$ is not saturating, then V_{max} will vary and V will have a linear dependence on the enzyme concentration [34].

One of the bottlenecks in the design of biosensors based upon enzyme-substrate kinetics and cellular physiology is the quantification of the Michaelis constant [38, 39]. Physically, K_M can also be an inverse measure of the affinity of an enzyme for a given substrate [38]. Since determining K_M frequently involves challenges and consumes substantial time, experimentally obtained values for this parameter are available for merely a minority of enzyme-substrate interactions, even within well-studied model organisms [39]. The middle illustration (in Fig. 3 (a)) portrays the application of AI-driven estimations to bridge the knowledge gap inherent in the determination of K_M values across diverse enzyme types and various living organisms [38]. The subsequent illustration in the lower part of the same figure underscores the potential of these AI-driven forecasts to not only advance the realm of metabolic engineering but also to foster innovative prospects within drug target exploration [38]. Kroll et al [39] have introduced a novel approach (Fig. 3 (c)) utilizing a generalizable and organism-independent machine learning algorithm for the prediction of Michaelis constant solely based on protein and substrate data. The upper portion of Fig. 3 (c) delineates the process of computing molecular fingerprints using the RDKit software, employing the databases of the substrates (provided via MDL Molfiles). These fingerprints, combined with global attributes such as molecular weight (MW) and octanol-water partition coefficient (LogP), serve as input features for the ANN, facilitating the subsequent prediction of K_M value. In the lower section of the same figure, the feature vectors obtained via a graph neural network are first aggregated with MW and LogP, and then the dataset subsequently undergoes training with the ANN with K_M assigned as the target feature.

Another major milestone in the development of AI-guided biosensor design and development is the establishment of the database of enzyme-substrate relationships. Especially, a significant disparity exists between the considerable number of proteins projected to have enzymatic functions and the limited experimental understanding of their corresponding substrate ranges [40]. While data are abundant regarding the enzymes (in the range of several millions of entries in well-known databases), only a tiny fraction of these entries have clear annotations of candidate small molecule substrates for associated catalytic reactions [40]. As illustrated in Fig. 3 (d), generative AI, or more specifically attention mechanism-based machine learning algorithm has been utilized in Kroll et al. [40] to estimate the candidate substrates for given enzymes.

Transport equation for ionic migration: Impedimetric biosensors [41] are utilized in the healthcare sector for bacterial detection. In such biodomain electrochemical sensors, the associated transport phenomena of ions are represented

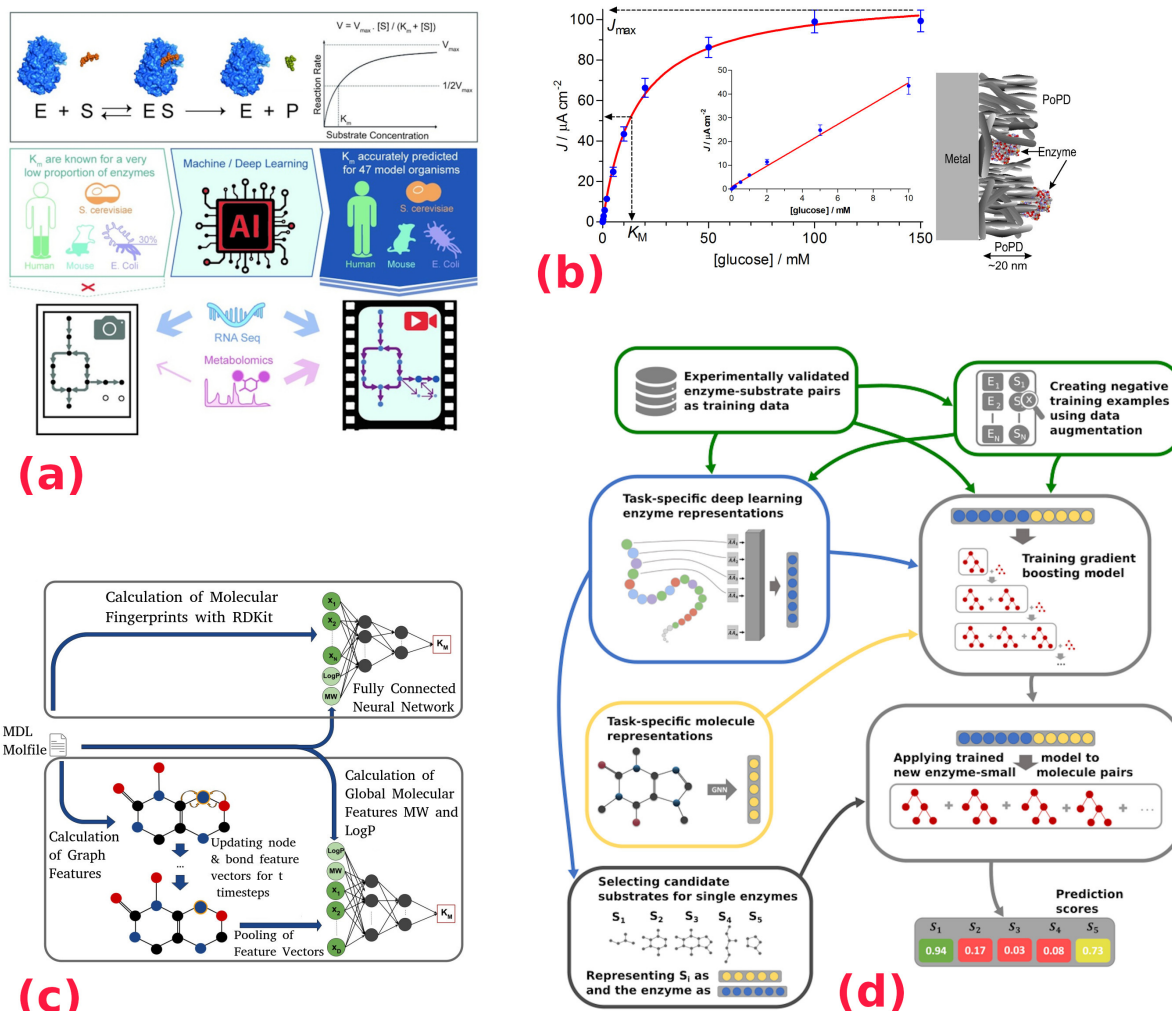


Figure 3: The top portion of (a) demonstrates the mathematical model for Michealis-Mentes kinetics associated with blue-colored enzyme (E), brown-colored substrate (S), and green-colored product (P) [38]. The Michaelis constant (K_M) has been introduced as the concentration of S at which the reaction rate is half of its maximum value [38]. The mid image illustrates how AI-based prediction can be used to fill the knowledge gap associated with the quantification of K_M for several types of enzymes in multiple living organisms [38]. The bottom image then shows the possibilities of such AI-based predictions on opening new avenues not only in the area of metabolic engineering but also in the field of drug target discovery [38]. In (b), the constant $K_M = 16 \pm 2$ mM, is determined in terms of the current density (J) for amperometric enzyme-based composite biosensor [37]. In ($Pt_C/PoPD-GO_x$), Platinum cylinder metal wire (Pt_C), is used as the electrode, and polypolyphenylenediamine (PoPD) polymer is used for the entrapment of Glucose Oxidase (GO_x) enzyme. Image (c) shows the procedure to determine K_M using artificial neural network [39]. The upper image in (c) illustrates how molecular fingerprints are calculated using RDKit software based on MDL Molfiles of the substrates. These fingerprints along with global features such as MW and LogP are supplied as input features in the ANN to subsequently predict the value of K_M . In the lower image of (c), feature vectors obtained via graph neural network are pooled together with the global features, and then trained with ANN for prediction of K_M [39]. The machine learning model of (d) can be utilized to estimate appropriate substrate candidates for given enzyme type [40]. The use of such integrated mathematical and data-driven models have a great potential for uncertainty quantification in sensor development.

by the following Nernst-Planck equation [41, 42]:

$$\frac{\partial c}{\partial t} + \vec{v} \cdot \nabla c = D \nabla^2 c + \mu \nabla c \nabla \phi \quad (2)$$

where, the ionic mobility (μ) appearing in the electrochemical migration term is defined as $\mu = \frac{zF}{RT}$. The symbols z , F , R , and T are ion charge number, Faraday constant, universal

gas constant, and temperature respectively. ϕ is the electric potential. The ionic concentration of the hydrated ions is denoted as c in Eq. 2. The velocity of the ion-containing liquid electrolyte represented as \vec{v} , appears in the advection term and will be zero if there is no flow. The parameter D in the diffusion term is the ionic diffusivity coefficient of

the hydrated ions. The partial differential equation (Eq. 2) allows the accurate modeling of the electrical double layers atop the oxides (the selectivity means to bind target bacteria) and bacterial cells in the capacitive biosensors [41].

On the other hand, the Nernst equation is expressed as follows:

$$E = E_0 - \left(\frac{RT}{zF} \right) \ln [c] \quad (3)$$

This equation stands as a fundamental principle that establishes a mathematical connection between the electrode potential E and the multitude of factors that influence it. In this equation, E_0 signifies the standard electrode potential, a measurement conducted under defined standard conditions.

Fig. 4 (a)-(f) highlight some of the special sensor applications in which the Nernst-Planck equation (Eq. 2) can be applied. The electrochemistry theory when combined with artificial intelligence can help in the accelerated design and discovery of wearable sweat sensors, electronic tongues, electronic noses, gas sensors, and selectivity-enhanced non-enzymatic electrochemical biosensors [43, 44, 45, 46, 47, 48]. It is now possible to study electrochemical sensors via physics-informed machine learning techniques. The partial differential equation (Eq. 2) as well as boundary conditions namely, the Nernst equation (Eq. 3) and Butler-Volmer equation can be easily incorporated into a physics-informed neural network (PINNs) for development of accurate electrochemical sensors [49]. In a schematic sketch of PINNs shown in Fig. 4(f), space (x) and time (t) serve as the output features of the neural network, whereas the ionic concentration (c) and coupled electrical potential (ϕ) are assigned the output features. The loss function (L) of the PINNs is usually the sum of individual loss functions associated with the residual of the Nernst-Planck equations, boundary conditions, initial conditions, and datasets. These PINNs allow not only induction-based learning on several electrochemical experiments but also the replacement of computationally expensive methods such as finite element method and finite difference method [49].

Smart materials and theories of solids : For solid-state smart sensing materials used in the measurement tasks, some of the well-established theoretical frameworks are Hooke's law and piezoelectric equations. The basic form of Hooke's Law for a sensor material component is given by the following equation:

$$F = -kx \quad (4)$$

Hooke's Law, expressed in Equation 4, describes the linear relationship between the force (F) applied to a spring (e.g. component No. 6 of the tensometer/myotonometer in Fig. 5(a)) and the resulting displacement (x exhibited by the spring) in a given direction from its equilibrium position [50]. The spring constant (k) characterizes the stiffness of the spring, indicating how it responds to the applied force F . This force is measured with the help of the force sensor (component No. 3) of the myotonometer

[50]. The generalized Hooke's law expressed in terms of stress tensor (σ_{ij}) and strain tensor (ϵ_{kl}) is $\sigma_{ij} = C_{ijkl}\epsilon_{kl}$. In this expression, C_{ijkl} is the fourth-order stiffness tensor of the sensor material. In terms of normal stress (σ) and normal strain (ϵ), Hooke's law for linearly elastic isotropic sensor materials can be simply reduced to $\sigma = E\epsilon$. The proportionality constant E is Young's modulus of elasticity. It has been quite cumbersome to quantify using traditional experimental methods, the values of elastic moduli and other coefficients constituting the stiffness tensor of the novel functional materials, composite materials, multi-materials, and meta-materials used in the sensor devices. In Fig. 5(b), the elastic moduli of the magnetic films constituting the tactile sensor (popularly known as electronic skin) relate the force of the ball to the magnetic flux density [51]. For accurate measurement by the tactile sensor, the correct estimation of the elastic modulus and shear modulus of the film is necessary. However, measurement of the properties in thin films (very small thickness) is challenging, and it may be not possible to retain magnetic properties in the materials using destructive testing methods such as vibration test, nanoindentation test, tensile test and bending test [52]. Moreover, when a newly developed magnetic film material is proposed for the construction of a tactile sensor, it will be again necessary to quantify the elastic moduli for this novel material. In the context of traditional elastographies for heterogeneous objects such as tissues, established with the consideration of stress uniformity are susceptible to inaccuracies [53]. The use of machine-learning algorithms built from reliable datasets can help in the prediction of the elasticity values that are otherwise difficult or impossible to obtain from conventional experimental techniques. Chen and Gu [53] have developed ElastNet by combining a deep learning approach with the theory of elasticity. As illustrated by the schematic methodology shown in Fig. 5(d), ElastNet is able to extract the values of hidden elasticity of heterogeneous objects based on the positional distributions of the measured strain values. In the future, there are possibilities that machine learning models such as Fourier Neural Operator [54], variational autoencoder [55] etc. could be utilized to accurately predict the strains and strain values in the component materials of sensor devices. As revealed by Fig. 5(c), the predictions of fourier neural operator model are validated by FEM-based results.

Another interesting group of solid-state functional materials that find large applications for sensor applications are those that demonstrate piezoelectric behavior. Piezoresistive materials are a sub-category of piezoelectric materials which show a significant change in their resistance upon application of mechanical force or displacement. The following equation of piezoresistivity is commonly utilized in sensor material design :

$$\Delta R/R = S_e \cdot \epsilon \quad (5)$$

The expression outlines the change in resistance per unit resistance ($\frac{\Delta R}{R}$) experienced by a material component

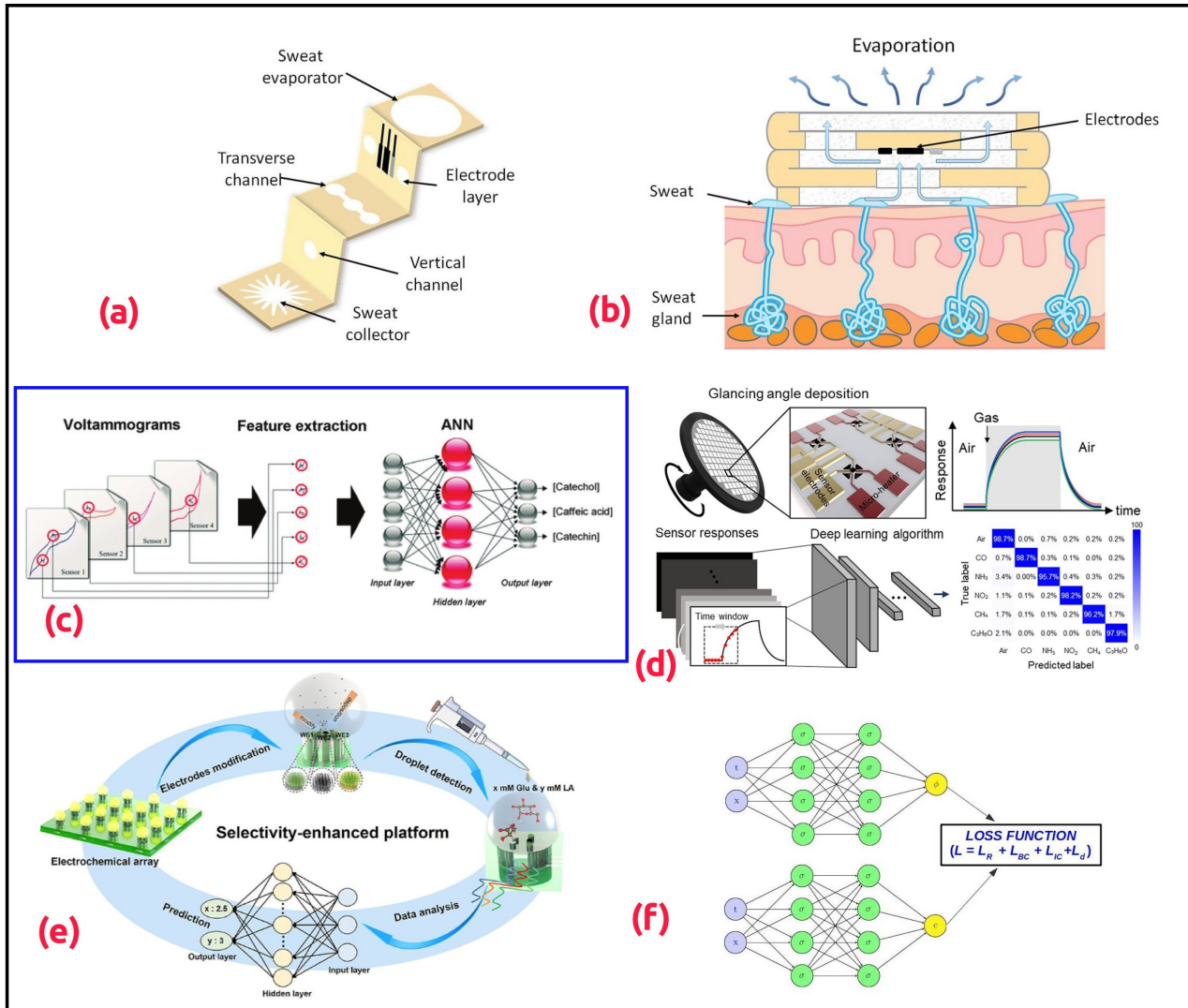


Figure 4: The schematic sketches of flexible electrochemical sweat sensor provided in (a) and (b) essentially highlight the practical application of Nernst-Planck equations [43]. The theory of electrochemistry when integrated with machine learning is finding widespread applications in the fabrication of ultra-modern sensors such as (c) electronic tongue for detection of polyphenolic antioxidant compounds with high resolution [44], (d) electronic nose for accurate sensing and real-time selective detection of gases [47], (e) non-enzymatic biosensors for lactase and glucose detection [48]. The PINNs shown schematically in (f) offer a route to solve the Nernst-Planck equations with the help of electrochemical sensor data.

of the sensor device due to applied mechanical strain (ϵ). The piezoresistive coefficient (S_e) quantifies the material's sensitivity to strain-induced resistance changes. Fig. 6(a) shows a flexible pressure sensor based upon piezoresistivity effect [36]. The sensitivity of the material can also be expressed in terms of applied pressure (Δp) to represent the response of pressure sensor [36, 56]. In such case, the equation for the sensitivity of the piezoresistive sensor becomes $\Delta R/R = S_p \cdot \Delta p$. The Ag/polydimethylsiloxane (Ag-PDMS) material-based sensor of Fig. 6(a) is found to exhibit a fast response time of 45 ms and a very high sensitivity ($S_p = 2.525 \text{ kPa}^{-1}$) for a broad pressure range of 312 kPa [36] thereby rendering it a highly promising candidate for tactile sensing in prosthetic and robotic applications.

The following equation mathematically explains the concept of piezoelectricity in sensor component material, and it also includes the piezoresistive effect as discussed above:

$$S_i = d_{ij} \cdot E_j \quad (6)$$

The piezoelectric equation 6 highlights the relationship between mechanical strain (S_i) and an applied electric field component (E_j) in a material. Demonstrating the electromechanical coupling via piezoelectric coefficient tensor (d_{ij}), this equation highlights how certain materials generate electric polarization under mechanical stress and vice versa. A smart glove is illustrated in Fig. 6(b) and is enabled by sensors based upon piezoelectric effect [57]. To establish a real-time virtual reality interaction mechanism, a long short-term memory (LSTM) model is integrated with this

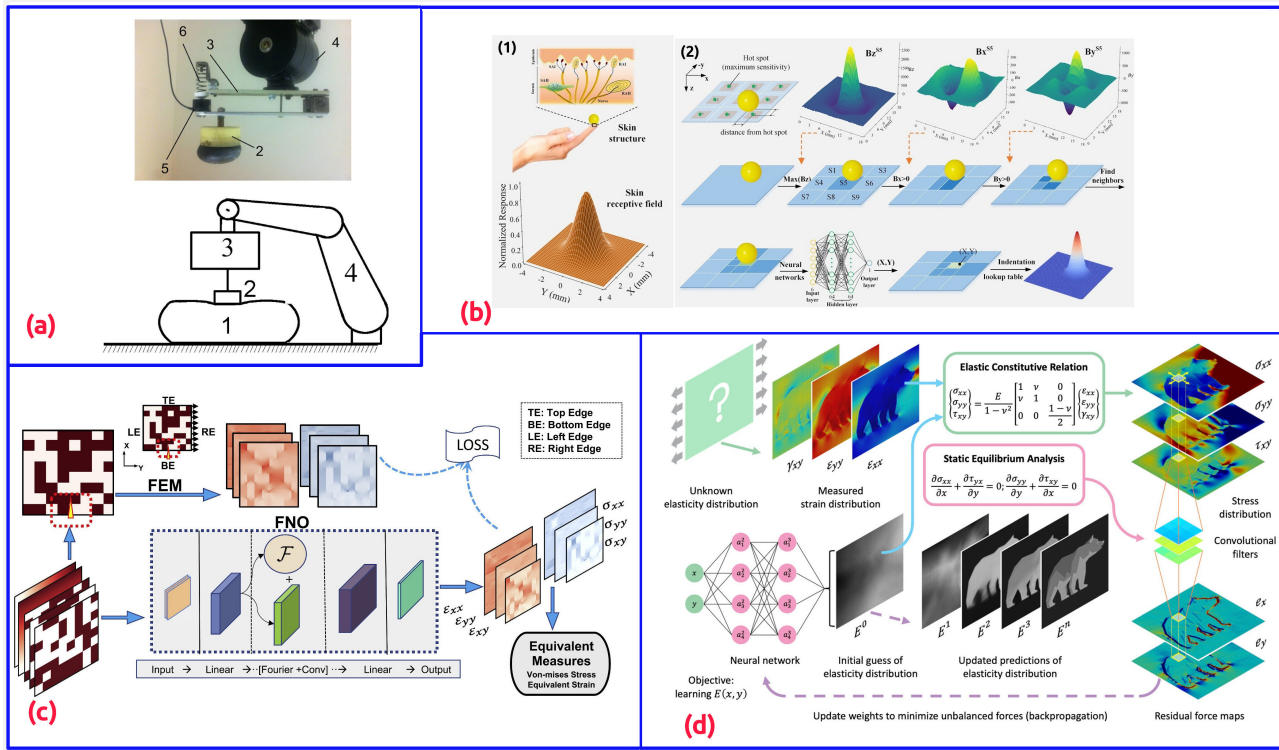


Figure 5: A typical myotonometer (tensometer) shown in the upper image of (a) demonstrates the practical application of Hooke's law [50]. For the schematic sketch in the lower part of (a), the number 1 denotes the biological tissue. The numbers 2,3 and 4 occurring in both images represent tool, force sensor, and robot respectively. Finally, 5 and 6 in the upper image mean strain gauge sensor and spring respectively. In (b)(1), the skin structure of the human figure and the mathematical representation of the receptive field are illustrated [51]. The tactile sensor of (b)(2) emulates human skin response [51]. During the contact of the ball with the taxel S5 with regions of differing magnitudes of magnetic flux density, the elastic moduli appear in the expression relating force components with the change in magnetic signals [51]. It is to be noted that the response of the tactile sensor can be improved by using a neural network. Fourier neural operator (FNO) model validated with the help of benchmark FEM model has been implemented in (c) to predict the values of von-mises strain and equivalent strains for composite materials [54]. ElastNet based upon deep neural network can predict the elasticity of a generic material as a function of the information of position p [53].

smart glove [57]. So et al [58] have combined silicon piezoresistors with a tailored deep learning data processing methodology to enable accurate evaluation and analysis of diverse stimuli, thereby obviating the necessity for intricate procedural intricacies. As shown schematically in Fig. 6(d), the deep learning-aided data translation integrated with the flexible epidermal piezoresistive sensor structure is aimed at efficiently recognizing not only the complex stimuli shape and magnitude but also the modulus of the skin [58]. A summary of the mechanical stimuli, mechanisms, and machine learning-assisted data processing techniques that are or could be implemented in flexible mechanical sensing technology [59] is provided in Fig. 6(c). Strain, pressure, shear force, and vibration have been listed as the most prominent source of stimuli whereas piezoresistive, piezoelectric, piezocapacitive, triboelectric, and iontronic effects are categorized as the commonly observed mechanisms [59]. Data decoupling, multimodal sensing, and array integration are the tasks in sensing technology that can be enhanced using aid from machine learning processing techniques

[59]. Finally, health monitoring, electronic skin, human-machine interface for [59] identification of hand gesture, voice, posture, as well as position, pressure prediction, and position recognition, etc. are the notable application areas of the flexible sensors [59].

4. Ushering in the new era: AI-guided sensor design

After elaborating on the fundamentals of the working of biomimetic sensors and biosensors in Sec. 2, it is now necessary to highlight the evolutionary paradigms dictating the growth and usage patterns of such sensors. This is the era of big data and machine learning, and it is quite clear that sensing technology is very much intertwined with AI methods. The intertwining is two-sided-(i) AI-aided sensor design and development, and (ii) sensors supporting the AI-based other technologies. This section will highlight the symbiotic relationship between AI and biochemical sensing technologies.

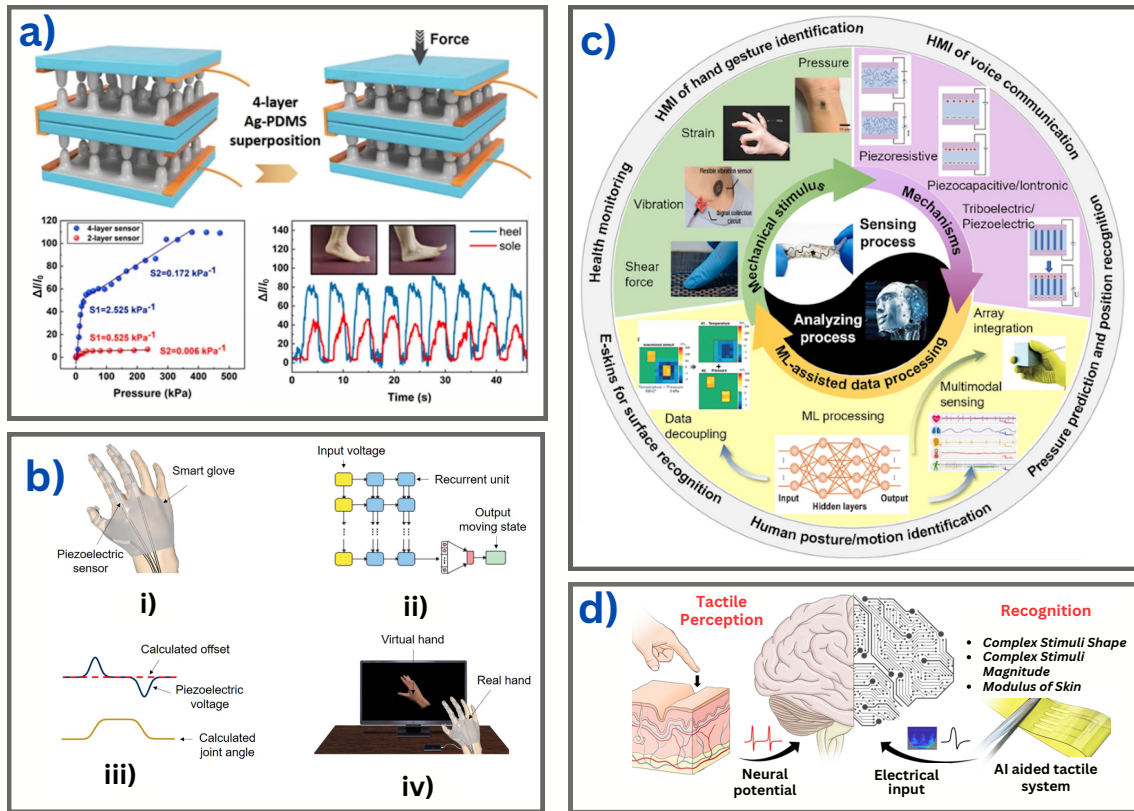


Figure 6: Figure showing a) Developed flexible piezoresistive pressure sensor with lotus leaf micropatterned polydimethylsiloxane achieves high sensitivity and wide pressure range, promising human-like tactile sensation in prosthetic and robotic systems [36] b) a smart glove equipped with piezoelectric sensors is utilized for hand movement detection. A network predicts movement states from the sensor data, enabling approximation of joint angles for virtual hand implementation [57]. c) Advancements in flexible sensing technology, coupled with machine learning, drive innovation in various applications including health monitoring, human-machine interfaces, and object recognition, promoting the development of artificial flexible mechanical sensing [59] d) Mechanical Activation of Skin Receptors vs. Machine-Aided Recognition in Artificial Sensor [58]

4.1. AI favoring the all-round growth of sensors, including those related to biochemical field

The growing interest in the fourth industrial revolution, characterized by advancements in AI, big data analytics, the IoT, and robotics, has reached unprecedented levels [60]. AI encompasses a collection of technologies that enable computers to emulate human-like thinking, decision-making, logical reasoning, and language processing. Figure 2(c)-(e) demonstrates how the continual development in AI techniques significantly impacts the progress of biosensors. While the illustrations are for biosensors, the utilization of AI techniques can impact the advancements of biomimetic and bioapplicable sensors as well. AI can be leveraged to enhance the creation of more precise biosensor models, facilitate biomarker detection, and design improved algorithms for data analysis. In recent years, AI has expanded into various subfields, including deep learning, machine learning, neural networks, robotics, the IoT, and digital twins, finding applications in diverse domains. This continual development in AI will have a profound influence on the evolutionary design of biosensors. One key component of AI, machine learning (ML), has emerged as a valuable tool

in materials science for data processing and analysis [61]. ML has the potential to offer innovative solutions to address challenges faced by biosensors. Moreover, it can enable the transformation of conventional biosensors into intelligent biosensors by incorporating decision-making systems that can automatically predict analyte species or concentrations. Machine learning algorithms, particularly neural networks, have been successfully applied in physical sensing systems such as strain and acceleration sensors for several years. They have played a significant role in gesture recognition [62], activity recognition [63], and object identification, showcasing the broad applicability of machine learning in sensor technologies.

4.2. Sensing and artificial intelligence: technologies in symbiosis

Continuous academic and industrial research efforts are focused on advancing the field of biosensors for monitoring in real-time. AI has emerged as a powerful tool to improve the efficiency and effectiveness of biosensors [64]. They have proven to be effective in improving biosensor performance in various aspects, such as signal processing,

data analysis, and decision-making. For instance, by employing a combination of AI techniques such as wavelet transform and artificial neural networks, researchers were able to optimize the signal-to-noise ratio of a biosensor designed for glucose level detection. The application of these AI algorithms significantly reduced noise interference, resulting in enhanced accuracy when measuring glucose levels [65]. AI-based algorithms (e.g. glucose prediction algorithm, calibration algorithm) have a far-reaching potential in terms of the advancement of continuous glucose monitoring (CGM) sensors [66], and this can be useful for diabetes management. The advancement of artificial intelligence has resulted in significant economic benefits for humankind and has positively impacted all areas of life. Additionally, it has dramatically promoted social development, ushering in a new era of progress [67]. Globally, there is a lot of concern about the safety and security of the environment. Scientists are exploring long-lasting methods for environmental monitoring since controlling toxic substances is crucial for remedying pollution. Typically, traditional chromatographic [68, 69, 70] and spectroscopic [71, 72, 73, 74] techniques are employed to identify pollutants, which are commonly recognized for their high sensitivity and specificity. Nevertheless, these techniques are time-intensive, require skilled manpower, and need multiple steps for sample preparation. The need for advanced biosensing devices arose from the requirement for faster, more precise, and more sensitive means of detecting and screening pollutants in real-time while also ensuring selectivity and accuracy. In the development of biosensors, the complexity of environmental samples must be taken into account since there is high demand for their use in technological applications [75, 76, 77]. The utilization of biosensors is crucial for monitoring the current state of soil, water, and air samples to identify pollutants such as pesticides, harmful elements, pathogens, toxins, and chemical compounds that interfere with an endocrine function [78]. Biosensors have undergone rapid and diverse advancements over the past few decades [79], owing to their capability to detect an extensive array of analytes such as pollutants, bacteria, fungi [76]. In the food industry, biosensors have multiple applications, including nutrient analysis, natural toxin, and antinutrient detection, food processing monitoring, and the detection of genetically modified organisms. Generally, Biosensors are used to prevent and minimize the bacteria or fungus from growing in fresh foods, detection of spoiled food, and food contamination [80]. Biosensors can also determine the levels of pesticides, antibiotics, proteins, B-complex vitamins, and fatty acids present in foods through enzymatic and immunogenic reactions [81].

The symbiotic relationship between AI and sensors (biosensors, biomimetic sensors, and bio-applicable sensors) represents a powerful synergy that drives advancements in sensor technologies. AI, with its ability to process and analyze vast amounts of data, provides valuable support to the sensors [82], enhancing their performance and capabilities. By harnessing AI algorithms, these sensors can achieve higher accuracy, sensitivity, and selectivity in detecting

target analytes. The integration of AI techniques, such as support vector machines and convolutional neural networks [83], empowers the sensors to learn from data patterns, enabling them to make informed predictions and decisions. Furthermore, AI plays a vital role in the development of intelligent biosensors, and biomimetic and bioapplicable sensors that can adapt to changing environmental conditions and optimize their performance for specific applications. In return, these sensors can offer a rich source of data that fuels AI algorithms, enabling them to learn and improve over time. For example, the studies on human-computer intelligent interactions and intelligent user interface fields, focusing on the intelligent recognition of gestures, emotions, and facial expressions, are conducted using sensor technologies, including but not limited to the gyroscope, camera, EEG, eye tracker, Kinect, and wearable sensors [83]. It could be said that in the fields of biological and biochemical sciences, the applications of artificial intelligence also will require biosensors, biomimetic sensors, and bioapplicable sensors for the acquisition of data from the sources. This mutually beneficial relationship between AI and biosensors holds tremendous potential in various fields, including healthcare, environmental monitoring, and agriculture, where precise and real-time sensing is crucial for decision-making and resource management. As the advancements in AI continue to unfold, the synergy between AI and biosensors is expected to drive significant innovations and unlock new possibilities for sensor technologies.

5. How well can the tools of AI be integrated with biosensors?

By now, it is already apparent that there is a large symbiosis between sensing technology and artificial intelligence. To solve emerging scientific and technological issues, it is important to ensure that the devices and technologies related to biosensing are fully integrated with AI. This section sheds light on some illustrations discussing the overall views on how well the integration has been done hitherto, the perspective on how it can proceed, and what benefits it might offer to human society. The aspects such as robotics, digital twins, machine learning, computer vision, text mining, natural language processing (NLP), etc. that are frequently utilized for operating the AI-operated hardware will be interlinked with biosensors in this section.

As already mentioned earlier, Figure 2(c) provides an overview of the tools of AI that could be utilized for the advancements of biosensors. It has to be noted that these tools are also applicable to the advancements of biomimetic and bio-applicable sensors. The design and discovery of biosensors are becoming increasingly data-driven, working in collaboration with various artificial intelligence techniques. In the past few years, there has been an increasing inclination towards utilizing data-driven approaches for the design and discovery of biosensors, with the incorporation of artificial intelligence (AI) technologies that aim to enhance the performance and efficiency of biosensors by improving

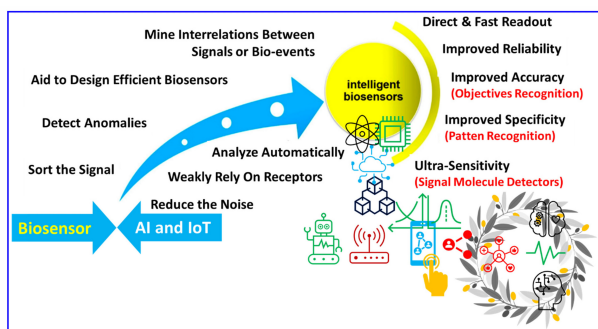


Figure 7: A roadmap illustrating how the action of AI integration enables conventional biosensors to be transformed into intelligent biosensors [82, 90]. When a conventional biosensor (represented by a rightward pointing arrow) meets AI/ML and IoT (AI + IoT represented by a leftward pointing arrow), then the performance of biosensors can improve by several folds. Abilities such as noise reduction, less reliance on receptors, automated analysis, anomalies detection, signal sorting, improved efficiency, the establishment of relationships between bio-events and signals, etc. can be incorporated into the existing conventional biosensors through the integration task, and these sensors are transformed into intelligent sensors (represented by a yellow colored circle). In particular, this AI integration helps in the improvement of the sensitivity, specificity, signal strength, and measurement time of the biosensors. Reproduced with permission from [82, 90].

accuracy and reducing costs [84]. In the study by [85] the authors have emphasized diverse AI techniques, such as machine learning, deep learning, and network analysis, utilized to discover novel biomarkers. This data-driven methodology enables the identification of appropriate targets for biosensor development, thereby enhancing diagnostic accuracy and specificity.

The AI integration with biosensing devices and environment, as illustrated in Fig. 7, can help in the achievement of a system characterized by enhanced sensitivity, signal strength, and specificity as well as a shortened response time [82]. Biosensors can be integrated via digital methods, such as pattern analysis and classification algorithms, to close the gap between data collection and interpretation and increase the accuracy of diagnostic and therapeutic procedures. Machine learning (ML) is a branch of AI that offers a method for understanding large amounts of data [86, 87, 88]. With the use of computational systems, ML allows an algorithm to perceive, identify and learn about its surroundings [89], and this is inherently needed for sensor design. [64].

Aptamers are commonly acknowledged as highly potential recognition elements suitable for implementation in biosensors. These aptamers offer several benefits over conventional antibodies [91]. Aptameric biosensors employ aptamers as the bioreceptor or sensing element. The integration of AI plays a vital role in advancing and designing aptamer-based biosensors. By leveraging AI, it becomes feasible to identify the most effective aptamer sequences for target molecules, as well as optimize the conditions for aptamer

binding, such as temperature and buffer pH, to increase the sensitivity and specificity of the biosensor. Machine learning algorithms can be applied for analyzing extensive datasets containing aptamer-binding information, which can identify patterns and connections, leading to the development of biosensors exhibiting improved accuracy, sensitivity, and selectivity in a wide range of applications, including healthcare, environmental monitoring, and food safety testing. [92] Chitin-based biosensors can benefit from the application of computational intelligence to enhance their precision, sensitivity, and overall performance. Through the use of AI algorithms, these biosensors can effectively process the vast amounts of data generated during the detection process, identify trends and irregularities, and achieve quick and dependable detection of target analytes in a sample. For the successful design of easy-to-use sensing applications of these chitin-based sensors, AI is the necessary tool that will eventually help in the integration of these sensors with concepts such as the Internet of medical things and the Internet of nano things [93].

5.1. Artificial intelligence and robotics in biosensors

In the field of biosensors, AI and robotics play significant roles, offering substantial contributions and advancements in various applications. For example, in recent years, there has been a rapid rise in the application of AI in biosensing, specifically in automating the monitoring and analysis of data. AI algorithms can be used to detect anomalies in biosensor data [90, 94, 95] and alert the user if it falls outside of a certain range. Additionally, AI can be used to interpret the data and provide personalized health advice [96] based on the individual's unique health metrics. Robotics can be used to control biosensors remotely, allowing for remote monitoring and intervention. Tiboni et al. [97] highlight the application of robotic sensors in measuring physiological signals like electromyography (EMG), electroencephalography (EEG), and electrocardiography (ECG) where these signals provide valuable information about the individual's physiological state and enable real-time health monitoring. Similarly, Dahiya et al. [98] highlights the advancement of tactile sensors for robots, designed to replicate the sensing capabilities of human skin where these sensors allow robots to effectively recognize and respond to various tactile sensations like touch and pressure, which holds vast potential for applications in areas such as prosthetics, robotics, interactions between humans and robots and so on. Likewise, by mimicking the human sense of taste and providing accurate assessments of taste attributes, biosensing robots play a significant role in taste discrimination in food samples. They use a variety of methods, including chemical sensing, machine learning, and data analysis, to identify and analyze the chemical elements found in food samples and assess their flavor attributes by offering precise measurements and eliminating subjective biases associated with human sensory panels in the food industry [99].

5.2. Machine learning and sensing technology

The effectiveness and accuracy of biosensors are enhanced by the use of suitable machine-learning algorithms. Numerous machine learning algorithms such as decision trees, support vector machine (SVM), Naive Bayes (NB), K-nearest neighbors (KNN), artificial neural network (ANN), deep neural network (DNN), convolutional neural network (CNN), random forest (RF), recurrent neural network (RNN), eXtreme Gradient Boosting (XGBoost) and many more, have been developed to process data. ANN using a back propagation algorithm can also be called a back propagation neural network (BPNN). Since a few years ago, ML algorithms, particularly neural networks, have been used in physical sensing systems (such as strain sensors and acceleration sensors) and have achieved advancements in the recognition of gestures [62], activity identification [63], and object detection [100]. Dimension reduction, feature extraction, picture recognition, classification, and prediction are a few examples of the various data processing and analysis phases that can be improved with the use of ML techniques. In order to further enhance the performance of biosensors used in the health sector, disease identification, environment monitoring, food safety, and analysis, machine learning (ML) algorithms may effectively transform unintelligible raw data into understandable and valuable information [87]. Machine learning can be broadly characterized as an algorithmic strategy for assessing sensor data and extracting valuable information using statistical techniques from the standpoint of biosensor applications [101]. Machine learning can directly, automatically, precisely, and quickly support biosensor readout, which is crucial for on-site detection or diagnosis. The Orringer group created an optical imaging technique that uses the CNN algorithm to anticipate the diagnostic test results [102]. A 1D CNN model was created by Lussier et al. [103] to evaluate chemical spectra for multiplexing SERS sensing which has two layers of convolutional, pooling, and densely coupled neurons. Figure 3 illustrates that, by integration of AI and ML technologies, biosensors can be designed to automatically learn and categorize specific patterns in sensor data, allowing for more precise and accurate detection of target molecules by improving specificity and reliability.

Table 1 summarizes a list of applications for ML algorithms integrated sensor devices in the two broadly defined categories: (a) health and safety; (b) agriculture and environment. It is to be noted that the algorithms such as ANN, SVM, BPNN, RF, XGBoost, RNN and LSTM are commonly employed for the design of sensors broadly utilized in the healthcare and safety sectors [104, 105, 106, 107, 108, 109, 110, 111]. ANN, DNN and RNN are also commonly employed in agricultural and environmental sectors [112, 113, 114].

5.3. Digital twins and real-time data

Digital twins (DTs) are an emerging and effective method for real-time interaction and further convergence between physical space and information space. It is a concept that

refers to the ability to simulate and analyze the behavior of physical objects in the digital world. They are created by capturing real-world data and then using that data to create a digital model that can be used to simulate, analyze, and monitor the behavior of the physical object in various contexts. Likewise, they have been used in a variety of fields including manufacturing, healthcare, automotive, aerospace, and consumer electronics [115, 116].

DTs are becoming increasingly important for the design and optimization of biosensors by evaluating their performance and accuracy, and identifying potential issues before they arise. Biosensors with applications of digital twins are becoming increasingly popular in a variety of industries, as they can provide real-time insights into the performance of biosensors enabling advanced monitoring, analysis, and optimization capabilities [117]. By integrating data from physical sensors with virtual models they provide real-time monitoring of biosensor performance allowing continuous assessment of the sensor's condition, enabling early identification of anomalies, and anticipating possible errors. With this information, proactive maintenance can be implemented, ensuring the reliable and durable performance of the biosensor [118].

In addition, the machine learning (ML) aspect of AI enables prediction or decision-making from heterogeneous digital data [119]. The concept of the digital twin in the healthcare industry was originally proposed and first used in product or equipment prognostics [118]. Angulo et al. [120] introduced a general-purpose proposal for creating DTs that apply to the health field, specifically lung cancer patients. In adopting DTs to specifically protect against COVID-19 in infected patients, Laubenbacher et al. [121] discussed how medical DTs are beneficial to mitigate COVID-19 viral infection and any future pandemic. Furthermore, they were concerned with combining medical DT with a mechanistic understanding of the physiology and viral replication and AI techniques for optimizing the treatment of patients infected with a virus.

5.4. Computer vision to upgrade automation capabilities of biosensors

Computer vision is a field of artificial intelligence that uses image processing and machine learning algorithms to analyze images and videos to identify objects, detect patterns, and recognize faces, among other tasks. Principally, it works by extracting features from an image or video, such as edges, shapes, and colors, and then using machine learning algorithms to identify patterns in these features. Machine vision can be used in the design and development of biosensors to detect and analyze biological signals. Computer vision and automation have become essential for advancing in the field of biosensors, facilitating the creation of effective and advanced sensing systems which enhance their overall performance and capabilities by improving signal acquisition, data processing, and decision-making processes [122, 123].

In the study, [124, 125] the authors provide a comprehensive review and analysis of computer vision and image

Table 1

List of machine learning algorithms employed along with the sensing devices in various sectors. The health and safety sector includes many sub-sectors including medicine, disease treatment, food-safety engineering etc., whereas other applications exclusively associated with the agriculture and environment sectors are grouped into a separate sector.

Sectors	Sensors/ Measurement tasks	ML Algorithm	Applications	Ref.
Health and Safety	Electronic nose, gas sensors arrays	ANN	Olfactory system's mechanism for odor classification	[104]
	Gold-nanoparticle sensor	SVM	Using breath samples for effective differentiation of different stages of chronic kidney disease (CKD).	[105]
	Arterial Pressure	ANN	Hypertension management and its potential to generate evidence for effective treatment	[106]
	MOS gas sensor	BPNN, RF, SVM, XGBoost	Analyzing and classifying various properties of wines.	[107]
	Glucose level	RNN	Instantaneous categorization of individuals with diabetes and prediction of future blood glucose levels	[108]
	Electronic nose	ANN	Differentiating lung cancer patients from healthy individuals via exhaled breath's (VOC) patterns.	[109]
	Accelerometers	RNN, LSTM	Recognition of human activities, detection of falls, and classification of sleep stages.	[110]
	MO _x gas sensor	SVM	Detecting and forecasting the existence of adulterants in contaminated milk.	[111]
Agriculture and Environment	Soil moisture sensors, spectral sensors	DNN, RF	Crop classification, disease detection, yield prediction.	[112]
	Environmental sensors	CNN	Predicting of Air Pollution	[113]
	Electrochemical biosensor	ANN	Recognizing contaminants (e.g. heavy metal salts, pesticides, petrochemicals) in water sources.	[114]

analysis studies focusing on the automated detection of malaria parasites in blood smear images where these works involve training machine learning algorithms to classify the presence of malaria parasites. By integrating computer vision techniques and automation, the diagnosis of malaria becomes faster and more accurate, thereby improving the effectiveness of biosensors in detecting and combating this disease. Likewise, Suzito et al [126] have applied the principles of computer vision for pH detection using a Butterfly pea flower biosensor. Machine learning algorithms implementing computer vision can be considered promising techniques for the detection, stratification, and classification of biological cells [127].

5.5. Inventing interactive biosensors with techniques employing text mining and NLP

An automated method that extracts important information from unstructured text with the help of natural language processing is referred to as text mining. By using machine learning and natural language processing, it finds trends and patterns in unstructured text data. Text mining has the potential to be used extensively in the fields of biochemical sciences and engineering. It is to be noted that text mining and knowledge discovery from biomedical literature plays vital roles in many areas including but not limited to drug

discovery, clinical therapy, development of biosensors, biological sensors, and bioapplicable sensors, pathology research, etc [128, 129]. Generative AI is a powerful tool that utilizes the methodologies of text mining and thereafter uses it in discovering useful biodomain sensors.

Natural Language Processing (NLP) is one of the powerful artificial intelligence and linguistics tools that is concerned with the interplay between human and computer language. This technology has largely gained popularity in analyzing, understanding, and generating human language, allowing a natural way of communication between humans and computers [130]. In the context of biosensors, NLP can be incorporated in analyzing a significant amount of data and extracting desired information from it [131]. It has also been applied in biosensors to enhance the correctness of their readings [132]. NLP can be used to interpret the data collected by the sensors (including biosensors) and to provide insights into the data that would not be visible from raw readings. For example, NLP applied to biosensor data of body temperature, heart rate, etc. can analyze contextual information for deeper insights, detect anomalies indicating potential health issues, identify trends and patterns over time, incorporate textual or voice inputs to understand the context, and provide a comprehensive health assessment, etc. Thus, NLP can be used to identify patterns in speech or text that may be indicative of certain health conditions and

alert the user. Such identifications help in detecting changes in data over time, allowing the user to identify potential problems before they become quite serious. In addition to these applications, NLP can also be used to generate recommendations and offer personalized advice based on the data collected by not only the biosensors but also the bio-inspired sensors and bio-applicable sensors [133, 134]. As a computer-driven approach to facilitate human language processing [135], the adoption of the NLP techniques for clinical information processing has been popular for decades.

6. Notable insights on data-driven sensing technology applications for biosensors as well as biomimetic and bioapplicable sensors

Sensors have played a pivotal role in the emulation of various human sensory modalities, thereby facilitating the creation of digital counterparts. Notably, the advancements in technology have enabled the integration of bioinspired algorithms mimicking biological sensory recognition processes into our daily routines, manifesting in the form of diverse applications. Delving into the realm of biosensors, these bioinspired techniques can be classified according to their association with the fundamental human senses, namely tactile perception, visual processing, olfaction, and gustation, as elucidated by Del Valle et al. [136]. To obtain methodological insights into biomimetic sensors, it is necessary to have a proper understanding of the analogies between the actual physical phenomena and the response of the sensors. By studying the sensors associated with mimicking the behavior of human sense organs such as touch, vision, taste, and smell; it will be easier to understand the analogies.

In the context of various fields, including but not limited to pharmaceuticals, forensics, environmental monitoring, healthcare, food safety, and agriculture, bioinspired, biosensors, and bioapplicable sensors have proven to be incredibly applicable. While the potential applications of the sensing procedures for biochemical fields are of large numbers, this section will provide a succinct overview of some notable applications:

6.1. Tactile and vision applications of biomimetic sensors

Perception, a cognitive process, helps the brain organize, sort, and understand external stimuli acquired by the abundant sensory organs of humans and higher animals, such as vision, hearing taste, touch, smell, and intuition. The concept of tactile and vision perception narrows down to the fields of vision and touch. Within the field of smart sensor technologies, there has been considerable focus on developing tactile-based and optical-based transduction methods, as these two senses (touch and vision) are crucial for human learning and interaction with the surrounding environment [137]. Tactile sensors are typically configured in the form of force sensor arrays that are designed to replicate the characteristics of

human skin [136]. The distinctive characteristics of tactile and vision-sensing technologies enable them to detect different types of information. Tactile sensors can identify physical properties like pressure and texture, whereas vision sensors can analyze properties such as color and shape. These technologies are versatile and can be used for various tasks, including object recognition [138, 139], human behavior analysis [140], and 3D information reconstruction [141, 142]. In the study by Luo et al [138], a recognition rate of 91.33 % has been obtained for the machine learning techniques associated with the Tactile-SIFT descriptor. Ito et al. [141] have clearly highlighted that in the condition of the availability of sufficient data, machine learning can be successfully applied for computer vision-based tactile sensing and shape prediction. Such a perspective provides an enormous futuristic potential for AI in shaping the design and applications of the biochemical sensor. Intelligent tactile and vision perception systems using flexible sensors with AI-driven ML algorithms have the potential to match or surpass human perception by accurately processing and recognizing external information, but the challenges of working on dynamic and irregular surfaces have been addressed via the introduction of functional materials and innovative structures, opening up new opportunities for AI development [143]. Flexible biomimetic sensing technology improved by advances in materials and sensing mechanisms, augmenting data interpretation capabilities via machine learning makes possible the realization of hyperconnected smart societies, by implementing smart sensors to improve productivity, health monitoring, human-machine interfaces, object or surface recognition, pressure prediction, and human posture or motion identification [144]. Qu et al. [145] have highlighted that artificial intelligence plays a critical role in enabling accurate identification of material type and roughness for tactile perception sensors developed using a smart finger with triboelectric sensing and machine learning integration. The triboelectric sensor array's construction in the context of the AI-guided tactile perception smart finger model [145] also was observed to increase the accuracy rate of identifying material types and roughness to 96.8 %. It is noteworthy to mention that the smart finger models could easily overcome the challenges faced by traditional artificial haptic-based tactile sensing technology. These all studies highlight the vital role data science and machine learning play in the design of sensors for vision and tactile applications.

6.2. Olfaction and gustation system sensing via biomimicry

The utilization of biosensors as a novel method is becoming more popular in the exploration of taste and smell sensing mechanisms, as well as investigations of ligands and modulators. These biosensors are usually created through the amalgamation of functional biological components from taste and olfactory systems with diverse transducers [146, 147]. A new type of electronic device called an electronic nose (or e-nose), has been developed to mimic the human

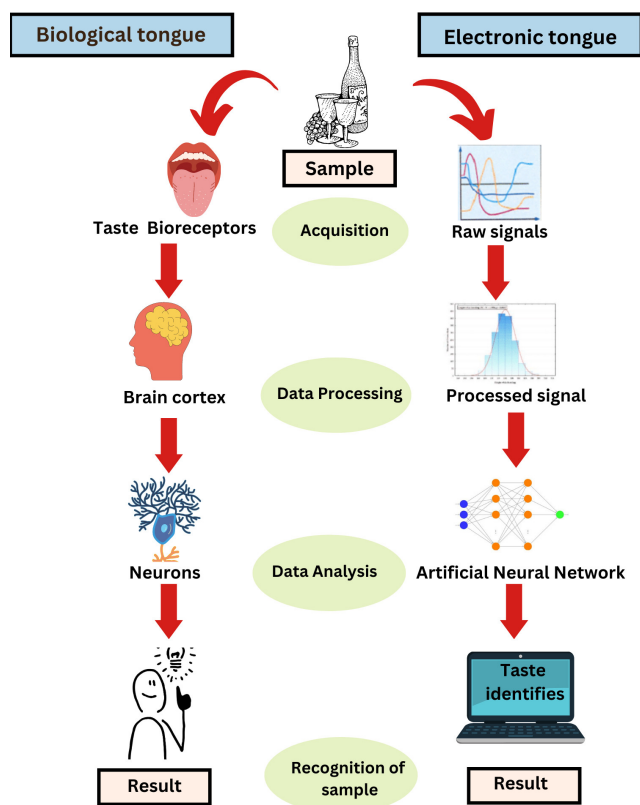


Figure 8: Comparison between the biological gustatory system and electronic tongue (e-tongue) technology. In the context of the biological gustatory system (left portion of the figure), the bioreceptors located in the tongue first acquire the data about the taste, and this data is transferred via neurons to the brain where it is processed and analyzed. Then the individual recognizes the taste type or category. Presented on the right side of the figure is the AI-aided biomimetic sensor system. This sensor system known as e-tongue employs signal generators to generate electrical signals of different profiles corresponding to the input taste type, signal processing devices (data processors) to enable the signals readable by a machine learning algorithm, and the ANN to analyze the machine-readable data. The activation function in the output layer of ANN defines it as a classifier model so that it can quantitatively describe the type of taste through the computer system. e-tongue can also be constructed by replacing ANN with other machine learning models such as support vector machine and random forest.

olfactory recognition system by utilizing an array of electronic sensors which is gaining popularity as a prominent example of an artificial olfactory system [148]. The development of electronic noses has been made possible due to the advancement in aroma-sensor technology, electronics, biochemistry, and artificial intelligence, which can measure and characterize volatile scents emitted from various sources for a variety of purposes. These devices were designed to imitate the mammalian olfactory system, which can generate consistent measurements and allow for the identification and categorization of fragrance combinations while removing the need for human operators to avoid exhaustion [149, 150,

151, 152, 153, 154]. In order to enhance the performance of these biosensors, computational neural network models have been utilized in combination with biosensing techniques. One example is the application of K-serial models, which are non-linear neuronal network models based on the concept of groups of nerve cells, as components of neuronal networks at various anatomical levels of olfactory systems [155]. Usually, an electronic nose setup comprises a collection of sensors, an information processing unit like an ANN, digital pattern-recognition algorithms embedded in software, and reference-library databases [156, 157, 158, 159]. An ANN was developed by Wang et al. based on the olfactory system's mechanism for classifying odors [104]. Electronic noses have a wide range of applications in various fields such as the food and beverage industry, quality control, environmental monitoring, medical diagnostics, and many more. In the context of cancer research, E-nose tools are frequently used to search for a typical "breath print" that can, at a preliminary level, distinguish between cancer patients and healthy controls, and, if fruitful, to compare the exhaled breath composition of various groups of cancer patients according to the severity of their condition [105]. This method could detect cancer at an early stage by looking at the unbalance in breath composition. This would open the door for a less invasive replacement for the pricey, inconvenient, and intrusive technologies currently employed for this purpose [160]. Compared to the laborious and inconvenient techniques of gas chromatography-mass spectrometry the electronic nose (E-nose) device is cost-effective and convenient and can detect low levels of volatile metabolites linked to various conditions and differentiate between them without requiring the identification of individual chemical compounds [161, 162]. Jiang et al utilized the Random Forests (RFs) algorithm to construct regression models and predict fatty acid profiles of pecans. Based on their findings, they concluded that RF could be a highly effective method for analyzing electronic nose (e-nose) data [163].

Similarly, the electronic tongue is designed to imitate the functions of the human tongue to detect taste sensations which are achieved by utilizing sensor arrays that are combined with chemometrics to detect and measure the presence of dissolved substances in liquid sample [164]. A comparison between the biological gustation system and Electronic tongue technology is demonstrated in figure 8. In the biological gustatory system, the taste receptors detect taste, which is then processed and then the taste is identified in the brain's olfactory cortex through the neurons. Similarly, in electronic tongue technology, an electronic sensor array detects taste, which is then processed through a preprocessor for feature extraction, and then analyzed using artificial intelligence (data analysis, pattern recognition, and machine learning algorithms) through an Artificial Neural network to identify and classify the input taste using extracted digital signatures [165].

6.3. In food processing, awareness, quality, and safety

For quality assurance and control objectives, biosensors have been widely used in the food sector. The current food sector faces a serious problem with food safety. The food chain can be contaminated with pathogens, toxins, allergens, etc., during different steps of production as they may build up in food while it is being stored or may even be created in the food through chemical reactions [166]. Food components with ultra-low concentrations can be detected using biosensors in a way that is highly sensitive, exact, and selective. After food production is complete, conventional techniques such as chromatography, mass spectrometry, ultraviolet detection, or fluorescence techniques are used to analyze the product [167, 168]. These conventional methods have a number of drawbacks. The first issue is that because the analysis is done at the end of the process, tainted products may go through the entire production chain or even be sold before contamination is discovered. Second, these analysis techniques are time-consuming, expensive, labor-intensive, call for huge sample quantities, and demand specialized staff [169]. A potential substitute that would enable food samples to be screened before the production process is complete is provided by biosensors [169]. Additionally, biosensors offer quick on-site monitoring and current data regarding the manufacturing process [170].

The objective of Eyvazi et al [171] study is to discuss the recent advances in designing and utilizing portable biosensors for the identification of biological contaminants in food, including bacteria, fungi, and related toxins. These pathogenic microorganisms can proliferate in food without any apparent alterations in smell, appearance, or flavor, potentially reaching harmful levels.

A quick and effective biosensor was created by Korecka et al [172] to screen milk samples for Salmonella contamination. Bacterial cells were isolated using immunomagnetic, and then a conjugate, or particular IgG molecule labeled with an electrochemical indicator, was used in the procedure afterward. Liu et al [107] utilized multiple machine learning (ML) algorithms to analyze and classify various properties of wine by processing data obtained from metal oxide semiconductor sensors. After testing several algorithms, SVM showed the highest performance in classifying different wine vintages and fermentation processes. Similarly, researchers have conducted a specific study where they developed an algorithm that leveraged hyperspectral imaging to identify and detect fecal contamination on leafy greens [173]. Various ML algorithms including Bayesian network, regression, decision tree, clustering, deep learning, and artificial neural networks are employed in predicting crop yield [174, 175, 176]. Additionally, Arora and Mangipudi [177] introduced the use of support vector machine classifiers and artificial neural network models for identifying the nitrosamine presence in red meat food samples where their analysis of the predictive modeling results revealed that the deep learning model achieved the highest testing accuracy among the different models considered.

6.4. Disease diagnoses and health monitoring

With the current state of healthcare, the use of biosensor technology in healthcare applications has the potential to improve the efficiency of diagnostic and treatment processes. Artificial intelligence (AI) techniques ranging from machine learning to deep learning play a critical role in many health-related fields, such as enhancing new clinical systems, managing patient information and records, and diagnosing different diseases [178, 179]. Diagnostic technologies, which underpin nearly 70% of medical decisions, are one of the market's major segments for biosensors [180]. Furthermore, AI and biosensors advance medical and life sciences. The application of medical imaging enhances diagnostics and personalized treatments through ML analysis of vast datasets. Integrated into IoT, biosensors enable real-time monitoring of physiological and chemical signals, supported by accelerated AI and edge computing [181].

Biosensors-based IoT networking systems have become increasingly important in digital healthcare in recent times. IOT-based systems like AI-assisted wearable biosensor networks (WAIBN), biosensors, electronic health records, Remote patient monitoring (RPM), predictive analytics, blockchain-based systems, and virtual health care portals [182] are introducing a comprehensive and innovative approach to patient care, through these systems it enables real-time monitoring and effective management of patient health and has the potential to revolutionize patient treatment and improve patient outcomes [183]. Figure 9 illustrates the overview of the implementation of IoT biomedical sensors and biosensors networks to optimize artificial intelligence systems in addressing healthcare issues, where multiple sensors including ECG, body temperature, blood sugar, glucose, EEG, airflow, body position, EMG, and galvanic skin sensors are incorporated into each of three implemented IOT sensor nodes. Data is collected from the patient by these sensor nodes and transmitted to the database server through the aid of sink nodes. Both the doctor's monitoring devices and the prescription system are linked to the database server. Once the server receives the relevant patient information associated with the patient ID, the doctor can suggest an appropriate prescription for the specific patient [182].

The increasing prevalence of diabetes in healthcare makes it crucial to regularly monitor blood glucose levels. An AI-based system was created by Khanam et al. [184] to precisely detect human glucose levels, using five input features including age, pregnancy, body mass index, glucose, and insulin levels to train the system. The data set was evaluated using machine learning algorithms such as RF, NN, DT, and KNN with hidden layers. The results demonstrated that all models provided an accurate measure of glucose, with a precision exceeding 70 % [184]. Kim et al developed a wearable biosensor that can simultaneously monitor both the glucose level in the interstitial fluid (ISF) and the alcohol level in sweat. By utilizing the anode to trigger sweat secretion and the cathode to extract the ISF, the biosensor functions as a unified tool that can measure both substances concurrently [185]. As the effectiveness of AI-integrated

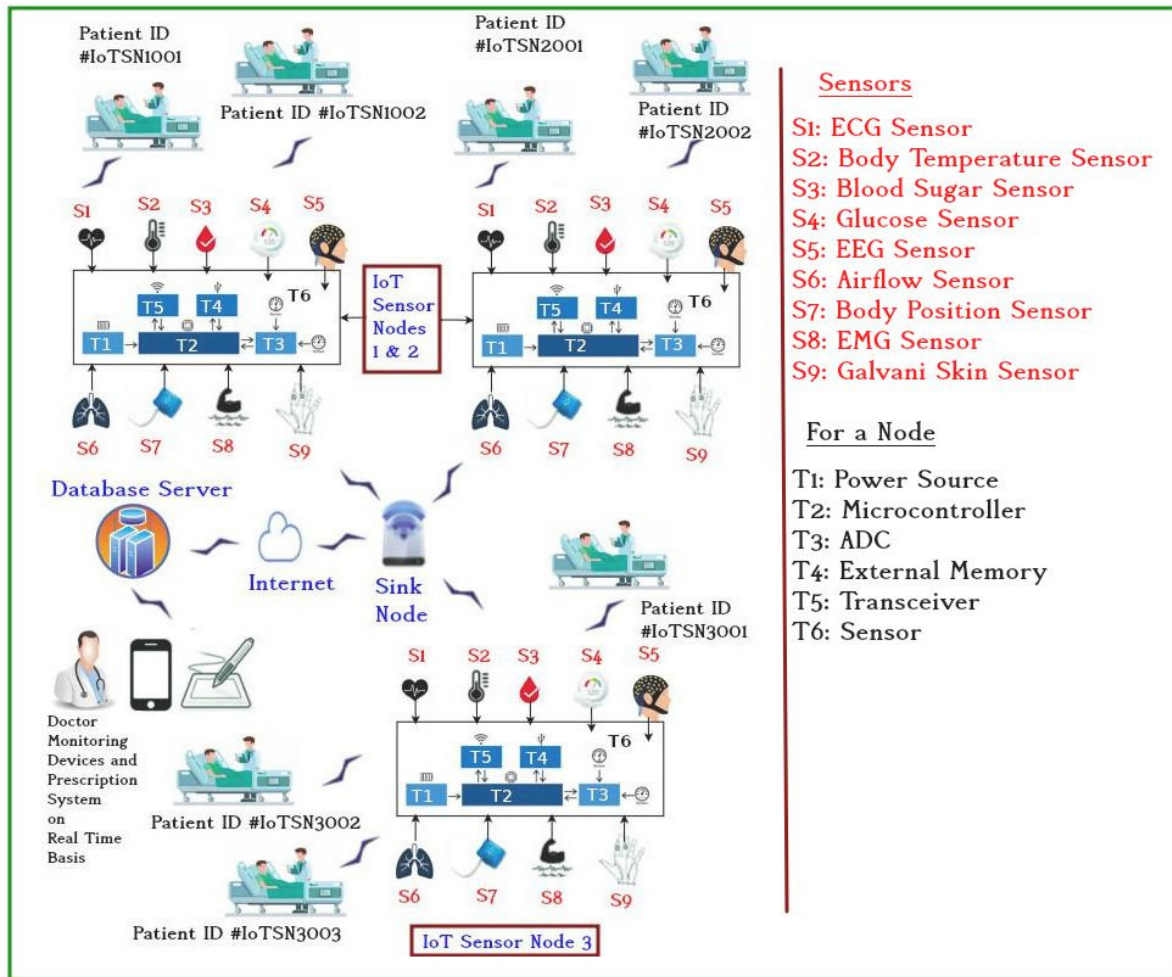


Figure 9: An overview of the implementation of IoT biomedical sensors and biosensor networks to optimize artificial intelligence systems in addressing healthcare issues. The prescription system and sink nodes are connected via the internet to the Database server in real-time. This image is adapted from Khan et al. [182].

CGM biosensors can be very good [66], future research works need to be aimed at designing WAIBN. Designing compact physiological sensors using computational (ML) approaches is challenging, typically relying on heuristics and expert training. This has been achieved by creating ultrathin skin-conformal patches and interactive textiles capturing sEMG, EDA, and ECG signals [186, 187]. Similarly, the development of a liver disease prediction model by Wu et al. [188] involved the use of four distinct machine learning algorithms (RF, NB, ANN, and linear regression). Among these algorithms, the RF classifier produced the most accurate results, achieving a top accuracy rate of 87.48%. Nam et al presented the Internet of Things concepts and digital biomarkers and explored their connections with current trends, including artificial intelligence. Furthermore, they explored how artificial intelligence could potentially contribute to leveraging IoT for the identification of chronic illnesses [189].

In their recent studies (Srinivasu et al., [190, 191]), a successful approach was introduced to aid physicians in diagnosing skin ailments more efficiently. By incorporating

MobileNet V2 and Long Short Term Memory (LSTM) into neural networks, the model attained an accuracy rate of 85%, surpassing other advanced deep learning neural network models. The technique employed by this system allowed for the analysis, processing, and organization of image data based on multiple characteristics, resulting in increased precision and faster outcomes when compared to conventional methodologies.

Koshimizu et al.(2020) [106] have presented the application of artificial intelligence in managing pulse or blood pressure. They utilized large-scale data to predict the likelihood of high blood pressure and highlighted the use of an ANN to control blood pressure. Their study aimed to demonstrate the benefits of using an ANN in hypertension management and its potential to generate medical evidence for the effective treatment of high blood pressure. Due to the abilities of large-scale data analysis and pattern recognition, ANNs can predict future outcomes by leveraging past patient data and forecasting the probability of complications, disease advancement, or the response to specific treatments [192].

The growing interest in maintaining a healthy lifestyle and improving overall well-being has led to a surge in research and development of wearable biosensing technologies from both the academic and industrial sectors [193, 194]. There is currently a strong focus on integrating WAIBN, primarily due to their excellent abilities in denoising, pattern recognition, and detecting abnormalities [195, 196, 197].

Numerous recent studies have shown that analyzing cancer-associated biomarkers in a patient's bodily fluids has the potential to enable early detection of cancer [198, 199, 200]. Biosensor devices, which comprise a biorecognition element and a transducer, can be utilized to detect biomarkers for diagnosing specific diseases [201, 202]. Within this framework, point-of-care (POC) biosensors are quick, sensitive, portable, user-friendly, affordable, and precise devices that can identify cancer cells even before the onset of symptoms [203, 204]. Likewise, Identifying different types of cancer at an early stage increases the likelihood of effective treatment, resulting in a greater chance of survival and decreased mortality rates. Additionally, it provides more economical treatment alternatives [205, 206, 207, 208, 209]. Among women, breast cancer poses a serious health risk. Worldwide, breast cancer is the fourth leading cause of cancer deaths in women, making it the most prevalent type of cancer [210]. Alsharif [211] has provided an in-depth review on the topic of medical applications of conventional computer-aided detection systems and AI-based technologies in the sector of breast imaging. The main emphasis of the article is on identifying, segmenting, and categorizing lesions, as well as analyzing breast density and evaluating the risk of cancer. Vashistha et al. [212] have mentioned that artificial intelligence approaches are at the center when it comes to the design of futuristic biosensors for cardiac health care. Figure 10 presents a concept of how the biosensors, biomarkers, and AI technique can be integrated to perform the holistic diagnosis of cardiovascular diseases and conditions [212]. The bio-receptors present in the biosensors can interact with the analyte and recognize it. As biomarkers can provide information about the specific state of cardiovascular health, the changes in their levels in the samples (urine, blood, sweat, serum, tears, etc.) are detected as an electrical signal. The primary signal data or collected secondary data is then analyzed with AI technique (e.g. machine learning) to make a robust prediction (presence or absence of the particular cardiovascular disease). It is noteworthy to mention that the utilization of AI can enable real-time cardiovascular health monitoring tasks.

6.5. In environment monitoring

With the increase in global population and rapid climate change, there is a growing requirement for affordable and straightforward biosensors to monitor the environment. Standalone conventional analytical methods such as gas and liquid chromatography often face significant challenges in terms of time and expense, which limits their frequent application. In this context, bio-applicable sensors can present

themselves as supportive tools to the existing analytical methods for environmental monitoring applications, due to their ability to detect analytes in complex matrices with high sensitivity and specificity in a relatively short time and at a reasonable cost. Pollutants exist in various forms, including chemical, physical, biological, and radiological compounds, and have a widespread presence in the environment, including the air, soil, and water. These pollutants have a significant impact on all living systems, particularly human health, and life, and can cause a range of adverse health effects [213]. One way to monitor environmental pollutants is through the use of specialized biosensors that employ a physical or chemical transducer coupled with a biological or biomimetic component capable of binding the analyte in a reversible manner where the sensing signals for the targeted pollutants from the sample are generated qualitatively and quantitatively by the detector, which identifies and converts the resulting reactions [214, 76]. Human activities and technological advancement have resulted in a variety of chemicals and by-products being released into the environment. These substances, such as pesticides, heavy metals [215], nitrate compounds [216], and polycyclic aromatic hydrocarbons (PAHs) are well-known environmental pollutants [217] that can harm the environment. Recent developments in biosensors have led to the creation of whole-cell metal biosensors for detecting heavy metals. A whole-cell metal biosensor is a specialized biosensor that employs living cells usually microorganisms like bacteria, which have been genetically modified to detect and quantify the presence or level of metal ions and are developed based on the metal stress signal/transduction pathways found in bacteria within the cells and are used in various applications, including environmental monitoring, industrial processes, by detecting and monitoring of metal contaminants [218, 219]. These biosensors react solely to the fraction of metal ions that are present, as demonstrated by Ivask et al. [220] who used a recombinant luminescent bacterial sensor. Belaidi et al [221] took the initial strides in creating a biosensor that utilizes two detection mechanisms. Their innovative approach involved combining electrochemical and optical detection techniques and relied on distinct responses from various algae to identify pesticides present in water samples. The results were encouraging, prompting the development of a biosensor mimicking this design, with the ability to identify multiple pollutants concurrently. The introduction of dual detection mechanisms in biosensors represents a significant advancement in environmental monitoring, facilitating faster and more precise detection of pollutants in various matrices such as soil and air.

In a study by [222], researchers have explored the classification of water contamination, categorizing water as either clean or polluted, through the utilization of machine learning techniques and IoT devices. The study presented a real-time monitoring system for detecting contamination in water, although the data collected was limited to a specific area.

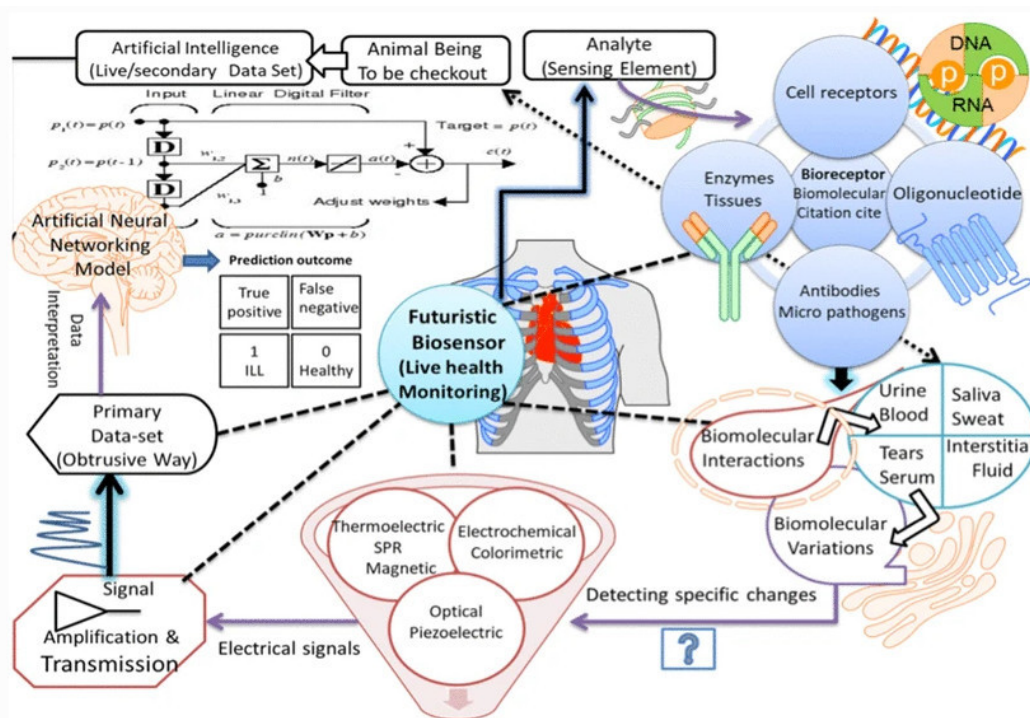


Figure 10: An all-inclusive diagnostic approach utilizing various biomarkers, biosensors, and AI-driven methods is schematically sketched in the figure. [212]. As shown in the top-right of the figure, the bio-receptors (enzymes, tissues, antibodies, cell receptors, etc.) present in the biosensors interact with the analyte and detect or recognize it. Urine, saliva, blood, sweat, interstitial fluid, tears, serum, etc. can contain biomarkers providing information about cardiovascular health. The specific changes in the levels of the biomarkers are quantified as electric signals when measured with sensors driven by thermoelectric, piezoelectric, etc. The collected primary data from signals or other secondary data is analyzed with ANN, and thus prediction can be made via AI.

The utilization of ML and IoT technologies for water classification holds great promise in addressing the hazards associated with waterborne diseases and pollution. This study highlights the potential of classification techniques to assist in monitoring efforts by providing precise, cost-effective, and real-time monitoring of water contamination in a wider range of water sources. Due to their accuracy, reliability, and predictive capabilities, ML algorithms can provide insights into potential changes or fluctuations in water quality and help in proactive decision-making, allowing stakeholders to take preventive measures or implement interventions in advance to aim to uphold or enhance water quality [223].

Figure 11 illustrates a system designed to address several challenges associated with environmental monitoring issues, including temperature, humidity, radiation, dust, and UV signals [224]. Such environmental monitoring systems [224] rely on a wireless sensor network (WSN) to create an interface between IoT devices and data that is captured by various types of AI-based smart sensors [225, 226]. The WSN backbone serves as the infrastructure for transmitting data from the sensors to the IoT devices [224], which allows for remote monitoring of environmental conditions. The use of data-driven smart biomimetic sensors, bioapplicable sensors, including but not limited to image, MEMS, and wearable sensors [226], and IoT devices are a promising technology for efficient and accurate environmental monitoring, aiding in mitigating environmental risks by enabling

real-time monitoring and analysis of environmental indicators.

6.6. In agriculture

The agriculture sector serves as the foundation of the modern world which requires ongoing development to achieve higher levels of productivity and quality. Farmers encounter several challenges throughout the process of crop production, such as crop diseases and pest infestations, inadequate storage management, and insufficient access to irrigation and drainage facilities. Research and development efforts are focused on enhancing the quality and output of agricultural products through the implementation of "smart farming" practices, which involve connecting and making agricultural processes more intelligent [227, 228]. This would require incorporating digital technologies, such as the IoT, to enable real-time monitoring and analysis of soil, water, and weather conditions, as well as pest and disease detection. In the realm of agriculture, AI is an emerging technology that has taken today's agriculture system to a different level. AI technology is being utilized to aid in the prompt detection and identification of pest infestations, illness, and nutrient deficiencies in farms [229, 230]. By implementing AI technology as part of agricultural practices, farmers can access almost real-time monitoring of potential problems, facilitating improved crop yields and reducing the use of unnecessary chemicals, leading to more sustainable farming

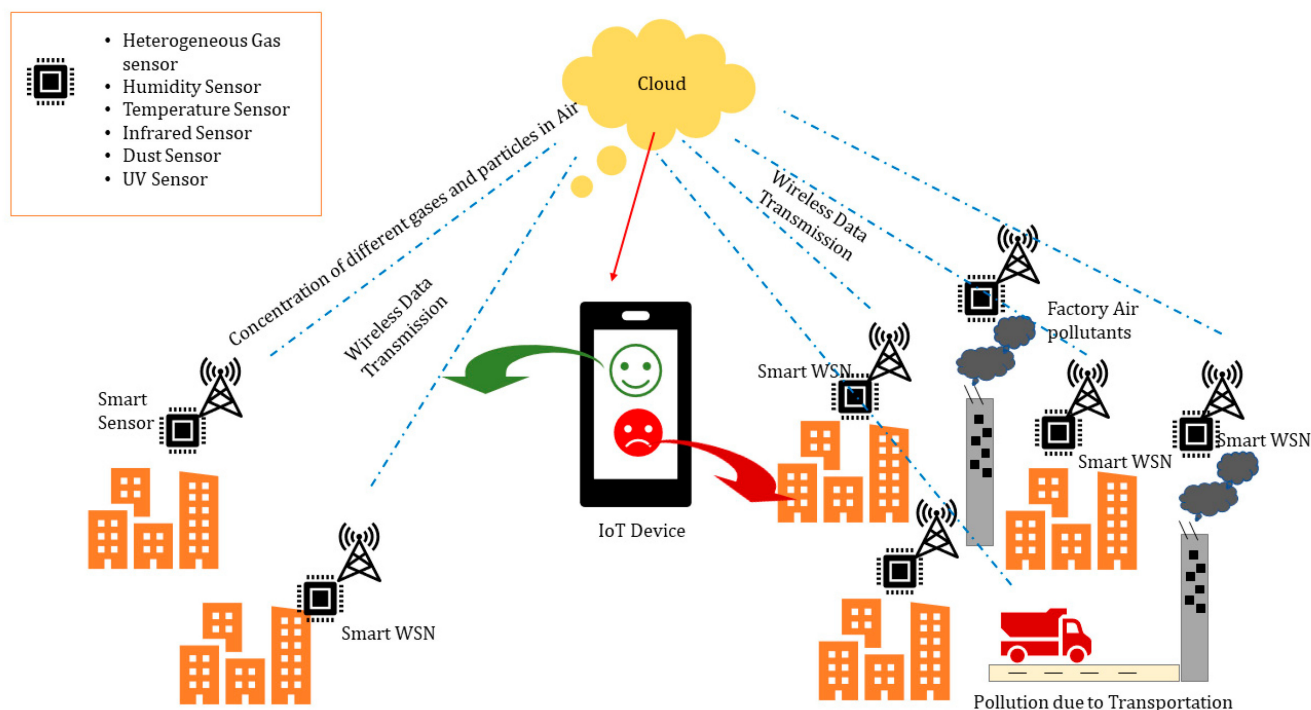


Figure 11: The image depicts a Smart Environment Monitoring (SEM) system that tackles multiple environmental issues through the application of wireless sensor networks (WSNs) and IoT devices [224]. As depicted in the inset, heterogeneous gas sensors, humidity sensors, temperature sensors, infrared sensors, dust sensors, and UV sensors are some of the commonly utilized sensors in an SEM system.

practices [231]. Sohrabi et. al [232] reviewed the recent advancement in sensing assays that utilize metal-organic framework (MOF) structures for the detection of pesticides.

7. Challenges and Future Directions

Exploration of the current state-of-the-art ML-enabled biosensors necessitates a nuanced discussion encompassing both hindrances and avenues for advancement. Current communication technologies potentially applied in wearable biosensors are Bluetooth, NFC, and the 5G cellular network [233]. The adoption of AI-assisted biosensors in human applications highlights the importance of digital literacy, particularly for elderly populations. Despite the benefits, digital literacy and visual impairments hinder the widespread acceptance of WAIBN [234, 235]. To tackle this challenge, the trend is shifting from sensors needing user input to those that work with fewer interactions. This change might help users by making devices less demanding while still giving accurate feedback [236]. Continued improvements in wearables aim to bridge the performance gap and enhance their role. WAINB combined with telehealth platforms is poised to reshape how health care is delivered, requiring teamwork across disciplines. These advancements envision smart homes equipped with integrated monitoring systems and diverse sensors, aiding residents to live independently while staying healthy. Such digital health advancements could extend to assisted living facilities and hospital-at-home settings, easing caregiving burdens [237].

However, human involvement remains crucial for training, interpretation, and response to data. Similarly, biosensors hold potential for agriculture and food industries but face hurdles. Concerns revolve around toxicity and environmental impact. Creating portable versions is vital for remote areas' accessibility, aiding cost reduction and environment-induced disease prevention. Affordable and stabilizing biomaterials like chitosan reduce fabrication costs [238]. While existing commercial sensors work well few biosensors address sustainable agriculture as most focus on common food contaminants only.

Uncertainty propagation is a problem that arises in every sector, including the application area of biodomain sensors. One of the major future directions regarding the utilization of AI techniques in context of biodomain sensors integrated with multiphysical models is the task of uncertainty quantification. Multiphysics models integrating diverse physical phenomena will continue to involve intricate relationships and interactions. AI sensors, continually monitoring and adapting parameters using real-time data, will advance these models [239]. This ongoing dynamic adjustment will further elevate model accuracy, offering an increasingly realistic portrayal of the studied systems. The uncertainty quantification will be useful in the sector of additive manufacturing [239, 240] of biomaterials and bioactive materials. AI sensors can collect diverse and high-dimensional data streams. By integrating this data into multiphysics models [241, 242], AI can assist in fusing information from various sources,

potentially improving the validation process of these models. These data fusion and validation tasks aid in capturing uncertainties stemming from different data sources and their interactions within the system. AI-enabled and multiphysics model governed sensors will be able to facilitate the assessment and quantification of propagated uncertainties. Such integrated techniques can handle probabilistic analyses, considering uncertainties in input parameters and their effects on the model's output [243]. AI sensors gather continuous data for real-time model adaptation and prediction, crucial for identifying anomalies, predicting system behavior, and suggesting corrective actions. Integrated with multiphysics models, they forecast potential failures in industrial settings due to uncertain conditions, allowing timely maintenance. This capability aids in understanding uncertainty propagation and designing preventive measures against failures and accidents [242]. Moreover, AI together with multiphysical models, when deployed in sensors, can aid in decision-making by quantifying uncertainties and their potential impacts on outcomes. The information from XAI is valuable for risk assessment and optimization strategies, enabling more informed and robust decision-making processes [244]. Currently, the endeavours for uncertainty quantification via integrated AI- and multiphysical models governed sensors has been more widespread in areas well beyond biodomain sensors. In future, efforts will have to be made to apply those concepts in the areas of biodomain sensors.

Challenges persist with interference, calibration, and long-term monitoring. Despite breakthroughs in biotechnology, food safety faces issues like sample preparation and cost reduction. Robust biosensor construction requires specific probes and effective probe-label interactions [245]. Future biosensors could benefit from nanotech, microfluidics, smartphones, and wireless tech. Emerging technologies like blockchain and AI will further enhance biosensors for agriculture and food safety [246]. Commercializing biosensors faces challenges, demanding field trials and user awareness. Adhering to food regulations poses additional hurdles, as some manufacturers are hesitant to disclose use, causing conflicts with consumers [247].

Developing biosensors aligned with Sustainable Development Goals (SDGs) for environmental monitoring requires quick and low-impact screening. Recent progress has enhanced detection, but sustainability, portability, and cost challenges persist. The use of nanomaterial raises cost as well as environmental concerns alarming safety exploration. Practical testing in real environmental conditions and safety assessments of modified biosensors are crucial for SDG-aligned applications [248, 249]. Developing Synthetic microbial community (SynCom) biosensors for diverse environments is complex due to understanding microbial physiology and integrating them with IoT. Collaboration for regulatory compliance is crucial. Breakthroughs in AI, synthetic biology, and IoT promise to enhance SynCom biosensing. It offers real-time applications in agriculture, biotherapeutics, and environmental monitoring thus emphasizing transformative potential and advantages over traditional biosensors

[250]. Safety and data privacy are a concern for personal applications as well as industrial applications of AI-interlinked sensors. Biosensors gather a lot of data, but the existing devices and technology struggle to handle and protect it. Using ML gives some advantages, aiding in faster processing and predicting desired application attributes. However, there are concerns about keeping this data safe [251]. Remote hacking is a serious safety concern, potentially risking users' lives. Data processing and security are harder for many users due to lower skills of hi-tech and cognitive aging. Strict rules and support can help improve confidence and use digital safely [252]. To fully use digital sensing devices, their accuracy needs post-processing and validation in large-scale trials. As an example, WAINB encounters challenges in stability, accuracy, and scope. They're affected by ambient conditions like temperature and humidity, thus demanding better protective coatings. Improving these sensors involves exploring new assays to monitor a wider range of biomarkers. Certain devices perform well compared to standard instruments, like continuous glucose monitors and vital sign measurements from WAINB [253].

8. Conclusions

In the era of Industry 4.0, sensing technology has received huge significance. The advancement of biosensors, bioinspired sensors, and bioapplicable sensors can be accelerated by integrating them with AI technology. This study reviews the state-of-the-art models for biomimetic sensors and biosensors. The synergy between machine learning and sensing technology showcases immense potential in addressing uncertainty through AI-guided sensors in complex models. In an attempt to enable the complete understanding of diverse interfaces for the integration of sensing technology with ML and AI-based technologies, several illustrations and engineering applications available in the literature are also reviewed. Among the several paradigms of artificial intelligence, we outline generative machine learning, digital twins, computer vision, natural language processing, and text mining as some of the tools that can be utilized for supporting or aiding the growth and development of sensing technology in an accelerated manner.

The pervasive integration of AI techniques across various devices, from computer vision to e-skin, e-tongue, and e-nose, signifies a transformative phase in technology. Moreover, generative AI's role in identifying suitable substrate pairs for specific enzymes highlights its pivotal role in advancing exploration within this domain. These advancements collectively underscore a profound trajectory in technological innovation, offering promising avenues for enhanced sensor capabilities, uncertainty reduction, and sophisticated substrate-enzyme interactions.

This paper also highlights the challenges and prospects of biosensors integrating machine learning. The challenges of WAINB are digital literacy and visual impairments. In agriculture and food industries, biosensors encounter issues of toxicity, sustainability, and long-term monitoring,

requiring cost-effective and stable materials. Concerns about privacy, security, and accuracy call for stricter rules and user confidence. Despite their potential to reshape healthcare and aid independent living, ensuring precision and durability remains crucial. With their capacity to produce a substantial amount of useful data; biosensors, bio-inspired sensors, and bioapplicable sensors will be considered very important in the development of robust AI techniques.

CRedit author statement

Rubi Thapa: Conceptualization, Investigation, Methodology, Visualization, Writing – original draft. **Sachin Poudel:** Conceptualization, Investigation, Validation, Visualization, Writing – review & editing. **Katarzyna Krukiewicz:** Conceptualization, Data curation, Supervision, Validation, Writing – review & editing. **Anil Kunwar:** Conceptualization, Data curation, Methodology, Supervision, Validation, Writing – review & editing.

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Declaration of Competing Interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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