Chapter

Classical and Quantum Artificial Intelligence and Blockchain Technologies for Next-Generation Biosensing Systems

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Abstract

Biosensing technologies are experiencing a major transformation driven by advances in artificial intelligence, quantum computing, and distributed digital infrastructures. Classical artificial intelligence (AI) has already demonstrated significant value in biosensing through improved signal processing, pattern recognition, and data-driven diagnostics. However, the increasing complexity of biosensor data, together with challenges such as limited datasets, noise, and real-time decision-making requirements, highlights the limitations of purely classical approaches. Quantum artificial intelligence (QAI), which combines quantum principles such as superposition, entanglement, and hybrid quantum–classical learning, offers a promising alternative by enabling improved feature extraction and enhanced performance in data-constrained environments. In parallel, blockchain technology introduces a decentralized and secure framework for managing biosensing data, supporting integrity, traceability, and trust in distributed diagnostic and monitoring systems. This chapter presents a comprehensive overview of classical AI, quantum AI, and blockchain technologies as applied to next-generation biosensing systems. It discusses their individual roles, synergies, and integration into unified architectures for secure, intelligent, and resilient biosensing. Applications in healthcare diagnostics, environmental monitoring, and point-of-care testing are highlighted, alongside key challenges, ethical considerations, and future research directions toward quantum-ready and trustworthy biosensing ecosystems. In addition, the chapter considers how these technologies may support the development of more adaptive biosensing platforms capable of learning from diverse data sources, operating across decentralized healthcare environments, and maintaining data security throughout the diagnostic workflow. Emphasis is placed on the importance of interdisciplinary design, where biosensor engineering, quantum machine learning, quantum information science, blockchain and biomedical development converge to address practical diagnostic challenges.

Keywords: Artificial Intelligence, biosensing, machine learning, large language models, Natural language processing, blockchain

1. Introduction

Over the last two decades, biosensing technologies have advanced significantly, allowing more accurate detection and monitoring of biological signals across diverse applications such as clinical diagnostics, environmental surveillance, and personalized medicine. Contemporary biosensors combine biological recognition components with physical transducers to transform biochemical interactions into quantifiable and measurable outputs. These technologies have been widely deployed in applications such as glucose monitoring, pathogen detection, wearable health monitoring devices, and point-of-care diagnostic platforms [1–4]. Despite substantial advances in sensor fabrication and detection modalities, the increasing complexity of biosensing data presents significant analytical challenges [2]. Contemporary biosensing systems frequently generate large volumes of heterogeneous, noisy, and high-dimensional data streams that must be processed in near real-time [3]. Traditional signal processing techniques are often insufficient to fully exploit the rich information contained in these datasets, particularly in settings involving complex biological interactions or multi-modal sensing platforms. As a result, artificial intelligence (AI) and machine learning (ML) approaches are greattools to extract meaningful patterns from biosensor data and improving diagnostic precision [5–7].

1.1 Artificial Intelligence in biosensing

Classical AI methods have demonstrated considerable success in biosensing applications by enabling automated feature extraction, pattern recognition, and predictive modeling. Machine learning techniques such as support vector machines, decision trees, and neural networks have been widely applied to biosensor data for tasks including disease classification, anomaly detection, and biomarker identification [8]. Deep learning approaches, in particular, have shown strong performance in medical signal analysis and imaging tasks, enabling improved detection of complex biological patterns that may be difficult to identify using conventional analytical techniques [5]. In biosensing contexts, these methods have been used to enhance signal processing pipelines, identify subtle biochemical signatures, and improve the robustness of diagnostic algorithms. Classical machine learning algorithms have also been shown in plasmonic biosensors as well as microcontroller based biosensors [9–11].

Machine learning is especially valuable for wearable biosensors and Internet-of-Things (IoT)-enabled medical devices, where continuous streams of physiological data must be analyzed in real time to detect anomalies or predict health outcomes[10] . For example, AI-enabled wearable sensors can monitor physiological parameters such as heart rate variability, blood oxygen levels, and glucose concentrations to support early disease detection and personalized treatment strategies [6]. However, several challenges limit the effectiveness of classical AI approaches in biosensing systems. One major challenge is the availability of large, high-quality training datasets. In many biomedical contexts, datasets are limited due to privacy constraints, the rarity of certain diseases, or the cost of experimental data collection. In addition, biosensor signals are often noisy and subject to environmental variability, making reliable feature extraction and model training more difficult. These limitations motivate the exploration of emerging computational paradigms capable of handling complex high-dimensional data with improved efficiency. One promising direction is the integration of quantum computing techniques with machine learning algorithms.

1.2 Quantum Artificial Intelligence and Quantum Machine Learning

Quantum computing has recently gained attention as a transformative computational paradigm capable of solving certain classes of problems more efficiently than classical computers. Quantum algorithms exploit fundamental quantum mechanical principles such as superposition, entanglement, and interference to process information in fundamentally different ways compared to classical systems [12].

Quantum artificial intelligence (QAI), also known as quantum machine learning (QML), seeks to combine the strengths of quantum computing with modern machine learning techniques. In this paradigm, quantum processors are used to enhance machine learning models through improved feature representation, faster optimization, and the ability to process complex probability distributions [13, 14]. Several quantum machine learning algorithms have been proposed, including quantum support vector machines, variational quantum classifiers, and quantum neural networks [15]. These approaches leverage quantum feature spaces and hybrid quantum–classical optimization strategies to improve performance on certain types of learning problems. In biomedical research, quantum machine learning has shown promise in applications such as medical image analysis, drug discovery, and genomic data processing [13, 16–18]. For example, quantum-enhanced classifiers have been explored for disease classification tasks where classical algorithms struggle with high-dimensional feature spaces or limited training data.

In the context of biosensing systems, quantum machine learning may enable more efficient analysis of complex biochemical signals and multi-modal sensing datasets. By leveraging quantum feature maps and entangled representations, QML models may capture subtle correlations in biosensor signals that are difficult to detect using classical algorithms alone. Nevertheless, practical deployment of quantum AI systems remains challenging due to the current limitations of quantum hardware. Most available quantum processors are categorized as Noisy Intermediate-Scale Quantum (NISQ) devices, which suffer from limited qubit counts and noise-induced errors [19]. Consequently, many current research efforts focus on hybrid quantum–classical architectures that combine classical computing infrastructure with quantum subroutines for specific computational tasks.

1.3 Blockchain for secure biomedical data management

While AI and quantum computing address the analytical challenges associated with biosensing data, secure data management remains another critical component of modern biosensing ecosystems. Biosensors and wearable health devices often generate sensitive personal health data that must be stored, shared, and analyzed in a secure and trustworthy manner. Blockchain technology has emerged as a promising decentralized framework for managing biomedical data due to its intrinsic properties of immutability, transparency, and distributed consensus [20]. Originally developed for cryptocurrencies, blockchain systems maintain a distributed ledger in which transactions are cryptographically linked and validated across a network of participants. In healthcare applications, blockchain can provide several important benefits for biomedical data management. These include improved data integrity, enhanced auditability, and decentralized data sharing across institutions without relying on centralized intermediaries [21]. Such capabilities are particularly valuable in collaborative research environments where multiple stakeholders must access and analyze shared biomedical datasets.

Recent systematic reviews have highlighted the growing interest in applying blockchain technology to biomedical data management, including applications in electronic health records (EHRs), clinical trial monitoring, distributed machine learning, and medical IoT systems [22]. These studies demonstrate that blockchain infrastructures can support secure data exchange while preserving transparency and traceability across healthcare systems.

Blockchain-based frameworks can also improve interoperability among healthcare institutions by providing standardized protocols for secure data sharing. This is particularly relevant for biosensing systems deployed across distributed networks of wearable devices, hospitals, and research laboratories. By leveraging blockchain architectures, these systems can maintain verifiable records of data access and modification, thereby enhancing trust among stakeholders. Despite these advantages, several challenges remain before blockchain technologies can be widely adopted in biomedical environments. Issues such as scalability, transaction latency, and data privacy must be addressed to support large-scale biosensing deployments. Additionally, integrating blockchain infrastructure with existing healthcare information systems requires careful consideration of regulatory frameworks and interoperability standards [23].

1.4 Towards integrated AI–Quantum–Blockchain biosensing architectures

The convergence of AI, QC, and blockchain technologies represents a promising direction for the development of next-generation biosensing systems. AI algorithms enable intelligent analysis of complex biosensor signals, while quantum machine learning offers the potential to enhance computational efficiency and feature representation. At the same time, blockchain infrastructures provide secure, decentralized frameworks for managing and sharing sensitive biomedical data. An integrated architecture combining these technologies could enable highly resilient biosensing ecosystems capable of supporting real-time diagnostics, collaborative biomedical research, and secure data exchange. In such systems, biosensors would continuously generate physiological data streams that are processed using AI or quantum-enhanced algorithms to detect clinically relevant patterns. The resulting insights could then be securely stored and shared using blockchain-based data management systems, ensuring transparency and data integrity across distributed networks. This paradigm may be particularly valuable for applications such as precision medicine, remote patient monitoring, environmental biosensing, and large-scale epidemiological surveillance. By enabling secure collaboration among healthcare providers, researchers, and patients, integrated biosensing infrastructures could accelerate biomedical discovery while maintaining strong data governance and privacy protections.

1.5 Scope of this chapter

This chapter presents a comprehensive overview of classical artificial intelligence, quantum artificial intelligence, and blockchain technologies in the context of modern biosensing systems. First, we review the role of classical machine learning techniques in biosensor signal processing and biomedical diagnostics. Next, we discuss emerging developments in quantum machine learning and their potential impact on biosensing data analysis. Finally, we examine the use of blockchain technologies for secure biomedical data management and explore the potential synergies among these technologies in future biosensing architectures.

By integrating these complementary technologies, future biosensing platforms may achieve unprecedented levels of intelligence, security, and scalability, enabling the development of robust, trustworthy, and quantum-ready biosensing ecosystems.

2. Classical machine learning for biosensing

The rapid evolution of biosensing technologies has resulted in the generation of large-scale, high-dimensional biological datasets derived from gene expression profiling, spectroscopy, imaging, and physiological monitoring systems. These datasets are often complex, noisy, and nonlinear, requiring advanced computational techniques for effective interpretation. Classical machine learning (ML) methods have emerged as essential tools for extracting meaningful patterns from biosensing data, enabling improved diagnostic accuracy, predictive modeling, and decision support in biomedical applications.

Machine learning plays a central role in precision medicine, where biological measurements such as gene expression profiles, biomarkers, and physiological signals are used to classify disease subtypes and guide treatment strategies. For example, machine learning has been successfully applied to classify non-small-cell lung cancer subtypes using gene expression data, achieving high diagnostic accuracy through a combination of feature selection and probabilistic modeling [24]. Such approaches demonstrate the potential of ML to uncover clinically relevant patterns from complex biosensing datasets.

2.1 Machine learning approaches

In biosensing, machine learning methods are commonly classified into supervised, unsupervised, and semi-supervised learning frameworks based on the presence of labeled datasets and the specific objectives of the analysis task. **Figure 1** illustrates the fundamental differences between supervised, unsupervised, and reinforcement learning approaches, highlighting their respective roles in modeling labeled, unlabeled, and sequential decision-making biosensing data.

2.1.1 Supervised learning

Supervised learning is the most widely used paradigm in biosensing applications, where models are trained on labeled datasets consisting of input signals paired with known outcomes. These outcomes may include disease classification, biomarker presence, or physiological states.

In biomedical contexts, supervised learning has been extensively used for disease classification tasks. For instance, gene expression data from cancer patients can be used to train classifiers that distinguish between disease subtypes. Jain et al. demonstrated that classical machine learning methods such as XGBoost, combined with feature selection techniques, can effectively reduce high-dimensional genomic data and achieve accurate classification of lung cancer subtypes [24].

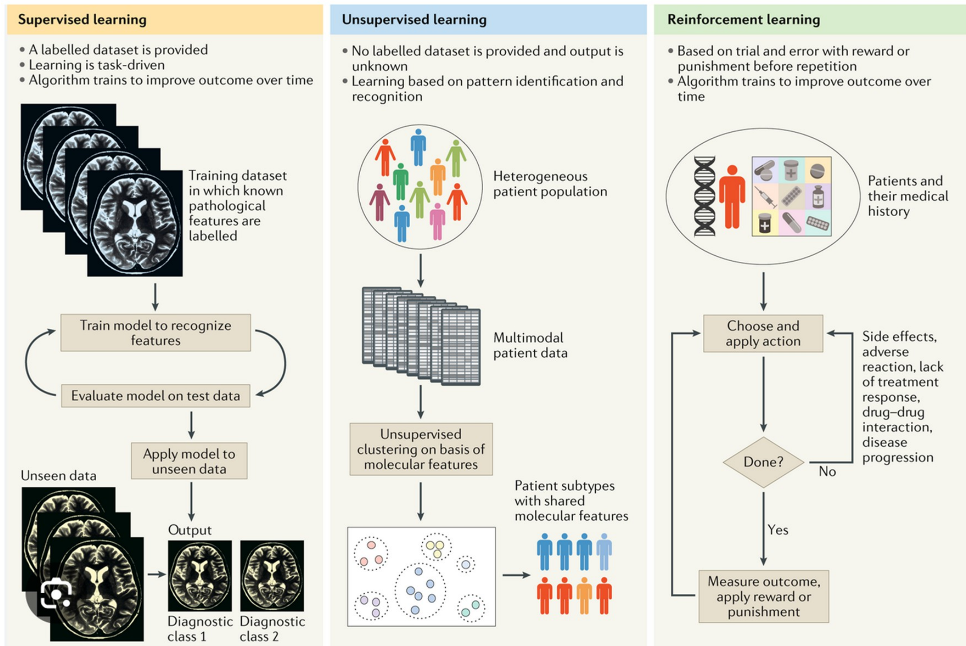

Figure 1.
Overview of supervised, unsupervised, and reinforcement learning paradigms. Supervised learning relies on labeled data, unsupervised learning identifies patterns in unlabeled data, and reinforcement learning optimizes actions based on rewards and penalties. Taken from [25].

Supervised learning models are also widely used in biosensor-based diagnostics, where sensor signals are mapped to clinically relevant outcomes. These models can learn complex nonlinear relationships between biosensor inputs and biological conditions, enabling early disease detection and improved clinical decision-making.

2.1.2 Unsupervised learning

Unsupervised learning is applied when data that has labels is not available or limited. In this paradigm, algorithms identify patterns, clusters, or structures within unlabeled biosensing datasets.

In biosensing applications, unsupervised learning is particularly useful for discovering hidden structures in high-dimensional biological data. For example, clustering techniques can group patients based on gene expression profiles, potentially revealing novel disease subtypes or biological phenotypes. This is especially important in precision medicine, where diseases such as cancer may consist of multiple underlying subpopulations with distinct molecular characteristics [24].

Making use of techniques that reduce dimentionality, such as principal component analysis (PCA), is also widely used in unsupervised learning to simplify complex biosensing data and enable visualization of underlying patterns. These methods help identify the most informative features in high-dimensional datasets, improving interpretability and reducing computational complexity.

2.1.3 Semi-Supervised learning

Semi-supervised learning refers to a type of training in which labeled data as well as unlabeled data are combined to improve model performance. This is typically used in biomedical applications, where labeled data are often scarce due to the cost and complexity of experimental validation.

In biosensing systems, semi-supervised learning models can take advantage of large volumes of unlabeled sensor data to enhance model generalization while requiring only a small labeled dataset. This is especially relevant in healthcare environments where data annotation requires expert knowledge.

Semi-supervised approaches are also relevant in distributed healthcare systems, where data is collected across multiple institutions. As highlighted in recent studies on biomedical data sharing, decentralized systems generate significantly big of data that may not always be labeled, necessitating learning approaches that can effectively utilize both labeled and unlabeled datasets [22].

2.1.4 Reinforcement learning

According to Sutton *et al.* "Reinforcement Learning (RL) [26] is a paradigm within machine learning in which an agent learns to make sequential decisions by interacting with an environment and receiving feedback in the form of rewards or penalties". The objective of the agent is to learn an optimal policy that maximizes cumulative reward over time, typically through trial-and-error exploration and exploitation strategies. Classical RL has found widespread applications in robotics, control systems, finance, drug discovery, medical diagnostics, and game playing. More recently, Quantum Reinforcement Learning (QRL) has emerged as an extension of RL that leverages principles of QC, such as superposition as well as entanglement, to enhance learning efficiency and policy optimization [27]. QRL aims to exploit quantum parallelism to accelerate decision-making processes and improve performance in complex, high-dimensional environments, although practical implementations remain in early stages due to current hardware limitations.

2.2 Deep learning in biosensing

Deep learning which is a branch of machine learning which uses structures called neural networks to learn patterns from significantly large amounts of data has significantly advanced the capabilities of machine learning in biosensing by enabling automatic extraction of hierarchical features from raw data. Unlike traditional ML methods, which rely heavily on manual feature engineering, deep learning models can learn complex representations directly from biosensor signals.

2.2.1 Convolutional neural networks for imaging

Convolutional neural networks (CNNs) are widely used for analyzing spatial data such as microscopy images and biomedical imaging datasets. In biosensing applications, CNNs enable automated analysis of imaging data generated by optical and fluorescence-based sensors.

These models can identify morphological patterns associated with diseases, detect cellular abnormalities, and classify biological samples with high accuracy. CNN-based approaches are particularly valuable in applications such as cancer detection, where imaging data play a critical role in diagnosis.

2.2.2 Recurrent neural networks and LSTM for time-series signals

Many biosensors generate time-series data representing dynamic biological processes, such as electrochemical responses or physiological signals. "Recurrent neural networks (RNNs) and long short-term memory (LSTM) networks are well suited for modeling such sequential data" [7].

These models capture temporal dependencies in biosensor signals, enabling detection of trends and anomalies over time. In healthcare applications, time-series biosensing data can be used to monitor disease progression, predict clinical events, and support continuous patient monitoring.

2.2.3 Autoencoders for feature extraction

Autoencoders are unsupervised deep learning models that learn compressed representations of input data. In biosensing systems, autoencoders are commonly used for feature extraction, noise reduction, and anomaly detection.

By learning latent representations of biosensor signals, autoencoders can capture essential features while removing noise and redundancy. This is particularly useful in high-dimensional datasets such as gene expression profiles, where efficient representation of data is critical for downstream analysis.

2.3 Feature engineering for biosensing

Feature engineering remains an important component of classical machine learning pipelines, particularly in biosensing systems where domain knowledge can enhance model performance.

2.3.1 Spectral feature extraction

Many biosensors generate spectral data, such as Raman or fluorescence spectra, which contain information about molecular interactions. Spectral feature extraction techniques identify key wavelength components associated with specific biochemical signatures.

These features are used as inputs to machine learning models for different tasks such as clasification as well as regression. In genomic and molecular biosensing, feature selection techniques such as those used by Jain et al. help reduce high-dimensional data to a smaller set of informative variables [24].

2.3.2 Signal filtering

Biosensor signals are often affected by noise from environmental factors, sensor variability, and biological processes. Signal filtering techniques are therefore used to improve signal quality prior to analysis.

Filtering methods remove noise while preserving relevant signal characteristics, enabling more accurate feature extraction and model training.

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2.3.3 Dimensionality reduction

Biosensing datasets which have high dimensionality tend to pose challenges for machine learning models due to increased computational complexity and risk of overfitting. Dimensionality reduction techniques transform data into lower-dimensional representations while preserving essential information.

In biomedical applications, reducing the number of features is critical for improving model performance and interpretability. For example, reducing gene expression datasets from thousands of variables to a small subset of key genes can significantly enhance classification accuracy [24].

2.4 Applications of machine learning in biosensing

Machine learning has enabled a long list of applications in biosensing systems across healthcare and environmental domains. The major applications of machine learning in biosensing, including disease diagnostics, pathogen detection, drug discovery, and environmental monitoring, are summarized in **Table 1**.

2.5 Limitations of classical AI

Despite their success, classical machine learning methods face several limitations in biosensing applications. As outlined in **Table 2**, classical machine learning approaches face several limitations, including data scarcity, overfitting, limited interpretability, and high computational cost.

These limitations motivate the exploration of advanced computational paradigms, including hybrid classical–quantum approaches and decentralized data architectures, to improve the efficiency, scalability, and interpretability of biosensing systems.

Application	Description	Role of Machine Learning
Disease Diagnostics	Machine learning models are used to classify biological samples and identify disease subtypes, particularly in oncology through gene expression analysis [24].	Enables accurate classification of diseases, identification of subtypes, and supports personalized treatment strategies.
Pathogen Detection	Biosensors combined with machine learning detect bacteria and viruses by analyzing biochemical signatures [28].	Provides rapid and accurate detection, supporting timely response to infectious disease outbreaks.
Drug Discovery	Machine learning is used to analyze molecular interactions and predict drug efficacy using biosensing-generated experimental data [29–31].	Facilitates the identification of new drug candidates and improves the pipeline for drug discovery.
Environmental Monitoring	Biosensors detect pollutants, toxins, and pathogens in environmental samples such as air, water, and soil [32].	Enables real-time analysis and early detection of environmental hazards through continuous monitoring.

Table 1.
Applications of machine learning in biosensing.

Limitation	Description
Data Hunger	In biomedical applications, acquiring such datasets is challenging due to high experimental costs and strict privacy constraints.
Overfitting	Models sometimes learn noise and/or patterns which are irrelevant during training which leads to poor generalization, particularly in small or noisy biosensing datasets.
Limited Interpretability	Many machine learning models operate as black boxes, making it difficult to interpret predictions. This lack of transparency limits trust and adoption in clinical settings.
Computational Cost	Training complex models on high-dimensional biosensing data is computationally intensive, limiting deployment in real-time or resource-constrained environments.

Table 2.
Key limitations of classical machine learning in biosensing applications.

3. Quantum machine learning for biosensing

The increasing complexity of biosensing data, particularly in genomics, spectroscopy, and multimodal sensing systems, has motivated the exploration of advanced computational paradigms beyond classical machine learning. "Quantum machine learning (QML) represents an emerging field that integrates quantum computing principles with machine learning techniques to enhance data processing capabilities and model performance" [13, 14]. The landscape of QML is categorized into three architectural paradigms, as illustrated in **Figure 2**.

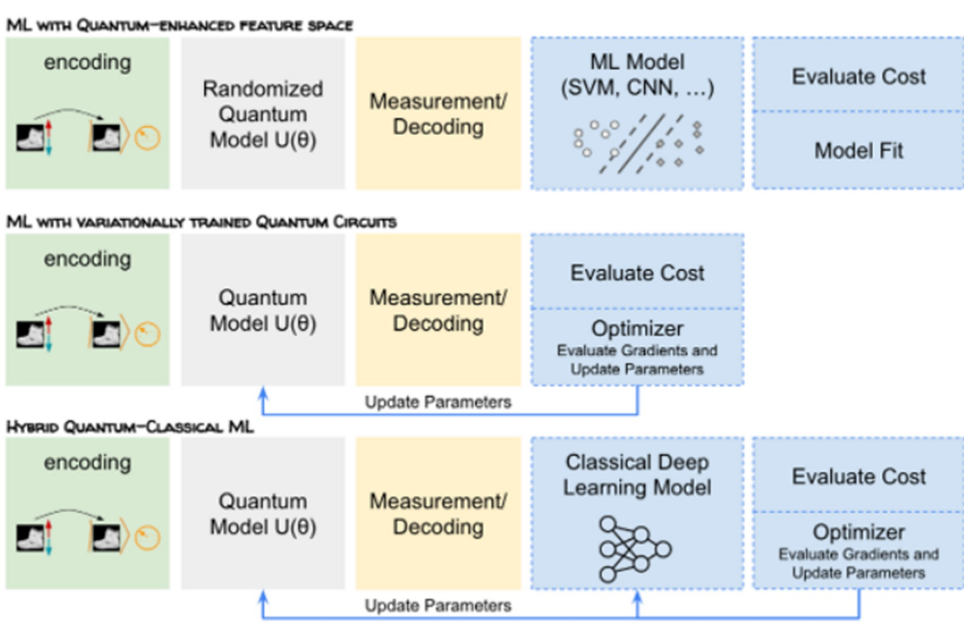

Figure 2.
Overview of three primary frameworks for QML: (top) quantum-enhanced feature spaces using classical models, (middle) VQC with classical optimizers, and (bottom) hybrid quantum-classical deep learning systems. Adapted from [33].

"Quantum computing leverages the principles of quantum mechanics, such as superposition and entanglement, to perform computations that may be infeasible for classical systems" [13]. In biosensing applications, where datasets are often high-dimensional and probabilistic in nature, QML offers the potential to improve feature representation, optimization, and classification performance.

3.1 Fundamentals of quantum computing

Quantum computing unlike classical computing based on bits, is based on quantum bits, or qubits. While classical bits exist in binary states (0 or 1), qubits can exist in superpositions of these states, enabling quantum systems to represent multiple configurations simultaneously [12].

In addition to superposition, quantum entanglement allows qubits to exhibit correlations that cannot be described classically. This property enables quantum systems to encode complex relationships between variables, which is particularly useful in modeling high-dimensional biosensing data.

Quantum computation is typically described in terms of quantum circuits, where quantum gates manipulate qubits to perform computations. "In practice, current quantum hardware operates in the noisy intermediate-scale quantum (NISQ) regime, characterized by limited qubit counts and susceptibility to noise" [19]. As a result, many practical QML approaches rely on hybrid quantum–classical architectures.

3.2 Quantum machine learning concepts

Quantum machine learning combines classical ML methods with quantum computational techniques to improve performance in tasks such as classification, clustering, and optimization [14]. One of the key ideas in QML is the use of quantum feature spaces, where classical data are encoded into quantum states. This encoding allows quantum algorithms to exploit high-dimensional Hilbert spaces for improved pattern recognition. In biosensing applications, this is particularly useful for handling complex datasets such as gene expression profiles and spectral signals. Another important concept is variational quantum algorithms, which use parameterized quantum circuits combined with classical optimization routines. These hybrid models iteratively adjust quantum circuit parameters to minimize a cost function, making them suitable for machine learning tasks on NISQ devices [13]. QML approaches are particularly promising for biosensing systems because they can model complex probability distributions and nonlinear relationships inherent in biological data. This capability is essential for applications such as disease classification, biomarker discovery, and molecular analysis.

3.3 Quantum algorithms for biosensing

Several QML algorithms have been identified for classification and data analysis tasks relevant to biosensing. Among the most important are quantum support vector machines, quantum neural networks, and quantum Boltzmann machines. As summarized in **Table 3**, quantum machine learning algorithms such as QNNs, QSVMs, and QBMs offer powerful approaches for modeling complex and high-dimensional biosensing data.

Algorithm	Description	Applications in Biosensing
Quantum Support Vector Machines (QSVMs)	"QSVMs extend classical support vector machines by using quantum feature maps to embed data into high-dimensional Hilbert spaces, enabling more expressive decision boundaries" [15].	Suitable for high-dimensional biosensing datasets such as genomic data and spectral measurements. Capable of capturing complex relationships between biosensor signals that are difficult to model using classical approaches.
Quantum Neural Networks (QNNs)	QNNs are quantum analogues of classical neural networks that utilize parameterized quantum circuits combined with classical optimization for learning tasks such as classification and regression [34].	Effective for modeling nonlinear patterns in biosensing data. Useful for detecting disease biomarkers, analyzing molecular interactions, and identifying complex biological signatures.
Quantum Boltzmann Machines (QBMs)	QBMs are generative models that extend classical Boltzmann machines into the quantum domain, enabling learning of probability distributions using quantum sampling techniques [35].	Particularly relevant for probabilistic biosensing data. Useful for modeling stochastic biological processes and improving classification in applications such as disease diagnosis and molecular profiling.

Table 3.
Summary of quantum machine learning algorithms and their applications in biosensing.

Jain et al. showed an example the application of a quantum Boltzmann machine for classifying non-small-cell lung cancer patients using gene expression data [24]. Their approach combined classical feature selection methods with quantum annealing techniques, achieving a classification accuracy of 95.24%. This work highlights the potential of QBMs to enhance biosensing-based diagnostics.

3.4 Hybrid Classical–Quantum models

Due to current limitations in quantum hardware, most practical QML systems adopt hybrid classical–quantum architectures. In these models, classical preprocessing techniques are used to reduce data dimensionality and extract relevant features, while quantum algorithms are applied to perform specific computational tasks such as classification or sampling. For example, in the study by Jain et al., classical feature selection methods such as XGBoost were used to reduce gene expression data from thousands of variables to a small set of significant features before applying a quantum Boltzmann machine for classification [24]. This hybrid approach allows quantum models to operate within hardware constraints while still benefiting from classical computational efficiency. Hybrid models are particularly well suited for biosensing systems, where data preprocessing and feature extraction can be performed classically, while quantum algorithms handle complex pattern recognition tasks.

3.5 Case studies in quantum biosensing

One of the most notable applications of QML in biosensing is the classification of non-small-cell lung cancer using gene expression data [24]. In this study, researchers combined classical ML techniques with a quantum Boltzmann machine implemented on a D-Wave quantum annealer. The dataset consisted of ≈ 20000 gene expression values for each patient. Through feature selection techniques, this high-dimensional dataset was reduced to a small subset of significant genes, including

SLC6A8, DSC3, and CLCA2. These genes were then used as inputs to the quantum model. The quantum Boltzmann machine was trained using a hybrid classical–quantum approach, where classical preprocessing steps were followed by quantum sampling on the annealer. The model achieved high classification accuracy in distinguishing between adenocarcinoma and squamous cell carcinoma. This case shows the potential of QML to enhance biosensing-based diagnostics by enabling efficient analysis of high-dimensional biological data. It also highlights the importance of hybrid approaches in leveraging the strengths of both classical and quantum computing.

3.6 Limitations of quantum AI

Despite its promise, quantum machine learning faces several challenges that limit its current applicability in biosensing systems. The key limitations of quantum machine learning in biosensing applications are summarized in **Table 4**.

These limitations highlight the need for continued research in quantum hardware, algorithm development, and hybrid system design. As quantum technologies mature, QML is expected to play an essential role in the development of next-generation biosensing systems.

4. Blockchain for biosensing and biomedical data

The rapid growth of biosensing technologies and digital healthcare systems has led to an unprecedented increase in the volume of biomedical data generated across clinical, research, and environmental domains. These data include electronic health records (EHRs), genomic data, biosensor signals, and real-time physiological measurements. Ensuring the security, integrity, and interoperability of such data remains a major challenge in modern healthcare systems.

Limitation	Description
Hardware Limitations	Current quantum computers are constrained by limited qubit counts, short coherence times, and high noise levels, restricting the size and complexity of problems that can be practically addressed [19].
Data Encoding Challenges	Encoding classical biosensing data into quantum states is nontrivial and often introduces significant computational overhead. Efficient and scalable encoding strategies are essential for practical QML implementations [19].
Algorithm Maturity	Many quantum machine learning algorithms remain in early stages of development and lack the robustness, stability, and scalability of classical approaches. Further research is required to achieve practical superiority [19].
Computational Overhead	Hybrid quantum–classical models require iterative communication between quantum and classical systems, increasing computational overhead and reducing overall efficiency [19].
Lack of Demonstrated Quantum Advantage	Despite promising theoretical results, clear and consistent evidence of quantum advantage in real-world biosensing applications remains limited, with many studies showing performance comparable to classical methods [19].

Table 4.
Key limitations of quantum machine learning in biosensing applications.

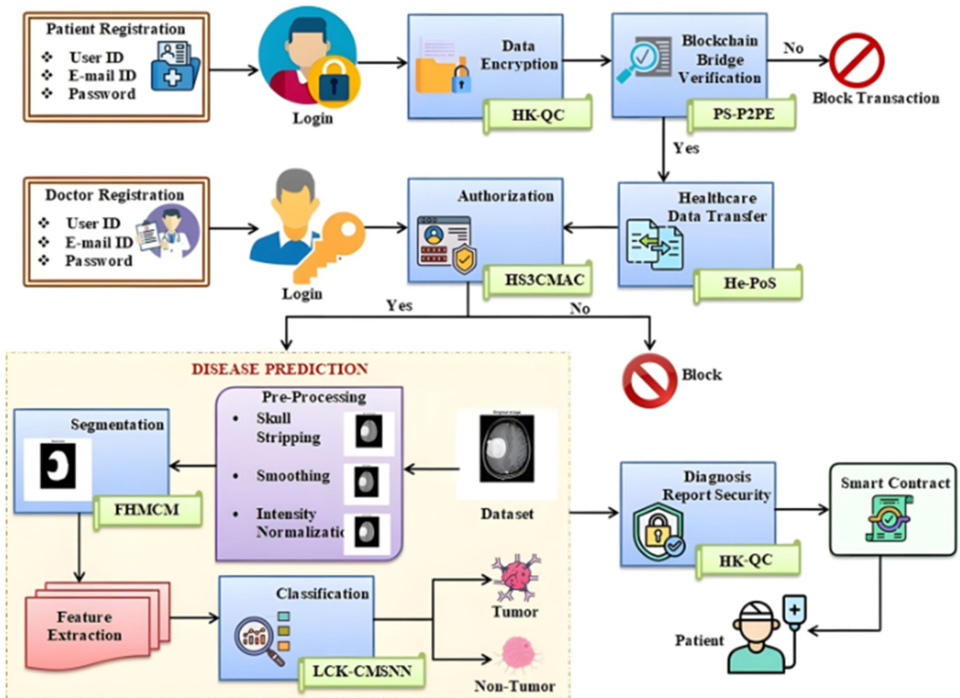

Figure 3.
Proposed blockchain-based framework for secure healthcare data management and brain tumor prediction. The framework integrates patient and doctor registration, secure data encryption using the HK-QC scheme, and Blockchain Bridge (BB) verification via the PS-P2PE algorithm. Verified data are transmitted through the blockchain using the he-pos mechanism, ensuring integrity and secure transfer. Authorized doctors are authenticated using the HS3CMAC approach prior to accessing patient data. The disease prediction pipeline includes preprocessing (skull stripping, smoothing, and intensity normalization), tumor segmentation using FHMCM, feature extraction, and classification into tumor and non-tumor classes using the LCK-CMSNN model. Finally, the diagnosis report is secured and delivered to the patient through a blockchain-enabled smart contract [36].

Blockchain technology has emerged as a promising solution for decentralized data management, offering features such as immutability, transparency, and distributed consensus. These properties make blockchain particularly suitable for biosensing applications, where sensitive data must be securely stored and shared across multiple stakeholders [22]. As illustrated in **Figure 3**, the proposed framework integrates blockchain security mechanisms with machine learning-based tumor prediction to ensure secure data transfer, robust authentication, and accurate diagnostic outcomes.

4.1 Fundamentals of blockchain

“Blockchain is a decentralized, distributed ledger technology that records transactions across a network of nodes” [20]. “Each transaction is stored in a block, and blocks are linked together in chronological order to form a chain”. This structure ensures that once data are recorded, they cannot be altered without consensus from the network [20].

Key characteristics of blockchain include:

- **Decentralization**: Data are distributed across multiple nodes, eliminating reliance on a central authority.
- **Immutability**: Once recorded, data cannot be modified, ensuring data integrity.
- **Transparency**: Transactions are visible to authorized participants, enhancing trust.
- **Security**: Cryptographic mechanisms protect data from unauthorized access.

These properties are particularly valuable in biomedical applications, where data integrity and traceability are critical. Blockchain systems also support smart contracts, which enable automated execution of predefined rules and workflows.

4.2 Blockchain in healthcare

Blockchain technology has been increasingly explored in healthcare for applications such as electronic health record management, clinical trial monitoring, and medical data sharing. "Traditional healthcare systems often rely on centralized databases, which are vulnerable to single points of failure, data breaches, and limited interoperability" [22]. Blockchain provides a decentralized alternative that allows multiple institutions to maintain synchronized copies of a shared ledger. This approach enhances data availability and reduces the risk of data loss or manipulation. Additionally, blockchain enables secure data sharing across institutions without requiring a trusted central authority. Recent systematic reviews have highlighted the growing adoption of blockchain in healthcare applications, including EHR sharing, Internet-of-Things (IoT) data management, and federated learning systems [22]. These applications demonstrate the potential of blockchain to improve data interoperability, security, and trust in healthcare systems.

4.3 Secure biosensor data management

Biosensors generate continuous streams of sensitive data, including physiological signals, biochemical measurements, and environmental readings. Managing these data securely is essential for ensuring patient privacy and data integrity. Blockchain technology provides a framework for secure biosensor data management by enabling decentralized storage and access control. In such systems, biosensor data can be encrypted and stored off-chain, while metadata and access permissions are recorded on the blockchain. This approach ensures data integrity while minimizing storage requirements. Blockchain-based biosensing systems can also provide verifiable audit trails, allowing stakeholders to track data access and modifications. This capability is particularly important in clinical settings, where data provenance and accountability are critical. Furthermore, blockchain can facilitate secure data sharing among healthcare providers, researchers, and patients. By enabling controlled access to biosensor data, blockchain supports collaborative research and personalized medicine while maintaining data privacy.

4.4 Smart contracts in biosensing systems

"Smart contracts are self-executing programs stored on a blockchain that automatically enforce predefined rules and conditions" [37]. "These contracts enable automation of processes such as data sharing, access control, and clinical workflows" [37].

In biosensing systems, smart contracts can be used to manage data access permissions, ensuring that only authorized parties can access specific datasets. For example, a smart contract could automatically grant access to a patient's biosensor data to a healthcare provider under specific conditions.

Smart contracts can also be used to automate clinical workflows, such as triggering alerts when biosensor measurements exceed predefined thresholds. This capability enables real-time monitoring and intervention in healthcare applications. Beyond data management, smart contracts can support the integration of biosensing systems with artificial intelligence models. For instance, smart contracts can facilitate secure data sharing for distributed machine learning applications, enabling collaborative model training across multiple institutions. The integration of smart contracts with biological systems has also been explored conceptually, where blockchain logic is used to model biological processes such as signaling pathways and cellular interactions [37]. This interdisciplinary approach highlights the potential of blockchain to extend beyond data management into computational biology.

4.5 Case studies in blockchain for biomedical data

A comprehensive systematic review by Lacson et al. analyzed blockchain implementations in biomedical applications, focusing on systems with practical deployments and quantitative evaluations [22]. The study identified several key application areas, including:

- Electronic health record (EHR) sharing
- Clinical trial management
- Medical IoT data storage
- Federated learning for healthcare

The review found that most implementations used private or permissioned blockchain networks, reflecting the need for controlled access in healthcare environments. Ethereum was the most commonly used platform, followed by Hyperledger Fabric and other frameworks. One notable finding was that only a small number of systems had been deployed in real-world clinical settings. Most implementations were prototypes or experimental systems, highlighting the early stage of blockchain adoption in healthcare. Performance metrics reported in these studies included transaction speed, query latency, and system scalability. While blockchain demonstrated feasibility for biomedical data management, challenges related to scalability and standardization remain.

Challenge	Description
Interoperability	Integrating blockchain with existing healthcare systems and biosensing platforms presents challenges related to interoperability and standardization. Ensuring compatibility across heterogeneous systems is essential for large-scale deployment.
Regulatory and Privacy Concerns	Healthcare data are subject to strict regulatory requirements related to privacy and security. Designing blockchain systems that comply with these regulations requires careful governance, particularly in balancing data immutability with privacy rights.
Adoption Barriers	The adoption of blockchain in healthcare is limited by factors such as high implementation costs, lack of technical expertise, and resistance to new technologies. Despite its potential, blockchain has not yet achieved widespread adoption in biomedical applications [22].

Table 5.
Key challenges associated with the adoption of blockchain in biosensing and healthcare systems.

4.6 Limitations and challenges

Despite its potential, blockchain technology faces several limitations that hinder its widespread adoption in biosensing and healthcare systems.

Blockchain technology offers a promising framework for secure and decentralized management of biosensing data. However, addressing its limitations and integrating it with existing healthcare infrastructures will be critical for realizing its full potential in next-generation biosensing systems. The key challenges associated with blockchain adoption in biosensing and healthcare systems are summarized in **Table 5**.

5. Advanced topics in intelligent biosensing systems

The convergence of artificial intelligence, quantum computing, and decentralized data infrastructures has opened new frontiers in biosensing systems. Beyond classical machine learning and blockchain integration, several advanced paradigms are emerging that promise to significantly enhance the intelligence, scalability, and interpretability of biosensing platforms. These include explainable artificial intelligence (XAI), federated learning, digital twins, and advanced sensing technologies such as photonic and quantum sensors.

5.1 Explainable AI in biosensing

While machine learning and deep learning models have demonstrated strong performance in biosensing applications, their lack of interpretability remains a critical limitation. In clinical and biomedical contexts, it is essential to understand how models arrive at their predictions, particularly when these predictions influence medical decisions. Explainable artificial intelligence (XAI) aims to address this challenge by providing interpretable insights into model behavior [8]. XAI techniques enable researchers and clinicians to identify which features or inputs contribute most significantly to model predictions. This is particularly important in biosensing applications involving high-dimensional data such as gene expression profiles, spectral signals, and physiological measurements. Common XAI approaches include feature importance analysis, saliency maps, and surrogate models such as decision trees that approximate complex models. In imaging-based biosensing systems, visualization techniques such as heatmaps can highlight regions of interest in microscopy images that influence classification outcomes. The integration of XAI into biosensing systems enhances trust, transparency, and regulatory compliance. As biosensing platforms become increasingly AI-driven, explainability will play a crucial role in ensuring their adoption in clinical practice.

5.2 Federated learning for healthcare

Federated learning (FL) is an emerging paradigm that enables collaborative machine learning without requiring centralized data sharing. Instead of transferring raw data to a central server, FL allows models to be trained locally on distributed datasets, with only model parameters shared across participating nodes. This approach is particularly relevant in healthcare, where data privacy and regulatory constraints limit data sharing across institutions. By keeping sensitive patient data locally while enabling collaborative model training, federated learning addresses key challenges in biomedical data management [22]. Blockchain technology can further enhance federated learning by providing secure and transparent coordination of model updates. For example, blockchain-based federated learning systems can ensure the integrity of model parameters and provide audit trails for data usage. In biosensing applications, federated learning enables the integration of data from multiple biosensor networks, hospitals, and research centers. This allows for the development of more robust and generalizable models while preserving data privacy.

5.3 Digital twins in biosensing

Digital twins represent virtual models of physical systems that are continuously updated using real-time data. In healthcare, digital twins can model individual patients by integrating data from biosensors, medical imaging, and clinical records. Biosensing systems play a central role in digital twin architectures by providing continuous streams of physiological and biochemical data. These data enable dynamic updates of digital twin models, allowing for real-time monitoring and prediction of patient health states. Digital twins have the potential to transform personalized medicine by enabling simulation-based decision-making. For example, clinicians can use digital twins to predict disease progression, evaluate treatment strategies, and optimize therapeutic interventions. The integration of machine learning and quantum computing with digital twin systems further enhances their predictive capabilities. AI models can analyze biosensor data to update the twin, while quantum algorithms may improve simulation efficiency for complex biological systems.

5.4 Photonic and quantum sensors

Advanced sensing technologies such as photonic and quantum sensors are playing an increasingly important role in next-generation biosensing systems [38]. These sensors offer high sensitivity, precision, and the ability to detect subtle biological signals that are difficult to measure using conventional techniques.

Photonic biosensors, including surface plasmon resonance (SPR) sensors, optical waveguide sensors, and interferometric sensors, are widely used for detecting biomolecular interactions. These sensors enable label-free detection and real-time monitoring of biological processes, making them valuable for applications such as disease diagnostics and drug discovery. Recent research has explored the integration of photonic sensing platforms with machine learning algorithms to enhance signal interpretation and detection accuracy. For example, AI-driven photonic biosensors can analyze complex optical signals to identify biomarkers and classify biological samples (see, e.g. [9, 11]). Quantum sensors represent another emerging class of biosensing technologies that leverage quantum phenomena such as entanglement and coherence to achieve ultra-high sensitivity. These sensors are capable of detecting minute changes in physical quantities such as magnetic fields, temperature, and molecular interactions. Quantum sensing technologies have potential applications in areas such as molecular imaging, single-cell analysis, and detection of low-concentration biomarkers [39, 40]. When combined with quantum machine learning algorithms, these sensors could enable highly advanced biosensing systems capable of extracting information from complex biological environments. Overall, these advanced topics represent the next stage in the evolution of biosensing systems. By integrating explainable AI, federated learning, digital twins, and advanced sensing technologies, future biosensing platforms will become more intelligent, secure, and capable of addressing complex biomedical challenges.

6. Challenges and open problems

Despite the significant progress in integrating artificial intelligence, quantum computing, and blockchain technologies into biosensing systems, several challenges remain that limit their widespread adoption and practical deployment. Addressing these challenges is essential for realizing the full potential of next-generation intelligent biosensing platforms.

6.1 Data scarcity

A major limitation in biosensing applications is the scarcity of high-quality labeled datasets. Machine learning models, particularly deep learning approaches, require large volumes of labeled data to achieve robust performance. However, in biomedical contexts, data collection is often expensive, time-consuming, and subject to strict privacy regulations. For example, gene expression datasets used in disease classification studies are typically limited in size, which can affect model reliability and generalization. Although feature selection techniques can reduce data dimensionality, the availability of labeled samples remains a bottleneck in training accurate models [24]. Furthermore, biosensor data are often heterogeneous and collected under varying conditions, making it difficult to standardize datasets across different studies. This lack of standardized datasets hinders the development of generalizable models and limits reproducibility.

6.2 Model generalization

Ensuring that machine learning models generalize well across different datasets and real-world conditions is a significant challenge in biosensing systems. Models trained on specific datasets may perform poorly when applied to new data due to differences in sensor configurations, environmental conditions, or patient populations. In clinical applications, poor generalization can lead to unreliable predictions and limit the adoption of AI-driven biosensing systems. This issue is particularly critical in precision medicine, where models must accurately capture variability across diverse patient populations. Techniques such as transfer learning, domain adaptation, and federated learning offer potential solutions, but further research is needed to develop models that are robust across heterogeneous biosensing environments.

6.3 Hardware limitations

The deployment of advanced computational models in biosensing systems is constrained by hardware limitations. "In the case of quantum computing, current devices operate in the noisy intermediate-scale quantum (NISQ) regime, characterized by limited qubit counts, short coherence times, and high error rates" [19]. These limitations restrict the complexity of quantum machine learning models that can be implemented in practice. As demonstrated in hybrid approaches such as the quantum Boltzmann machine used for lung cancer classification, classical preprocessing is still required to reduce data to manageable sizes before quantum processing [24]. Similarly, edge computing devices used in wearable and portable biosensing systems have limited computational resources, memory, and power. Deploying complex machine learning models on these devices requires efficient model compression and optimization techniques.

6.4 Regulatory and ethical issues

The use of AI and blockchain in biosensing systems raises important regulatory and ethical considerations. Biomedical data are highly sensitive, and ensuring privacy, security, and compliance with regulations such as GDPR and HIPAA is critical. Blockchain technology offers potential solutions for secure data management, but its implementation must be carefully designed to comply with regulatory requirements. For example, the immutability of blockchain records can conflict with regulations that require data modification or deletion under certain conditions. Ethical concerns also arise in the use of AI for medical decision-making. Lack of transparency in machine learning models can lead to challenges in accountability and trust. Ensuring fairness and avoiding bias in AI models is particularly important in healthcare applications.

6.5 Interoperability

Interoperability remains a major challenge in integrating biosensing systems with existing healthcare infrastructure. Biosensors, electronic health records, and data analytics platforms often operate using different standards and protocols, making seamless data exchange difficult. Blockchain-based systems can improve interoperability by providing standardized frameworks for data sharing. However, integrating these systems with legacy healthcare infrastructure requires significant effort and coordination. The lack of standardized data formats and communication protocols also limits the scalability of biosensing systems across different institutions and regions. Addressing interoperability challenges will be essential for enabling large-scale deployment of intelligent biosensing networks. These challenges highlight the need for continued research and development in data acquisition, model design, hardware optimization, and regulatory frameworks to support the next generation of biosensing systems.

7. Future directions

The integration of artificial intelligence, quantum computing, and blockchain technologies is expected to drive the next generation of biosensing systems. These advancements will enable more accurate diagnostics, secure data sharing, and real-time monitoring of complex biological processes. Several promising directions are emerging that will shape the future of intelligent biosensing.

7.1 Quantum advantage in biosensing

One of the most anticipated developments in quantum machine learning is the achievement of quantum advantage, where quantum algorithms outperform classical methods in practical applications. In biosensing, this could enable efficient analysis of high-dimensional datasets such as genomic data, molecular interactions, and multimodal sensor signals. Quantum Boltzmann machines and quantum-enhanced classifiers have already demonstrated potential in biomedical classification tasks, such as distinguishing lung cancer subtypes from gene expression data [24]. As quantum hardware continues to improve, these approaches may provide significant performance gains in biosensing applications. Future research will focus on developing scalable quantum algorithms and improving data encoding techniques to fully leverage quantum computational capabilities.

7.2 AI-driven personalized medicine

The integration of biosensing systems with AI is expected to play a central role in personalized medicine. By continuously monitoring physiological and biochemical signals, biosensors can provide real-time data that enable individualized treatment strategies. Machine learning models can analyze these data to identify patterns specific to individual patients, allowing for early detection of diseases and tailored therapeutic interventions. This approach aligns with the broader goal of precision medicine, where treatments are customized based on patient-specific characteristics. Advances in AI and biosensing technologies will enable more accurate prediction of disease progression, improved treatment outcomes, and enhanced patient care.

7.3 Fully autonomous biosensing systems

Future biosensing systems are expected to become increasingly autonomous, integrating sensing, data processing, and decision-making capabilities into unified platforms. These systems will leverage AI algorithms to analyze biosensor data in real time and trigger appropriate actions without human intervention. For example, autonomous biosensing systems could monitor patient health continuously and automatically alert healthcare providers or administer treatments when abnormalities are detected. Such systems will be particularly valuable in remote and resource-limited settings. The development of autonomous biosensing systems will require advances in edge computing, machine learning, and sensor technologies, as well as robust mechanisms for ensuring reliability and safety.

7.4 Blockchain-Enabled Global health networks

Blockchain technology has the potential to enable global health networks that facilitate secure and decentralized sharing of biomedical data. By providing a trusted framework for data exchange, blockchain can support collaborative research and large-scale data analysis across institutions and countries. In biosensing applications, blockchain can enable secure sharing of sensor data, allowing researchers to aggregate data from diverse sources while preserving privacy and data ownership. This capability is particularly important for addressing global health challenges such as pandemics and environmental monitoring. Recent studies have demonstrated the feasibility of blockchain-based systems for healthcare data sharing, although widespread adoption remains limited [22]. Future work will focus on improving scalability, interoperability, and regulatory compliance to enable global deployment. The future of biosensing lies in the convergence of advanced computational and sensing technologies. By addressing current challenges and leveraging emerging innovations, next-generation biosensing systems will become more intelligent, secure, and capable of transforming healthcare and biomedical research.

8. Conclusion

This chapter has explored the convergence of classical machine learning, quantum machine learning, and blockchain technologies in the context of modern biosensing systems. The integration of these technologies represents a significant paradigm shift in how biological data are acquired, processed, and utilized for healthcare and environmental applications.

8.1 Summary of key findings

Throughout this work, we have demonstrated that classical machine learning techniques provide a strong foundation for biosensing data analysis. Supervised, unsupervised, and deep learning approaches enable the extraction of meaningful patterns from complex biosensor signals, supporting applications such as disease diagnostics, pathogen detection, and environmental monitoring. However, classical approaches face limitations related to data requirements, model generalization, and computational complexity. Quantum machine learning has emerged as a promising extension, offering new ways to model high-dimensional and probabilistic data. In particular, hybrid classical–quantum approaches, such as quantum Boltzmann machines, have demonstrated potential in biomedical classification tasks, including cancer subtype identification [24]. In parallel, blockchain technology provides a robust framework for secure and decentralized management of biosensing data. By ensuring data integrity, transparency, and controlled access, blockchain systems address critical challenges in biomedical data sharing and interoperability [22]. The integration of smart contracts further enables automation of workflows and enhances the functionality of biosensing systems. Advanced topics such as explainable AI, federated learning, digital twins, and photonic and quantum sensors highlight the rapid evolution of the field. These technologies contribute to improving interpretability, scalability, and sensing precision, paving the way for next-generation intelligent biosensing platforms.

8.2 Importance of integration

A central theme of this work is the importance of integrating multiple technological paradigms to address the complexity of biosensing systems. While each technology offers unique advantages, their combined application provides a more comprehensive solution. Artificial intelligence enables intelligent analysis and prediction, quantum computing enhances computational capabilities for complex datasets, and blockchain ensures secure and trustworthy data management. Together, these technologies form a synergistic framework for developing robust biosensing systems. For example, biosensors can generate real-time data that are analyzed using AI models, enhanced by quantum algorithms for improved performance, and securely stored and shared blockchain infrastructures. Such integrated systems can support precision medicine, real-time diagnostics, and large-scale biomedical research. The importance of this integration is particularly evident in applications involving distributed data sources, such as wearable biosensors and global health monitoring networks. By combining AI, quantum computing, and blockchain, it is possible to create scalable, secure, and intelligent biosensing ecosystems.

8.3 Final outlook

Looking forward, the field of biosensing is expected to undergo significant transformation driven by advances in computational and sensing technologies. Quantum computing is is going to have an increasingly important role as hardware capabilities improve and quantum algorithms mature. Similarly, AI-driven biosensing systems will become more autonomous, enabling real-time decision-making and personalized healthcare. Blockchain technology will continue to evolve as a key enabler of secure data sharing and decentralized healthcare systems. As challenges related to scalability and interoperability are addressed, blockchain-based infrastructures may support global health networks and collaborative research initiatives. Despite current limitations, the convergence of these technologies offers unprecedented opportunities for innovation in biosensing. Future research will focus on developing scalable, interpretable, and efficient models, as well as addressing regulatory and ethical considerations. In conclusion, the integration of AI, QML, and blockchain technologies represents a transformative approach to biosensing. By leveraging the strengths of each paradigm, next-generation biosensing systems will be better equipped to address complex biomedical challenges, ultimately improving healthcare outcomes and advancing scientific discovery.

Software usage statement

During the preparation of this book chapter, artificial intelligence-assisted writing tools were used to support language refinement and editorial improvement. Specifically, Writefull was used to assist with academic language enhancement, sentence structure refinement, clarity improvement, and grammar correction. Grammarly was additionally used for proofreading, grammar checking, punctuation correction, and overall readability enhancement.

Nomenclature

AI	Artificial Intelligence
ML	Machine Learning
DL	Deep Learning
QAI	Quantum Artificial Intelligence
QML	Quantum Machine Learning
CNN	Convolutional Neural Network
RNN	Recurrent Neural Network
LSTM	Long Short-Term Memory
SVM	Support Vector Machine
QSVM	Quantum Support Vector Machine
QNN	Quantum Neural Network
QBM	Quantum Boltzmann Machine
PQC	Parameterized Quantum Circuit
VQC	Variational Quantum Classifier
VQE	Variational Quantum Eigensolver
QAOA	Quantum Approximate Optimization Algorithm
NISQ	Noisy Intermediate-Scale Quantum
QC	Quantum Computing
SPR	Surface Plasmon Resonance
LSPR	Localized Surface Plasmon Resonance
QSPR	Quantum Surface Plasmon Resonance
POC	Point-of-Care
DNA	Deoxyribonucleic Acid
RNA	Ribonucleic Acid
PCR	Polymerase Chain Reaction
LAMP	Loop-Mediated Isothermal Amplification
IoT	Internet of Things
IoMT	Internet of Medical Things
FL	Federated Learning
XAI	Explainable Artificial Intelligence
EHR	Electronic Health Records

EMR	Electronic Medical Records
DLT	Distributed Ledger Technology
API	Application Programming Interface
GPU	Graphics Processing Unit
TPU	Tensor Processing Unit
GDPR	General Data Protection Regulation
HIPAA	Health Insurance Portability and Accountability Act
CAR-T	Chimeric Antigen Receptor T-cell

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Conflict of Interest

The authors declare no conflict of interest.

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