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SURVEY

Quantum Machine Learning Revolution in Healthcare: A Systematic Review of Emerging Perspectives and Applications

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ABSTRACT Quantum computing (QC) stands apart from traditional computing systems by employing revolutionary techniques for processing information. It leverages the power of quantum bits (qubits) and harnesses the unique properties exhibited by subatomic particles, such as superposition, entanglement, and interference. These quantum phenomena enable quantum computers to operate on an entirely different level, exponentially surpassing the computational capabilities of classical computers. By manipulating qubits and capitalising on their quantum states, QC holds the promise of solving complex problems that are currently intractable in the case of traditional computers. The potential impact of QC extends beyond its computational power and reaches into various critical sectors, including healthcare. Scientists and engineers are working diligently to overcome various challenges and limitations associated with QC technology. These include issues related to qubit stability, error correction, scalability, and noise reduction. In such a scenario, our proposed work provides a concise summary of the most recent state of the art based on articles published between 2018 and 2023 in the healthcare domain. Additionally, the approach follows the necessary guidelines for conducting a systematic literature review. This includes utilising research questions and evaluating the quality of the articles using specific metrics. Initially, a total of 2,038 records were acquired from multiple databases, with 468 duplicate records and 1,053 records unrelated to healthcare subsequently excluded. A further 258, 68, and 39 records were eliminated based on title, abstract, and full-text criteria, respectively. Ultimately, the remaining 49 articles were subject to evaluation, thus providing a brief overview of the recent literature and contributing to existing knowledge and comprehension of Quantum Machine Learning (QML) algorithms and their applications in the healthcare sector. This analysis establishes a foundational framework for forthcoming research and development at the intersection of QC and machine learning, ultimately paving the way for innovative approaches to addressing complex challenges within the healthcare domain.

INDEX TERMS Quantum computing, quantum machine learning algorithms, healthcare, systematic review.

I. INTRODUCTION

Machine Learning (ML) is a rapidly emerging computer field that is fuelled by massive amounts of data sent, collected, and analysed every day [1]. There are numerous ML applications and implementations with QC in the real world. The science of QC is exciting and has many practical applications which cover a wide range of topics [2]. The recent advancement of QC technology has made the processing of large data scale feasible, with QC

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demonstrating that it is able to solve challenging tasks much more quickly than classical computers [3], [4]. Quantum methods for computing offer new concepts and strategies to the field of machine learning and the development of computer-based technologies grounded in the principles of quantum theory [5]. The nature and behaviour of energy and matter at a quantum level are described by quantum theory, where QC constitutes a collection of bits that work together to solve problems [6]. In the field of quantum machine learning, classical machine learning and quantum physics are combined. A symbiotic link exists between the construction of quantum versions of machine learning algorithms using quantum computers and the analysis of quantum systems using machine learning algorithms [7]. In the past few years, there has been notable growth in deep learning and machine learning, with these advanced technologies having found extensive application across various industries, ranging from the military, aerospace, and agriculture to banking and healthcare. Models developed through these methods have been widely adopted in these sectors [8], [9], [10].

Recently, the fields of machine learning and QC have been gaining prominence and expanding opportunities in the field of Artificial Intelligence (AI) [11], and numerous researchers have successfully applied diverse quantum algorithms to real healthcare datasets. Among these applications QML stands out as a highly promising field, with multiple research teams actively engaged in its research [12]. Particularly significant is the exploration of novel machine learning approaches that leverage the advantages of QC within the healthcare domain. In this context, supervised learning has emerged as a noteworthy QML model that has garnered considerable attention from both academia and in healthcare. In the case of classification and diagnosing problems, exponential experimental improvements have been achieved through various contributions [13]. These include the development of quantum support vector machines (QSVM), variational quantum classifiers (VQC), hybrid algorithms, quantum deep learning models, and error minimisation algorithms, as well as pre-processing techniques. The design and implementation of Quantum Artificial Neural Networks (QANN) have provided a gateway for the application of additional algorithms in quantum states [14], [15]. Furthermore, there are several methods for encoding classical data into quantum states that offer advantages such as reduced exploratory costs in terms of resources and the incorporation of non-linearity in the data [16]. Kernel-based methodologies have proven useful in achieving data linearity for linear classifiers. Similar to classical machine learning algorithms, researchers are also now concentrating their efforts on establishing comprehensive quantum algorithms capable of solving classification problems specific to the healthcare industry. QC techniques have been merged with classical ML for various applications, with these algorithms using different private and publicly available datasets such as the University of California Irvine (UCI) ML repository, Iris, and MNIST dataset [17], [18].

QML has the potential to revolutionise healthcare by leveraging the power of QC in order to analyse complex healthcare data and make more accurate predictions [19]. It can process large and diverse healthcare datasets, including electronic health records (EHRs), medical imaging data, genomic data, and sensor data, with a view to improving disease diagnosis and prognosis [20]. EHRs contain a wealth of patient information, including medical history, diagnoses, treatments, laboratory results, and so on, and these comprehensive datasets offer great potential for advancing healthcare research and in improving patient outcomes [21]. QML techniques can be further used to leverage the power of QC and extract valuable insights from EHRs. Moreover, QML holds tremendous potential in the field of medical imaging, where it can make a significant impact. Medical imaging techniques, such as X-rays, CT scans, MRI scans, and ultrasound, play a critical role in diagnosing and treating various diseases and conditions. However, these imaging processes often require substantial computational power and can be time-consuming, leading to delays in diagnosis and treatment [22]. Moreover, the advent of QML brings the promise of speeding up image processing and analysis, thus revolutionising the field of medical imaging. By harnessing the principles of quantum mechanics, quantum algorithms can tackle complex computational tasks more efficiently than classical algorithms, with this advancement opening up new possibilities for doctors and medical professionals in providing faster and more accurate diagnoses. By analysing these datasets, QML algorithms can identify patterns, correlations, and bio-markers that traditional machine learning algorithms might miss, leading to more accurate predictions of diseases and their progression [23], [24].

II. MATERIALS AND METHOD

This review aims to demonstrate solutions and advancements for the development and adaptation of various quantum processing methods, quantum machine learning models, and quantum simulation tools in the healthcare domain. The work serves as an introduction to this emerging area, along with a review of recent developments and a presentation of the issues that have yet to be resolved in earlier survey studies [25], [26], [27], [28]. In comparison to classical computing (CC), QC is an emerging field. We will focus on the developments and applications of the previous seven years as a result, and will contrast the various approaches used as well as the challenges.

A. SEARCH DATABASES

Papers that fit the criteria for this review include those that (a) concentrate on learning patient representations, (b) use patient data, such as EHR, images, and ECG signals, and (c) employ quantum machine learning and quantum deep learning models. In contrast to other techniques, ML and DL are a practical data-driven solution to build robust representation simultaneously from a variety of resources, and it is thus noteworthy that we consider research utilising QC techniques

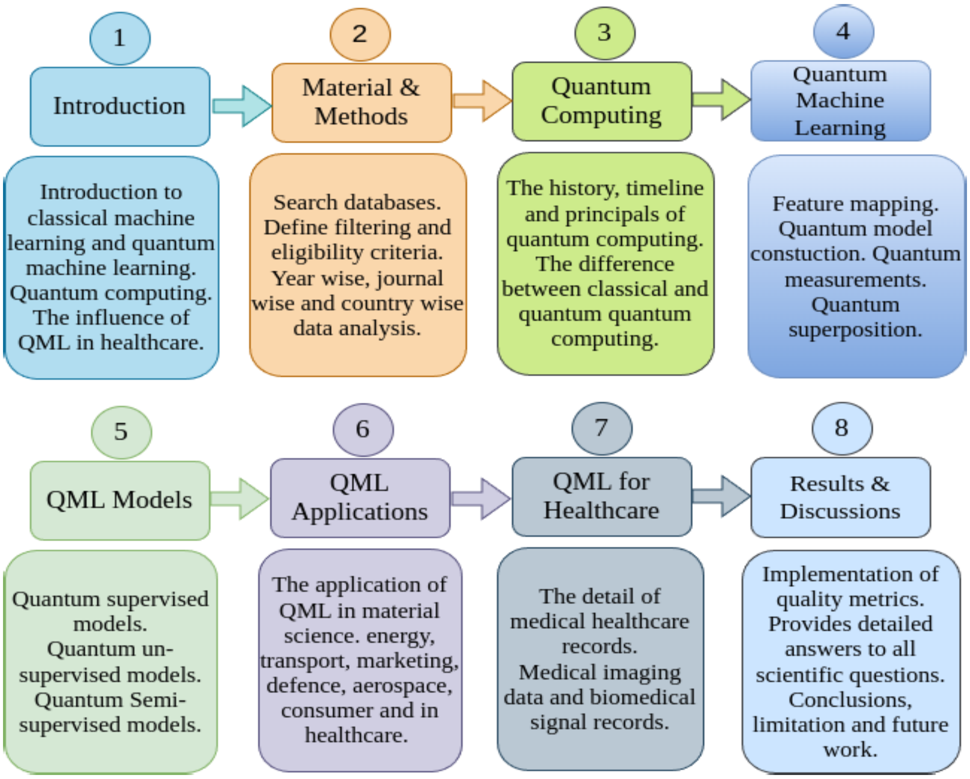

FIGURE 1. **Hierarchy model for the entire manuscript.**

as one criterion. This is because QC techniques have unique characteristics that make them a viable data-driven solution. Keyword searching queries for literature database searches were generated by applying these criteria, and articles from the past five years from 2019 to 2023 were extracted from four distinct databases, including Web of Science, Scopus, IEEE Explore Digital Library, and Springer Nature.

B. FILTERING CRITERIA

In terms of publication characteristics, we restricted our search to English-language academic papers and concentrated only on conference proceedings and peer-reviewed journals (posters and pre-prints were excluded). Only study designs relevant to creating a quantum ML or quantum DL based on any type of health-related dataset were taken into account as study features. The study results should also be used to downstream clinical prediction evaluations. It is important to note that review papers, proceeding summaries, and QML articles not connected to healthcare applications were excluded from the study. By using a snowballing strategy [29], duplicate records were eliminated and additional records were added, which were gathered based on references in the papers and personal readings. From out of the total 2038 records collected from four open sources database, 468 articles were deleted in the filtering criteria stage which were most likely duplicated. Additionally, from 1570 records, a further 1034 were eliminated after filtering again, because most of them were not related to QML or considered to be other data for model evaluation purposes, as shown in Figure 2.

C. ELIGIBILITY CRITERIA

Eligibility criteria include three essential reading techniques: reading the title, reading the abstract, and reading the entire article. Following filtering criteria, 272 records were considered for further processing in order to check their eligibility. We obtained 272 records following the filtering stage, from which 116 more records were eliminated at the title screening stage because the topic under consideration did not meet our specific requirements. Furthermore, 68 additional records were excluded after reading the abstract. Any articles that use classical ML instead of quantum ML, use text datasets, or are related to industrial, material science, or transportation applications were removed. From the remaining 88 records, 40 records were further excluded in accordance with the criteria of the full text screening stage, where each study was researched in full detail to ensure the relevant records. Finally, 49 records were selected based on three categories: the Electronic Healthcare Record (EHR) dataset, imaging dataset records and biomedical signal record, which are the most appropriate for the purpose of our proposed work.

D. INCLUSION CRITERIA

Finally, in inclusion criteria, we selected 47 of those records, which are linked to QML, QDL and QC related to healthcare

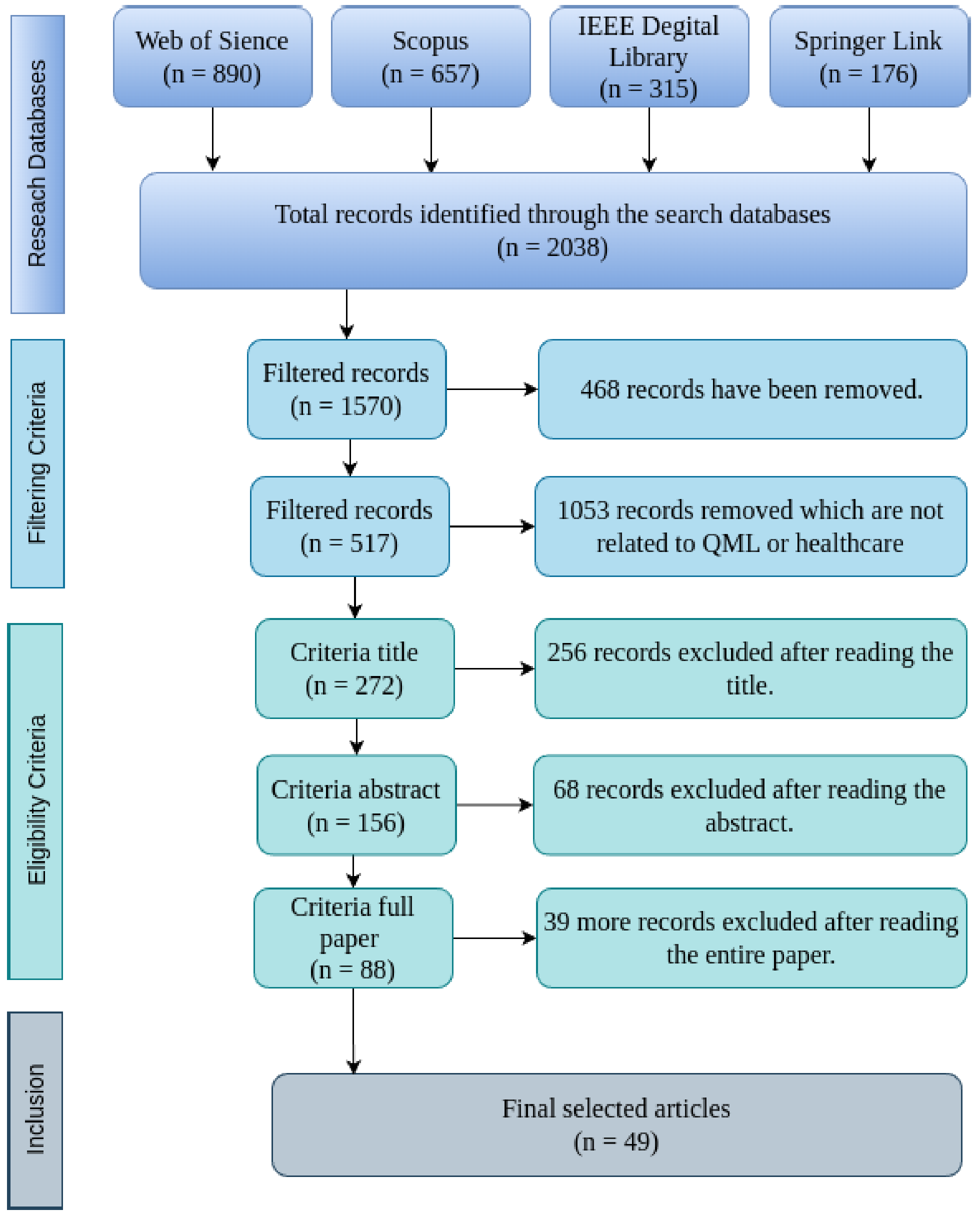

FIGURE 2. Prisma diagram for the records selected.

applications. We also included those articles whose solutions either use software to implement them or can be simulated or implemented in quantum devices or simulators. Records contained in peer-reviewed journals or conference proceedings that were published between 2019 and 2023 were also included.

E. DATA ANALYSIS

This section contains data scrutiny and data categorisation for the records selected. All the data was analysed by taking three different strategies into consideration, and the corresponding complete texts of 49 records that met the necessary requirements were deemed eligible for review were then evaluated. As a consequence, the following information was obtained.

1) YEAR WISE EVALUATION

The records selected were assessed based on their respective years with a view to examining the level of interest among scholars in working with QML over the past few decades. As shown in Figure 4, notable contributions in the field of QML for healthcare began to emerge after 2018. In 2019, there were 8 records, followed by 10 in 2020, 9 in 2021, 12 in 2022, and up to the present date in 2023, 15 articles in total have been published exploring the intersection of QML and healthcare.

2) COUNTRY WISE EVALUATION

Additionally, we conducted a country-wise analysis of the records selected, as illustrated in Figure 5, and this evaluation generated further interest in the subject by taking both the

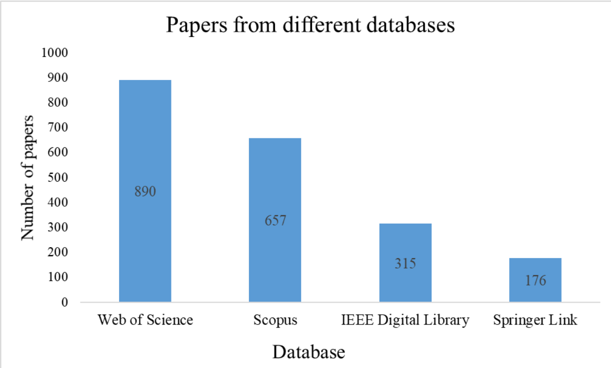

FIGURE 3. Number of papers from different data bases.

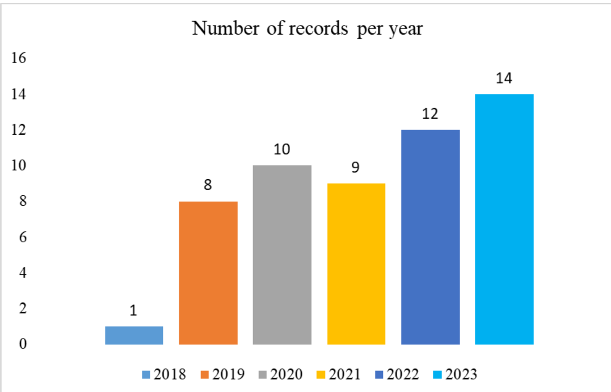

FIGURE 4. Number of papers per year.

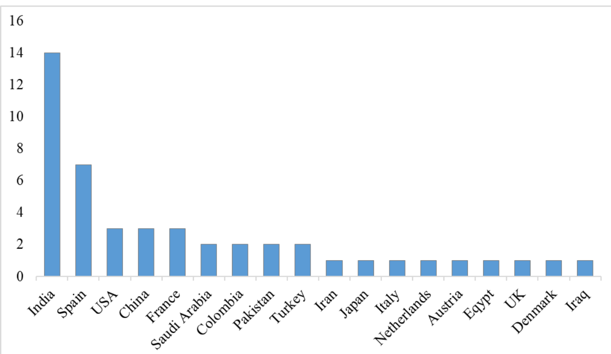

FIGURE 5. Published articles country-wise.

publication year and the different geographical locations into consideration. Among the research studies examining the adoption of QML in the healthcare industry, India stands out as the leading contributor with 14 papers, followed by Spain as the second-highest contributor with 7 articles to date.

3) TYPE OF SELECTED ARTICLES

Moreover, the articles that were chosen underwent a thorough evaluation based on type of article, with Figure 6 illustrating the various types of articles considered in this study. Out of total records, it was found that 37 records, accounting for

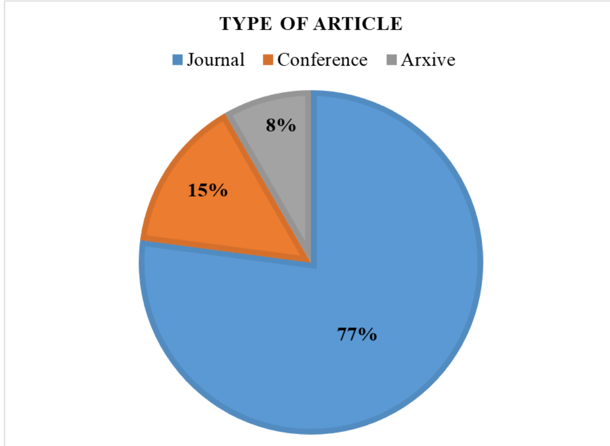

FIGURE 6. Types of selected published articles.

approximately 77%, originated from international journals. Furthermore, 7 records, constituting approximately 15% of the total, were sourced from international conferences. Finally, 4 records, making up approximately 8% of the total, were selected from arXiv.

Furthermore, following evaluation and analysis of the desired records selected, we defined a couple of research questions and proposed a point-oriented quality based metric as shown in Table 1 and Table 2 respectively.

III. WHAT IS QUANTUM COMPUTING

The concept of QC was introduced in the early 1980s by Benioff and Feynman, who stated that quantum-based computers outperformed their classical equivalents when it came to solving particular problems [30]. Feynman suggested that quantum mechanics could be used to solve computational problems by simulating complex quantum systems with standard quantum systems. This approach allows problems to be solved that classical computers are unable to solve [31]. Feynman's idea had a direct impact on the advancement of QC, and gave rise to the notion of a quantum Turing machine, also leading to the theoretical proof of the existence of universal models based on quantum mechanics [32]. Quantum algorithms can also be used to ascertain the processing power of classical computers, with development of one of the earliest quantum algorithms that offered a speed advantage over its classical counterparts being provided in [33]. The algorithm was designed to probabilistically determine whether a two-bit function is balanced or constant using just one function call. Researchers have proposed subsequent quantum algorithms in [34] and [35] that demonstrate the superiority of QC over classical computers in solving specific problems. However, these problems are manually designed, and their practical applications are limited.

QC relies on the principles of quantum mechanics, which employs observable quantum phenomena such as quantum entanglement and quantum superposition and quantum

TABLE 1. The point guided quality metrics proposed for selected record evaluation.

Type of Metrics	S.No	Overview	Merit	Points
Flow of the paper (50 points)	1	A well-explained precise abstract was provided - a short overview of the proposed model and datasets used; the solution to the problem or an improvement in experimental results was provided.	0 to 10	10
	2	The highlighted problem and background to it were briefly explained in the introduction.	0 to 10	10
	3	Simulation or optimisation of the proposed QML model was explained in detail, with mathematical modelling and diagrams.	0 to 20	20
	4	The challenges and limitations of the work were discussed and the methodology adopted to overcome these challenges explained.	0 to 10	10
Materials presented in the paper (30 points)	5	Experimental results were discussed in detail in the form of plots or confusion metrics; results were compared to recently published models.	0 to 10	10
	6	Materials used were briefly discussed and the type of dataset used and its availability clearly described.	0 to 10	10
	7	The code for the proposed work is publicly available.	0 to 5	5
	8	Originality or innovation of the proposed research work	0 to 5	5
Outcome presentation (15 points)	9	Determining system in terms of accuracy, loss function, and error.	0 to 15	15
Additional Quality Measures (5 points)	10	No of Citation	0 to 5	5

TABLE 2. Possible research questions.

Question	Purpose
Question1: How can quantum machine learning algorithms be utilised to enhance medical data analysis, such as improving disease segmentation, classification, or anomaly detection?	Explore the potential of QML models, such as QSVM, QKNN, QRF or quantum neural networks, such as QNN, QCNN in extracting meaningful insights from electronic healthcare records for diagnosis, treatment planning, or personalised medicine.
Question2: How can quantum machine learning models be integrated with classical machine learning approaches to leveraging the strengths of both in healthcare data analysis?	Research into hybrid approaches that combine classical and quantum machine learning techniques to exploit the computational power of quantum algorithms while leveraging the robustness and interpretability of classical models, enabling enhanced analysis and interpretation of healthcare data across various domains.
Question3: What are the fundamental limitations and advantages of quantum machine learning models in handling healthcare data compared to classical machine learning models?	Explore the unique properties of quantum machine learning models, such as quantum superposition and entanglement, and assess their potential benefits and limitations when applied to healthcare data analysis tasks, taking factors such as interpretability, scalability, and the computational resources required into consideration.
Question4: What are the considerations and methodologies for evaluating the robustness and generalisability of quantum machine learning models when applied to diverse healthcare datasets, including data from different hospitals, regions, or demographic groups?	Ensure that the models can perform reliably and accurately across different settings, populations, and data sources. This evaluation helps identify any biases, limitations, or performance variations that may arise and enables the development of more effective and equitable healthcare applications using quantum machine learning techniques.
Question5: Which types of data can be used for adoption of a quantum predictive model, and is it feasible to use open access datasets for evaluating such models? Additionally, what specific quantum computing devices are applicable for evaluating QML models using healthcare data?	How can different types of datasets, including private and open-access datasets, be evaluated for quantum machine learning models? What are the options available for accessing quantum simulators, quantum real devices, and quantum processing units (QPUs) in order to assess the performance of these models with healthcare data?

interference [36]. The quantum entanglement property is a non-intuitive phenomenon, famously referred to by Einstein as "spooky action at a distance," whereby an entangled pair of electrons always spin in opposite directions and influence each other through time and space, even when not physically connected. This property provides quantum algorithms with significantly more power than conventional ones. The quantum superposition is the property of an electron in which its position cannot be precisely determined at any given time. Instead, the electron's position is described by a probability distribution, where it has a chance to exist in all possible locations simultaneously, with varying probabilities.

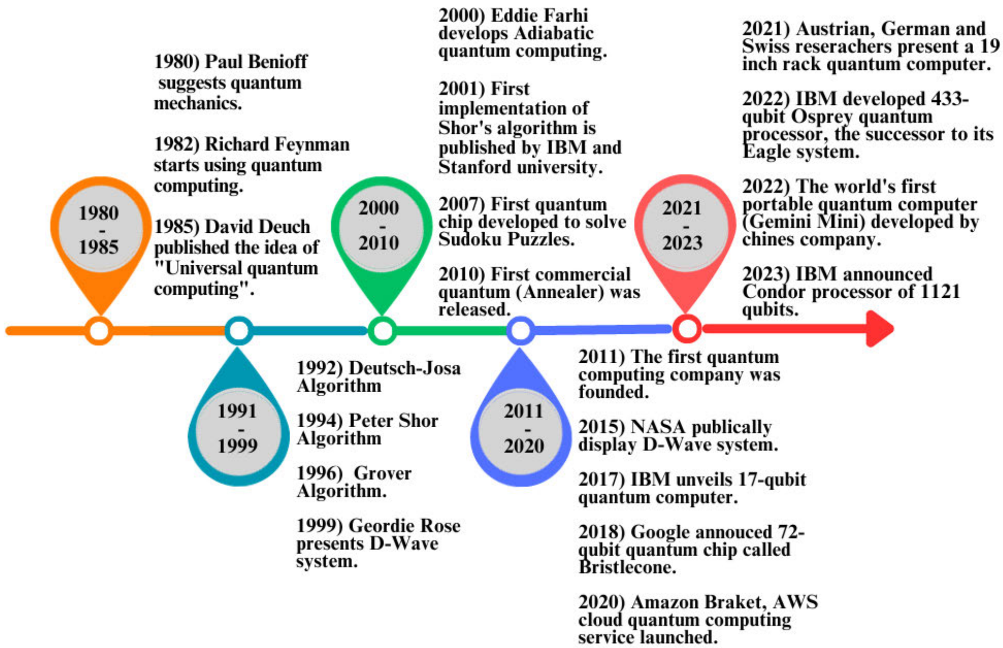

FIGURE 7. Quantum development timeline till to date.

The quantum interference property refers to the ability of an individual particle, such as a photon, to interfere with its own trajectory and alter its path's direction. The technology used for constructing qubits, which are the fundamental units of quantum computers, is rapidly advancing. A quantum computer leverages an unusual observation from quantum physics in which a single bit can exist in both states of '1' and '0' at the same time, this unique bit being referred to as a quantum bit or qubit [37]. By utilising these principles it builds a highly efficient computing system that can process multiple data pieces concurrently, resulting in the ability to handle massive amounts of information in a real-time scenario [38]. The basic concept of QC is to research into the inherent challenges of data analysis, data storage and its processing [39], and quantum mechanical systems are established by encoding information, which is commonly known as quantum information in terms of the state of a quantum system [38], [40].

There are several differences between CC and QC in terms of capabilities, computational power and error rates. In CC, information is processed using bits that represent 0 or 1, while QC employs quantum bits or qubits capable of representing 0, 1, or even both states simultaneously through superposition. CC relies on multiple transistors to create logical switches and gates, whereas QC utilises quantum dots and superconducting loops to create qubits, with several qubits forming a logical qubit. In terms of scalability, CC's computing power increases linearly with the addition of more transistors, while QC's potential grows exponentially with the inclusion of more qubits. Moreover, CC operates at room temperature with relatively low error rates and finds applications in general-purpose computing. Conversely, QC operates under extremely low temperatures, has a higher error rate, and specialises in tasks such as factoring, optimisation, and complex processing, as shown in Figure 8.

IV. WHAT IS QUANTUM MACHINE LEARNING

In quantum machine learning, quantum algorithms have been developed to address fundamental machine learning challenges while using the computational capability of QC. The standard approach to achieving this is to modify classical algorithms or their substantial subroutines so that they may function on a hypothetical quantum computer [41], [42]. Generally, QC and machine learning is combined in four different ways, i.e, classical data quantum model, quantum data classical model, classical data quantum model, and quantum data quantum model, as shown in Figure 9. In such a scenario, our focus is on a third "quantum enhanced-machine learning" approach which is most frequently employed for analysis of classical data using quantum models [43]. In order to improve computing speed and data storage, qubits and quantum operations are utilised in the QML algorithm, and computationally challenging subroutines are handed off to a quantum device in hybrid approaches that combine classical machine learning approaches with QC, as shown in Figure 10. On a quantum computer, such processes may be more complex and run faster [44], [45], [46], [47].

The workflow of QML typically involves several steps, including system backend, state preparation, feature mapping, unitary gate operation, and quantum measurement, as illustrated in Figure 11. Feature mapping is the process involving encoding classical data into a quantum state representation. In classical machine learning, features are

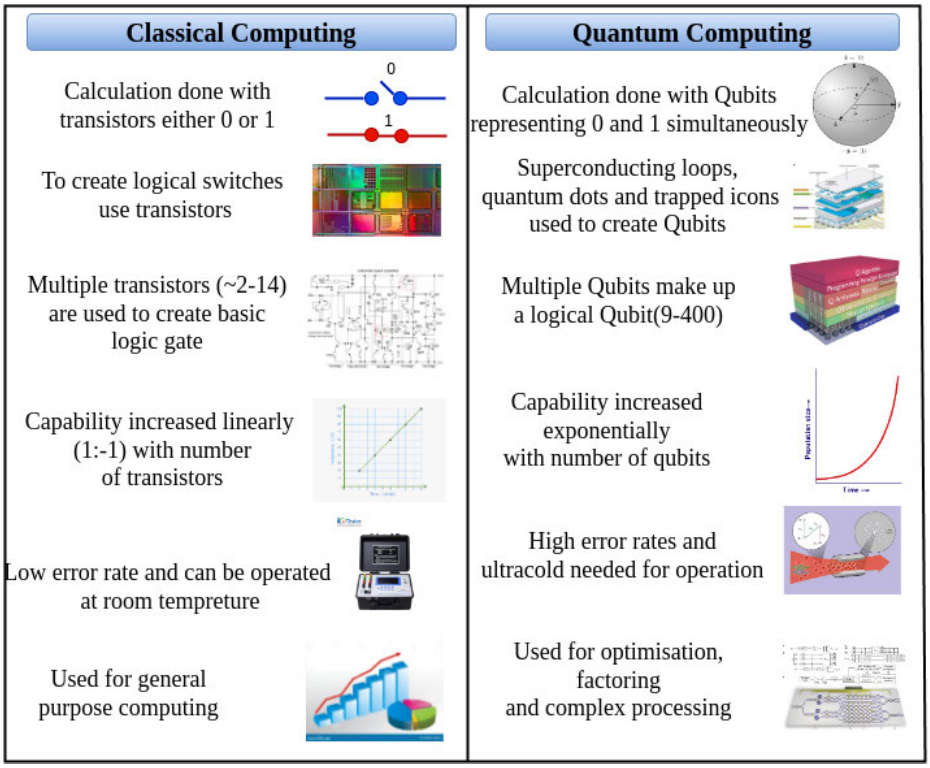

FIGURE 8. Classical computing vs quantum computing.

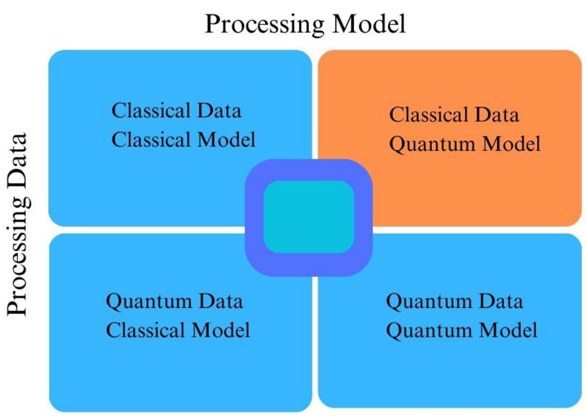

FIGURE 9. Matrix of various QML algorithms.

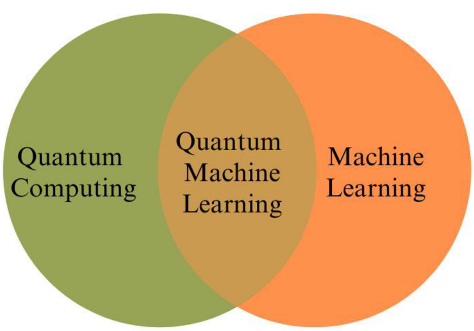

FIGURE 10. Quantum machine learning intersection.

usually represented as vectors or matrices, while in quantum machine learning, these classical features are transformed

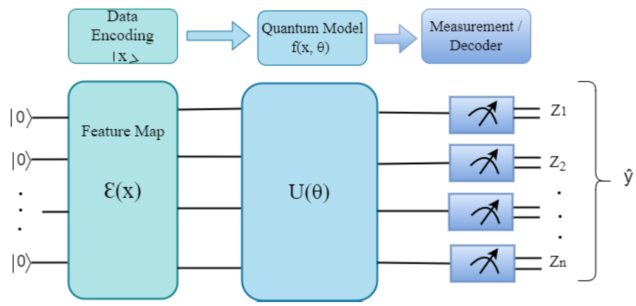

FIGURE 11. Basic working principle of qml models.

into quantum states by mapping them onto qubits. There are various techniques that can be used for feature mapping, depending on the specific problem and the quantum algorithms available, with one common approach being to use quantum circuits to transform classical features into quantum states. Once the classical data is mapped to a quantum representation, a quantum model is then constructed in order to process and analyse the quantum states. The quantum model is typically composed of quantum gates, which are operations that act on the qubits and manipulate their quantum states. Different quantum models can be employed depending on the specific learning task - for example, a quantum neural network (QNN) can be constructed using layers of quantum gates to perform computations analogous to classical neural networks.

The parameters of the quantum gates in the model are adjusted during the training process to optimise the

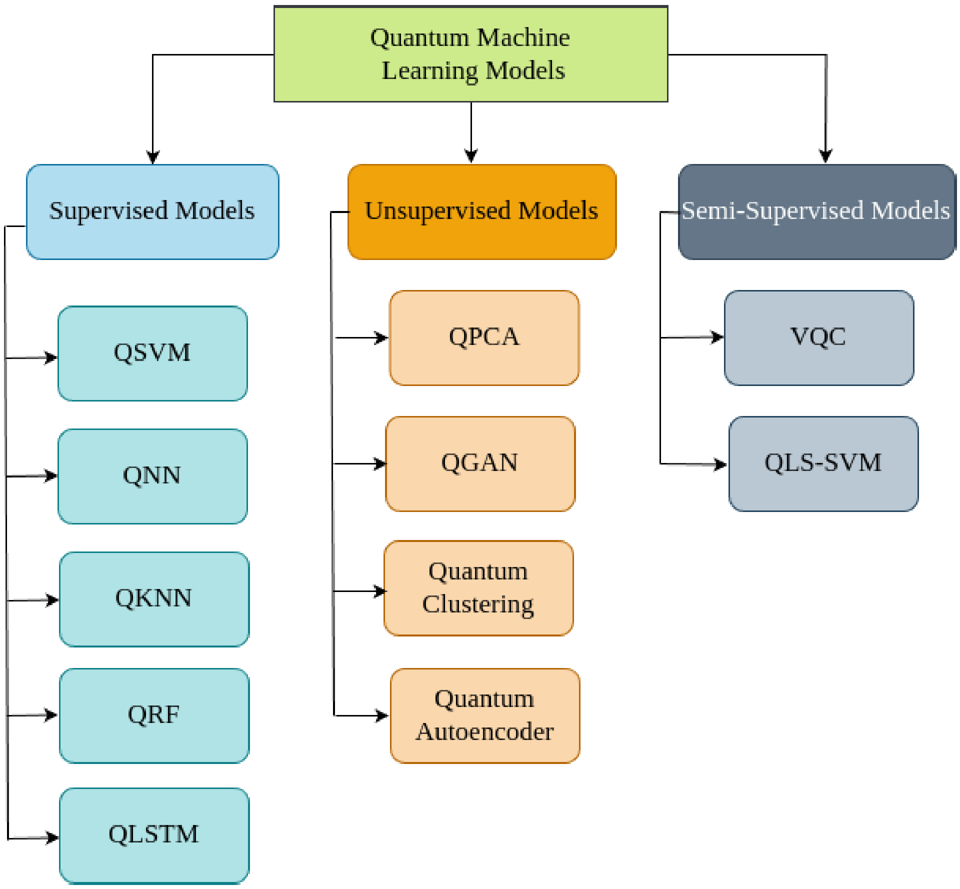

FIGURE 12. Various type of QML models.

model's performance. Likewise, there is the quantum support vector machine (QSVM), which utilises quantum circuits and quantum algorithms to perform classification tasks. QSVM maps the input data to quantum states, performs quantum computations on these states, and uses quantum measurements to classify new instances.

Eventually, once the quantum model has processed the data, a quantum measurement is then taken to obtain classical output results. In quantum mechanics, when a quantum system is measured, its superposition collapses into a specific state with a certain probability, and in the context of quantum machine learning, the quantum measurement operation extracts classical information from the quantum states and provides the output for the model. The measurement outcome is typically a classical bit string representing the result of the computation. Statistical techniques are often applied to analyse the measurement outcomes and extract relevant information or make predictions. For instance, in classification tasks, the measurement outcome can correspond to a class label. It is important to note that the measurement operation inherently introduces randomness due to the probabilistic nature of quantum systems, and so consequently, quantum machine learning models may require repeated measurements or statistical sampling in order to obtain reliable results.

V. QUANTUM MACHINE LEARNING MODELS

QML models are categorised into three basic categories: supervised model, unsupervised and semi-supervised, as shown in Figure 12 and as follows:

A. QUANTUM SUPERVISED MODELS

Supervised ML is a type of ML where a model learns from labelled training data to make predictions or decisions. According to this approach, the model is provided with input data along with corresponding output labels or target values. There are various supervised machine learning models available, and the choice of model depends on the specific problem you are trying to solve and the nature of the data. Here are a few commonly used supervised learning models:

1) QUANTUM SUPPORT VECTOR MACHINE (QSVM)

A QSVM is an ML algorithm that combines the principles of QC with the concept of a classical SVM. It is designed to perform classification tasks on quantum data or to exploit quantum effects for improved classical SVM training. For its part, an SVM is a supervised learning algorithm used for classification and regression tasks. Given a set of labelled training data, the purpose of the SVM is to find a hyperplane in a high-dimensional feature space that best separates the data into different classes. The hyperplane is chosen to

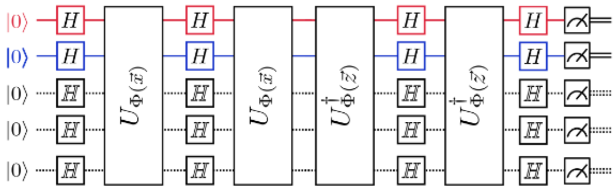

FIGURE 13. QSVM circuit diagram.

maximise the margin, which is the distance between the hyperplane and the nearest data points of each class. QC, on the other hand, leverages quantum phenomena such as superposition and entanglement to perform computations on quantum bits or qubits. Qubits can exist in multiple states simultaneously, allowing for parallel processing and potentially more efficient algorithms. In a QSVM, the classical SVM is enhanced using quantum techniques, and the main idea is to map the input data to a quantum feature space, where the QSVM can perform classification, and this mapping is done using a quantum kernel function [48]. In classical SVM, a kernel function computes the similarity or distance between data points in the input space, while in the case of QSVM, the quantum kernel computes the similarity or distance between data points mapped to a quantum feature space. The input classical data is encoded into quantum states by using various quantum algorithms, and the quantum data is then fed into a quantum circuit that applies the quantum kernel function. This circuit takes advantage of quantum operations and entanglement to perform computations on the quantum data. As shown in Figure 13, in the case of quantum kernel computation, measurements are taken on the quantum circuit in order to obtain classical information and the measurement circuit then extracts the relevant features from the quantum state.

2) QUANTUM NEURAL NETWORK (QNN)

A computational neural network model based on the principle of quantum mechanics is known as a QNN. In 1995, Kak [50] and Ezhov and Dan [51] independently published the initial concepts regarding quantum neural computation. Traditional computers store and process information as binary bits, which can represent either a 0 or a 1. In contrast, quantum computers use quantum bits, or qubits, which can exist in a superposition of both 0 and 1 states simultaneously. This allows quantum computers to perform certain calculations much faster than classical computers in the case of certain types of problems. In QNN, the basic building block is the addition of a quantum layer, which is analogous to the artificial neuron in a classical neural network as shown in Figure 14. The quantum neuron processes and transmits information using quantum operations. Typically, a qubit is used to represent the state of the quantum neuron, with the state being manipulated using quantum gates. The activation function in a classical neural network is replaced by a quantum gate, which transforms the state of the qubit based on the input. Various types of quantum gates can be used, such as the Hadamard gate, controlled-phase gate, or any other gate that is able to manipulate the quantum state, and these gates introduce quantum effects, such as superposition and entanglement, into the computation. Training a quantum neural network involves adjusting the parameters of the quantum gates to optimise the network's performance in a specific task. One of the potential advantages of quantum neural networks is their ability to process and analyse large amounts of data simultaneously, thanks to quantum superposition. This can be especially useful for tasks such as pattern recognition, optimisation, and machine learning, where large-scale parallelism can provide computational advantages.

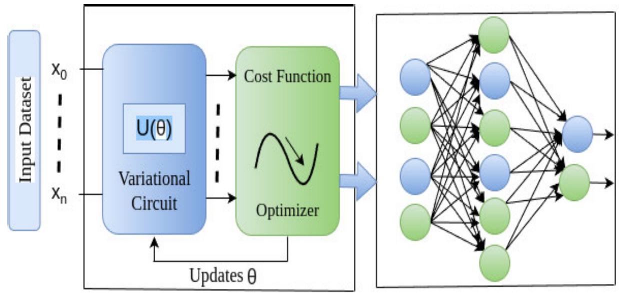

FIGURE 14. QNN model.

3) QUANTUM K NEAREST NEIGHBOR (QKNN)

Quantum KNN is also a supervised ML algorithm, which uses the quantum properties (superposition and parallelism) to process the classical KNN classification algorithm. The QKNN algorithm introduces quantum mechanics principles, specifically quantum superposition and quantum interference, to improve the performance of the KNN algorithm. It utilises a quantum representation of data and exploits quantum parallelism in order to perform the distance calculations more efficiently, while the input training and testing dataset can be converted into vectors. The classical CC method requires n bit registers for the desired dataset, while the QC needs n qubit superposition quantum states. All of the binary numbers in the datasets can be converted into n qubit states with the appropriate probability, which reduces storage capacity. As shown in Figure 15, the five registers contain five qubits, with the first auxiliary qubit being operated by Hadamard gate. The second and third registers are used for testing the dataset, while the fourth and fifth registers are used for training it. In the QKNN algorithm, quantum parallelism is leveraged to calculate the distances between the encoded new data point and all the encoded training data points simultaneously, with this parallel distance calculation being obtained using quantum gates and quantum circuits. Finally, the class label predicted is determined based on the outcome of the measurement. The QKNN algorithm assigns the class label that is most prevalent among the K nearest neighbors in the collapsed quantum state.

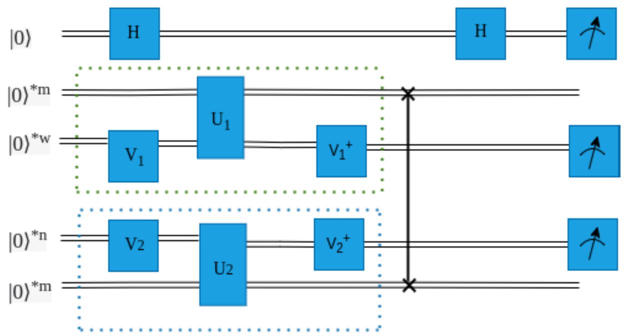

FIGURE 15. QKNN circuit diagram [52].

4) QUANTUM RANDOM FOREST (QRF)

A quantum RF is a variant of the classical random forest algorithm that incorporates principles and techniques from QC. It leverages the power of quantum properties, such as superposition and entanglement, to enhance performance and capabilities of the random forest model. In a classical random forest, multiple decision trees are created and trained on different subsets of the training data, and each decision tree is built using a random selection of features and employs a majority voting scheme to make predictions. The final prediction of the random forest is determined by aggregating the predictions of all the individual decision trees. In a quantum random forest, the underlying decision trees are replaced by quantum decision trees, which are quantum circuit representations of decision trees, and these quantum decision trees utilise quantum gates and qubits instead of classical bits and logic gates, as shown in Figure 16. A qubit is the fundamental unit of quantum information, and can exist in a superposition of states, representing both 0 and 1 simultaneously. To form a quantum random forest, an ensemble of quantum decision trees is created through a process called quantum bootstrap aggregating or quantum bagging. Multiple copies of the training data are created, and each copy is randomly perturbed to introduce diversity. Quantum decision trees are then built on these perturbed copies, and the final prediction is obtained by aggregating the predictions of all the quantum decision trees through majority voting.

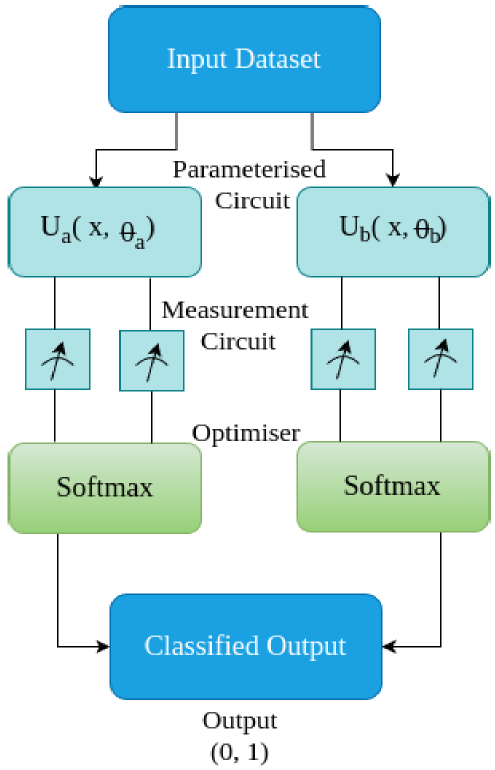

FIGURE 16. QRF diagram [71].

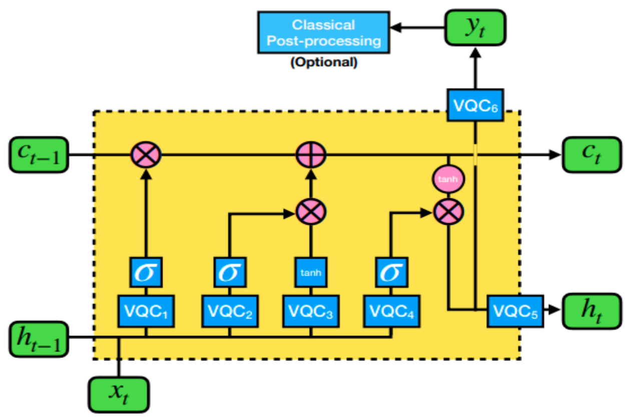

FIGURE 17. Schematic architecture of QLSTM [53].

5) QUANTUM LONG SHORT TERM MEMORY (QLSTM)

LSTM networks are a type of recurrent neural network (RNN) designed to handle long-term dependencies in sequential data. They are particularly effective in tasks such as speech recognition, language translation, and time series analysis. LSTMs are composed of cells that maintain an internal memory state, allowing them to remember information over extended time intervals. Each cell is equipped with three main components: an input gate, a forget gate, and an output gate, and these gates regulate the flow of information into, out of, and within the cell. By replacing the classical neural networks in the LSTM cells with VQCs, the classical LSTM can likewise be transformed into the quantum state [53]. The QLSTM schematic architecture shown in Figure 17 consists of three layers - the data encoding layer, the variational layer, and the quantum measurement. The input classical vector is converted into a quantum state by the data encoder layer and the variational layer is the learnable component, where an optimisation technique is used to update the circuit parameters. Eventually, the quantum measurements are employed in order to obtain the values required for further processing.

B. UNSUPERVISED MODELS

Unsupervised learning analyses and clusters unlabelled information using machine learning algorithms to identify data groupings or hidden patterns without requiring human involvement.

1) QUANTUM PRINCIPAL COMPONENT ANALYSIS (QPCA)

Quantum PCA is a QC algorithm that is an extension of the classical PCA technique used in machine learning and data analysis. PCA is a dimensionality reduction method whose purpose is to find the most significant features or patterns in a dataset by projecting it onto a lower-dimensional subspace. The input dataset is transformed into quantum states by encoding it in the amplitudes of a set of quantum bits (qubits). The number of qubits required depends on the size of the dataset and the desired precision. The encoded quantum states are then prepared on a quantum computer using quantum gates and operations, and this step initialises the quantum system in order to represent the input data. For its part, the quantum PCA algorithm employs quantum phase estimation to estimate the eigenvalues of the covariance matrix, with this step being critical in determining the principal components. The eigenvalues are estimated from the results of the quantum phase estimation, which provides information about the variance captured by each principal component. Estimated eigenvalues are used to identify the principal components, while the eigenvectors corresponding to the largest eigenvalues represent the principal components of the dataset. The quantum states representing the principal components are then measured to obtain classical information, although additional classical post-processing may be required in order to finalise the output and interpret the results.

2) QUANTUM GENERATIVE ADVERSARIAL NETWORK (QGAN)

The quantum GAN use two neural networks a generator and a discriminator that are simultaneously trained are used to generate data that is identical to the original data used in training. The generator generates fake data that mimics the actual training dataset, while the discriminator works like a detective, aiming to differentiate between actual and fake data. The QGAN model is based on the patch approach [54], which employs a number of quantum generators, each of which is in charge of creating a small patch of the final output, as shown in Figure 18. The generator is a quantum variational circuit comprising alternating layers of single qubit rotation gates and two-qubit entanglement gates. Additionally, a first layer of Hadamard gates provides a superposition of all computational basis states with equal weight. In the context of training, the generator and discriminator are alternately optimised to create a probability that closely resembles the target distribution, while the discriminator input contains continuous scalar real data and discrete integral fake data.

3) QUANTUM CLUSTERING

Clustering is the process of grouping similar data points together based on their characteristics or proximity. Traditional clustering methods, such as k-means, partition data into clusters based on classical distance measures. In quantum clustering, the data points are represented as quantum states instead of using classical distance measures, and these quantum states can be created using techniques such as quantum superposition and quantum entanglement. By encoding the data into quantum states, quantum clustering allows for the exploration of complex relationships and interactions among data points. The quantum clustering algorithm operates by applying quantum gates and measurements to the quantum states representing the data. These operations can manipulate the quantum states to reveal underlying patterns and structures in the data, the goal being to find clusters that have close intra-cluster similarity and low inter-cluster similarity. Figure 19 indicates the key advantages of quantum clustering by handling the high-dimensional and complex data more effectively than classical clustering methods. Quantum systems can simultaneously process multiple states and explore a much larger search space, potentially leading to more accurate clustering results.

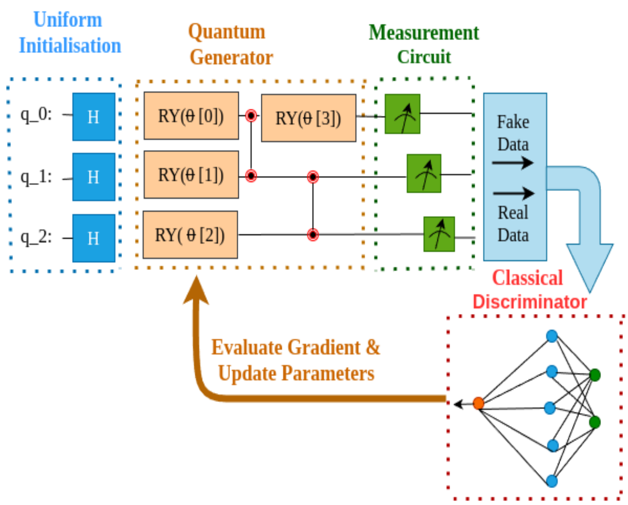

FIGURE 18. Schematic diagram of QGAN model [55].

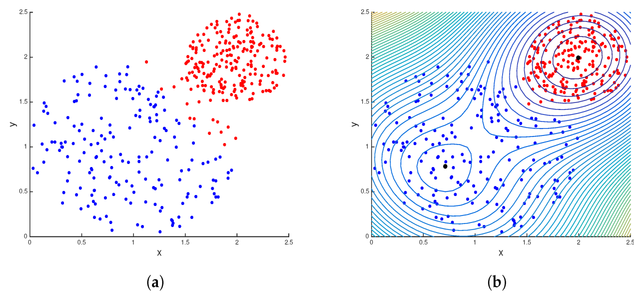

FIGURE 19. K mean clustering vs quantum clustering [56].

4) QUANTUM AUTOENCODER

A quantum autoencoder is a quantum machine learning algorithm that leverages the principles of quantum mechanics in order to perform data compression and feature extraction. A quantum autoencoder follows a similar principle, but instead of using classical bits, operates on quantum bits or

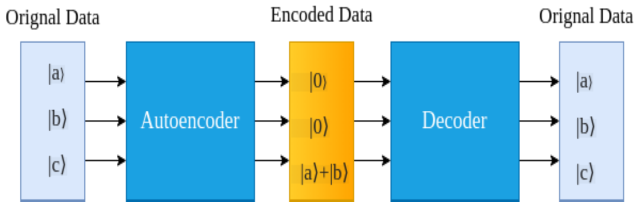

FIGURE 20. Structural diagram of quantum autoencoder [56].

qubits. Qubits can exist in superpositions of 0 and 1, allowing for more complex representations and computations. Quantum autoencoders are typically implemented using quantum circuits and quantum gates, and their architecture consists of two main components: the quantum encoder and the quantum decoder, as shown in Figure 20. The quantum encoder maps the input data, represented as quantum states, into a lower-dimensional code. This is achieved by applying a series of quantum gates and transformations to the input qubits, with the resulting code qubits capturing the essential features of the input data. Once the input data is encoded, the quantum decoder then performs the reverse process, transforming the code qubits back into an output state that approximates the original input data. The aim of the decoder is to reconstruct the data with minimal error, while the reconstruction process involves applying a series of quantum gates and operations that are the reverse of those used in the encoder. Quantum autoencoders have the potential to offer advantages over classical autoencoders in certain scenarios, while quantum systems can capture complex relationships and correlations that may be challenging for classical systems. Additionally, quantum autoencoders can exploit the properties of quantum entanglement and superposition in order to represent and process information in more powerful ways.

C. SEMI-SUPERVISED MODELS

Semi-supervised learning is a type of machine learning that builds models using both an enormous quantity of unlabelled data and a small amount of labelled data.

1) VARIATIONAL QUANTUM CLASSIFIER (VQC)

VQC is a semi-supervised QML approach that enables the use of NISQ devices to acquire experimental results without the use of extra error-correction methods. This technique is a hybrid approach whereby the parameters are updated and optimised in a traditional computer, allowing for optimisation without improving the coherence times required. The device's iterative measurements are used to calculate the cost function, which is based on a system aimed at reducing errors by integrating noisy measurements in optimisation calculations [57]. The amplitude encoding, which maps features to quantum states, is an appropriate solution for data pre-processing when utilising the VQC model, as demonstrated in [58] and [59]. The feature map is one of the major components which transform data into a quantum system's potentially substantially higher-dimensional Hilbert space, making it possible to efficiently compute across non-linear fundamental functions on the feature space. As shown in Figure 21, a VQC model contains 3 main components: a feature map that converts classical data into quantum states; a variational circuit with layers of short depth unitary circuits and θ-parameters that is iteratively tuned and has been trained by minimising a cost function in a classical device; and at the end of the VQC model, a measurement circuit is used which returns the quantum variable decoded into classical output.

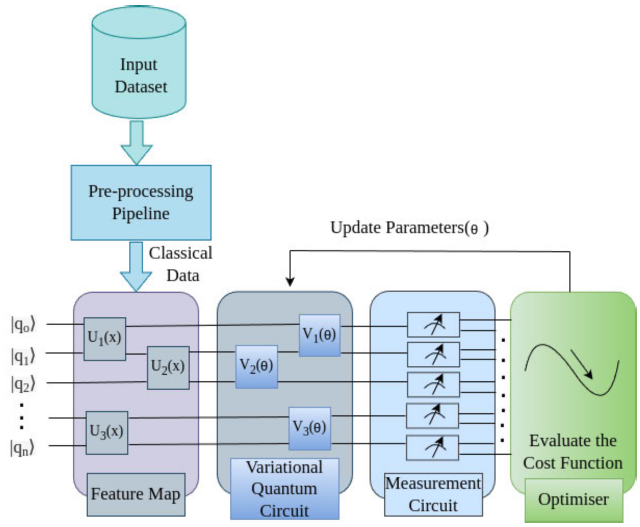

FIGURE 21. Block diagram of VQC.

2) QUANTUM LEAST SQUARE SVM (QLS-SVM)

A QLS-SVM is a variant of the traditional SVM algorithm. The aim of the QLS-SVM is to find a linear or non-linear hyperplane that best separates classes in a dataset by minimising the squared error rather than maximising the margin as in the standard SVM. Like classical SVM, QLS-SVM operates in a high-dimensional feature space. The input data consists of labelled examples, whereby each example is represented by a feature vector and belongs to a specific class, and uses a kernel function to implicitly map the input data into a high-dimensional feature space. This transformation allows the algorithm to find non-linear decision boundaries in the original input space, formulating the classification problem as a constrained optimisation problem. The goal is to minimise the sum of squared errors between predicted outputs and desired outputs, subject to some constraints. The desired outputs are typically represented as $+1$ or -1 in the case of binary classification tasks. To solve the optimisation problem, QLS-SVM employs a technique known as Lagrange multipliers - by introducing these, the problem is transformed into a dual problem that can be solved more efficiently. The solution involves finding the support vectors, which will be the data points that lie closest to the decision boundary. Once the QLS-SVM model is trained, it can be used to make predictions on new, unseen data, with prediction being based on the sign of the learned function, which determines the class

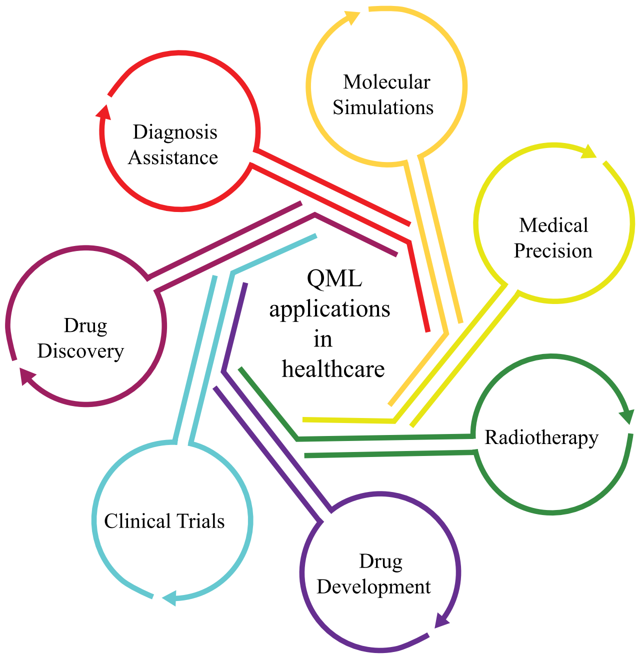

FIGURE 22. QML applications in the healthcare industry.

label. If the output is positive, the sample is classified as one class, and if negative, it belongs to the other class.

VI. QML APPLICATIONS

Healthcare industry has made significant advancements with QC interms of data management, clinical studies, disease diagnosing, EHR, and medical device inspections. Moreover, QML is widely been using in various healthcare applications,i.e, molecular simulation, medical precision, radiotherapy, drug development, clinical trials and diagnose assistant as shown in Figure 22. It also offers a significant increase in processing capacity, which resulted in improvements in the healthcare industry. Personalised treatment is provided using deoxyribonucleic acid (DNA) [60] sequencing with QC, and advanced therapies and medications are created using systematic modeling. QC addresses complex optimisation challenges, such as devising effective radiation plans to eradicate specific cancer cells while minimising harm to healthy organs and body parts [61], [62]. Qubit processing allows the quick sequencing and analysis of genomes, and cloud-based hospital infrastructure migration makes it possible to forecast chronic disease issues and protect medical data. Integrating QC into healthcare systems brings a substantial advantages, including enhanced patient management, improved medical professional experiences, reduced costs, and superior patient treatment outcomes [63], [64].

A. DIAGNOSIS ASSISTANCE

QML algorithms are utilised to provide early-stage disease detection, leading to reduced healthcare costs and improved diagnosis and treatment. For example, early detection of cancer and Covid-19 can significantly decrease treatment expenses. While diagnosis tools such as X-rays, MRIs, and CT scans are expensive computer-aided devices that are evolving rapidly [65], and still facing challenges related to noise, quality, replicability, and safety. In this regard, QC aids diagnosis by examining medical images through edge detection and enhancing the diagnosis more quickly. Moreover, categorising cells based on biochemical and physical characteristics requires ample space due to the abundance of predictor variables [66]. These challenges can be addressed by leveraging quantum-enhanced ML techniques such as quantum vector space, which in turn enhances single-cell diagnosis. The integration of QC enables repetitive diagnosis and treatment to be avoid and allows for regular monitoring of individual health.

B. MOLECULAR SIMULATIONS

Quantum computers offer a fundamentally different approach to data processing compared to classical computing, which relies integrated circuits for speed. Quantum computers utilise qubits and leverage quantum entanglement, allowing for the development of quantum algorithms that exploit quantum phenomena. In the healthcare industry, quantum computers can be utilised to enhance ML techniques, optimisation, AI techniques for complex simulations. This is particularly valuable in modelling complex correlations and dependencies among highly interconnected elements, such as molecular structures where multiple electrons may interact. QML provides an efficient means of analysing healthcare processes. Additionally, QC enables complex simulations to be undertaken that would otherwise be challenging for classical algorithms due to scaling limitations. As the size of the problem increases, classical algorithms often face exponential increases in resource requirement, while QC offers a potential solution to managing these challenges effectively.

C. MEDICAL PRECISION

The aim of medical precision is to provide personalised treatment to individual patients based on their specific diseases. Consequently, in the coming years, patient-focused medical care will be crucial in dealing with the intricate biological systems of human beings. However, medical expenses constitute only 10%−20% of healthcare costs, with the remaining 80%−90% associated with various other factors such as socio-economic conditions, environmental influences, and challenges related to health behaviour. Additionally, conventional drug-based therapies may not yield effective results in the case of certain individuals and could even lead to fatal drug reactions. Therefore, early intervention and preventive measures can improve healthcare goals and reduce expenses through QML and QC techniques. Traditional approaches are reasonably effective in predicting future risks of disease while rendering noise, low data quality, small size, and high complexity. Therefore, quantum-based ML techniques enhance the accuracy of early disease detection. Healthcare practitioners can leverage medical devices to facilitate disease identification and manage risks through continuous monitoring and providing appropriate treatment. As a result, QML can enhance patient-centered treatment by continuously streaming data from medical devices, enabling uninterrupted services to patients to be provided.

D. RADIOTHERAPY

Radiotherapy is a cancer treatment method that utilises electromagnetic energy to destroy cancer cells and prevent their growth. However, it is a delicate technique that is essential for meticulous calculations in order to accurately target the disease without causing harm to healthy organs. The administering of radiotherapy involves the use of highly precise devices that require complex optimisation problems to be solved using a high level of precision. Thus, ensuring precise radiographic procedures entails conducting multiple accurate and sophisticated simulations in order to find an effective solution. The adoption of QC enables various simulation recommendations to be implemented, allowing for the concurrent execution of numerous simulations and facilitating enabling an effective solution to be determined faster.

E. DRUG DEVELOPMENT

Medical professionals can now model intricate chemical interactions at an atomic level thanks to QC, which is essential for medical research, i.e, disease diagnosing, and treatment. The ability to encode proteins in the human genome and simulate their interactions with current medication has been made possible by developments in QC, and applying AI methods to assist in patient diagnosis is becoming more and more popular. The vast majority of ML techniques currently in use are pattern recognition techniques, where various ML models are trained utilising a large amount of patient data to create computer-assisted diagnosis systems. QC significantly enhances the processing of information far more efficiently than conventional computing methods. In such a scenario, the objective may involve leveraging the aforementioned comparisons in order to facilitate accurate diagnosis.

F. CLINICAL TRIALS

QC and QML can be used to revolutionize clinical trials in several ways, i.e, quantum computers can process vast amounts of clinical data much faster, which allows more complex and comprehensive data analysis, identifying patterns and correlations. Furthermore, QML can optimize clinical trial designs by accurately predicting patient outcomes and treatment efficacy. This leads to more efficient trials with a higher chance of success. QC can enhance medical imaging techniques, providing clearer and more detailed images, which are crucial for accurate diagnosis and treatment planning. QML can process real-time data from clinical trials, allowing for immediate adjustments and interventions, thereby increasing the safety and effectiveness of trials. QC facilitates the sharing and analysis of clinical data across different geographical locations, promoting global collaboration in medical research and trials.

G. DRUG DISCOVERY

Novel opportunities for medication discovery are presented by QML and QC. They facilitate accurate drug-biotarget interaction modelling by emulating molecular interactions at the quantum level. Compared to conventional approaches, this sophisticated modelling aids in the more precise prediction of pharmacological features including toxicity and efficacy. The identification of interesting chemicals, the optimisation of medication formulations, and the customisation of treatments to individual genetic profiles can all be greatly accelerated by quantum algorithms. The pharmaceutical business could undergo a transformation thanks to this technology, which offers the promise of personalised therapy quicker, and more affordable in medical development.

VII. THE EMERGENCE OF QML IN HEALTHCARE

The promise of QML in healthcare is becoming more and more apparent. As healthcare organisations work to enhance patient outcomes and reduce expenses, QML offers great potential. QC is used by QML, a type of artificial intelligence (AI), to analyse and predict enormous amounts of data. It relies on the concepts of quantum mechanics, which perform considerably faster data manipulation than is possible with conventional computing. Considering the complexity and size of the data in healthcare applications, QML is especially well suited to such applications. Identifying patterns in data that might normally be too challenging can be found easily using QML - for instance, it can be used to identify possible drug targets, find early disease symptoms, and predict how well treatments would work. Additionally, it can be utilised to examine patient records and provide individualised therapies.

A. MEDICAL HEALTHCARE RECORD (MHR)

Medical Healthcare Records (MHRs) play a vital role in the field of healthcare, providing a comprehensive and digitised collection of patients' medical information. With the advent of cutting-edge technologies like QML models, the importance of MHRs has become even more pronounced in predicting and improving patient outcomes. QML models have the potential to revolutionide healthcare by offering enhanced predictive capabilities and personalised treatment strategies. MHRs act as a repository for patient data, containing a variety of data including medical history, diagnosis, medication, lab results, imaging studies, and other disease-related parameters. Obtaining longitudinal patient data is one of the main benefits of using MHRs for QML model predictions, and MHRs offer a comprehensive overview of a patient's medical history throughout time, allowing physicians to track the occurrence of diseases and spot patterns that might otherwise be difficult to pinpoint. Furthermore, MHRs also include a significant amount of both structured and unstructured data. Unstructured data consists of clinical notes, medical imaging reports, and pathology reports, whereas structured data consists of information such as demographics, vital signs, and lab values.

Recently, there has been growing interest in utilising QML models for various healthcare tasks. These models, such as Quantum Support Vector Machines (QSVM), Quantum Random Forests (QRF), Quantum Neural Networks (QNN), Quantum Convolutional Neural Networks (QCNN), Variational Quantum Classifier (VQC), Quantum K-Nearest Neighbor (QKNN), and Quantum Decision Trees (QDT), have the potential to reform the healthcare sector by offering enhanced predictive capabilities and personalised treatment strategies. To classify cardio disease [67] an optimised QSVM and Hybrid Quantum Multi Layer Perception (HQMLP) models were combined using a privet MHR cardio dataset, while feature dimensions were reduced using the wrapper and filter method. The proposed models are compared to their classical version and their competency ensured, and the distinction between classical and quantum ML shown in [68]. To classify mellitus diabetes, the classical SVM and DT models are compared to the Qboost classifier by taking the kernel PCA method into consideration. The quantum model improves accuracy by 10%-15% by correctly observing the pattern for the desired dataset. In QML, ensemble learning is a popular ML approach that combines several QML models in order to make more precise predictions, while in [69], three QML models - QSVC, QNN and VQC - are combined to undertake ensemble learning in order to classify heart disease. The UCI Cleveland dataset is used and the results are compared to the classical ensemble model, with results demonstrating that the bagging ensemble model is effective in improving quantum classifiers with a view to ensuring accurate prediction. Breast cancer, which is discussed in [70], is one of the leading causes of death in women worldwide. A VQC model with amplitude encoding along with an EfficientSU2 circuit made up of a single qubit layer using CX entanglements was considered for such purpose. The publicly available breast cancer dataset with 2 feature and 4 feature datasets obtains the greatest accuracy - 95% and 94% - in the case of the quantum VQC model. Moreover, Ullah et al. [71] proposed two quantum models to classify Covid-19. The enhanced QSVM and Quantum Random Forest (QRF) classifiers with 10 features on a privet dataset were used for such purpose, and the competency of the models was ensured by comparing them to classical models and previous quantum models. The hybrid technique also proves fruitful in QML for tackling some classification problems, while the QML framework with classical DL was described in [72], where a PIMA Indian diabetes dataset was used for the VQC model, and pre-processing and exploratory-data analysis was explored and found essential for the purpose of robust prediction. Another hybrid QNN and hybrid QRF for early heart disease detection using the Cleveland and Statlog heart disease dataset was also described in [73], with the models having been evaluated by adopting 10-fold cross validation with different qubits and different layers, and where the results show the robustness of the models. Currently, the QCNN model can be used to predict ischemic heart disease earlier by collecting heart patients' data [74], while the data cleaning technique and selection of important features is also important when simulating a predictive model. These combinations, along with an appropriate state of preparation, results in accurate prediction.

Moreover, a quantum-inspired approach with ensemble learning was modelled in [75], where the pima indian dataset was considered for decision-making purposes. The quantum encoding contains object encoding and an RF classifier is used for ensemble learning, which results in accurate prediction. A VQC model for heart disease and breast cancer prediction which takes different encoding techniques into consideration is also described in [76]. During pre-processing a quantum random access coding (QRAC) was used to map the discrete future, which outperforms in terms of accuracy compared to the ZZ-FeatureMaping technique. Another contribution using amplitude encoded VQC and QSVM models for diabetes classification was modelled in [77], whereby the feature dimension was reduced in pre-processing by taking the intersection of RF, LR and SVM outputs. Reference [78] demonstrated the importance of the pre-processing technique for the quantum model and claimed that it reduces model complexity. The quantum version of SVM was used after reducing the dimension of the breast cancer dataset, which improves prediction accuracy. For its part, the practical implementation of a kernel based QSVM algorithm to tackle a classification problem using breast cancer Wisconsin datasets is shown in [79], which demonstrates that quantum-driven ML could deliver a quantum speedup in solving many challenging tasks. The results claimed that the quantum computer is much faster than the classical computer. The hybrid feature selection approach was used in [80], taking quantum Oracle operation, amplitude estimation and amplitude amplification into consideration for the breast cancer dataset, with results indicating the strong performance and major searchability, with a high level of efficiency and less complexity than the classical method. Most QML models are based on use of the classical model, as discussed in [81], where various models are used to create a new voting model results in ensemble learning. Furthermore, the diabetes dataset contains the MHR records of various patients used to evaluate the model; in comparison to classical models, the new quantum model is 55 times computationally faster. The importance of state preparation for the VQC model is also researched by the authors [82], and the diabetes dataset was mapped using stock parameters to solve the Noisy Intermediate Scale Quantum device (NISQ) classification problem. The Poincaré sphere representation is used with two experiments for 2 qubit and 3 qubit, obtaining the greatest accuracy of 70% and 72% respectively, while the classical quantum hybrid algorithm for supervised binary classification task was modelled in [83], where a VQC model was used to classify the UCI ML breast cancer dataset. The highest testing accuracy of 2 and 3 qubits with 2000 shots was recorded as 91% and 73% respectively. The VQC is now garnering a lot of interest, since it can be used with upcoming quantum computers - the framework, whereby the classical ML is merged with the VQC model for classification of MNIST breast cancer dataset, is described in [84], and in the case of back propagation, various optimisers were used to reduce the loss. The healthcare sector has been further revolutionised using unsupervised models for disease classification. Additionally, three quantum distances prototypes-based clustering models are analysed and compared in [85], where K-means outperform other clustering approaches. The work concluded that the quantum version K-means models take logarithmic time while the classical one takes polynomial time complexity. A quantum-inspired neural network based on fuzzy logic was also published in [86]; Fuzzy C-Means (FCM) clustering is used in learning, and neurons are added to the hidden layer in order to constructively develop NN architecture. Lastly, various healthcare datasets - i.e, breast cancer, diabetes, liver disorder, and heart disease - are taken into consideration, and an overview of medical healthcare records is shown in Table 3

B. MEDICAL IMAGING DATA

QC provides exponentially higher computational power, which enables large-scale medical imaging datasets to be processed and analysed with increased speed and efficiency. Complex algorithms for tasks such as image reconstruction, feature extraction, and classification can be executed more quickly, allowing for faster and more accurate diagnoses. For effective processing and analysing of imaging data, quantum algorithms can enhance the accuracy of disease detection, image segmentation, and classification, which can lead to more precise diagnoses and personalised treatment plans. Furthermore, feature selection is a critical step in medical image analysis. Quantum machine learning algorithms can efficiently explore vast feature spaces and identify the most relevant and informative features for the purposes of diagnosis, which leads to improved accuracy by reducing noise, irrelevant data, and the risk of overfitting. Image reconstruction techniques, such as CT scan or MRI, can benefit from quantum machine learning algorithms, while quantum-enhanced optimisation algorithms can improve the quality of reconstructed images by solving complex inverse problems more effectively. It can also enhance image segmentation - the process involving delineating different regions or structures within medical images. Quantum algorithms can optimise the segmentation algorithms, leading to more accurate and efficient delineation of organs, tumors, and other pathological regions. In such a scenario, neuro-degenerative disease may be diagnosed as in [87], where the classical AlexNet is used with a VQC model to form a hybrid by taking two MRI datasets from PPMI and ADNI into consideration. The results indicate that the classical model helps the quantum model by securing the greatest accuracy of 97% and 96% respectively. Another improved hybrid model including additional explainable strategy is described in [88]. To diagnose abnormal activities in breast cancer and knees, a local interpretable model explanation is merged with quantum K-means algorithm using MRI images, and this improved model performed well in terms of accuracy with 92.6% and 93.7% in the case of breast cancer and knee MRI datasets. A 3D self supervised quantum inspired NN for diagnosing medical data is introduced in [89], whereby MR brain images and liver tumor data is used, and a quantum fuzzy logic processes the information of low level and high level features of the local image in order to form accurate segmentation of the 3D medical data and obtain the greatest accuracy of 99% and 98.9% respectively. For cervical cancer classification, further quantum inspired weed optimisation with DL is described in [90]. A Gabor filtering is used during pre-processing, whereby features are extracted using a DCNN based on the SqueezeNet approach, and a deep variational autoencoder is used and maximum accuracy of 99.07 obtained%. Furthermore, research into feasibility utilising QML on a real healthcare dataset is described by Moradi et al. [91]. Using IBM hardware the two QML algorithms - i.e, quantum distance classifier (qDS) and simplified quantum kernel SVM (sqkSVM) - were proposed, and the models were tested using the breast cancer dataset, bone narrow transplant dataset and heart failure dataset with maximum accuracy of 91% and 87%. For the classification and prediction of COVID-19, [92] provides the hybrid quantum-classical convolutional neural network (HQ-CNN) model, whereby the main model was divided into two categories: quantum and classical. The quantum section used a quantum convolutional layer, whereas the traditional network included two convolutional layers, three maximum pooling layers, and two fully connected layers. In the case of the Covid-19 X-ray image dataset, extensive trials showed that current CNNs perform better. Another 2-qubit quantum CNN model referred to as Javeria was described in [93], where the encrypted brain tumor data was obtained using the SHA-256 algorithm. The model consists of two dense layers and a Keras layer with Softmax activation function. Four brain image datasets - BraTS2018 with 191 samples, BraTS2019 with 335 samples, BraTS2020 with 335 samples and BraTS2021 with 1251 samples were taken into consideration and maximum accuracy obtained of 98%, recall 99%, F1-score 98%, and precision 99%. The article [94] describes a quantum-inspired deep probabilistic learning ordinal regression model for diagnosing medical images that makes use of the representational strength of deep learning and the inherent ordinal information of disease. Two distinct medical image analysis tasks are used to gauge the model's performance. Using eye fundus images, prostate cancer is diagnosed and the degree of diabetic

TABLE 3. Overview of medical history record articles.

Year Published	Author Citation	Methodology Used	Dataset Used	Task Targeted	Result	Country
2023	D.Maheshwari et al. [67]	Wrapper and filter technique used for pre-processing. The wrapper technique consists of RFE and logistic regression, while mRMR, an optimised QSVM and a hybrid QML are taken into consideration in the case of the filter technique.	Ischemic health disease dataset	Classification	Obtained 94% accuracy in the case of the IHD dataset with OQSVM and 93% in that of the HQMLP model.	Spain
2023	B.Prakash et al. [68]	Ensemble method used, Qboost classifier, XGboost, quantum model compared to classical Kernel PCA, DT, SVM and Bayesian network.	Diabetic mellitus dataset	Classification and regression	Obtained 73.35% accuracy for Qboost, 68.34% for Kernel PCA-SVM, 69.9% for Bayesian network and 57.27% for DT model.	India
2023	G.Abdulsalam et al. [69]	Three QML models, QSVC, QNN and VQC combined to undertake ensemble learning to classify heart disease; an ensemble model is formed	UCI heart disease dataset	Binary Classification	Obtained maximum accuracy of 88.52% for QSVC, 86.84% for QNN, and 86.89% for VQC respectively.	Saudi Arabia
2023	S.Diaz-Santos et al. [70]	A VQC model with amplitude encoding is used; an EfficientSU2 circuit made up of a single qubit layer and CX entanglements used	Breast cancer dataset	Classification	Obtained 95% accuracy for 2 VQC features and 94% for 4 features respectively.	Spain
2022	U.Ullah et al. [71]	Features are extracted using Pearson correlation and feature ranking formed; enhanced QSVM and QRF forest is taken into consideration	Covid-19 dataset	Binary classification	Obtained 78% accuracy for E-QSVM and 75% for QRF model.	Spain
2022	H.Gupta et al. [72]	A hybrid quantum classical technique with VQC model is taken into consideration; xploratory data analysis explored	PIMA Indian diabetes dataset	Binary classification	Obtained 95% and 74% accuracy for the proposed model.	India
2022	H.Heidar et al. [73]	Hybrid quantum NN (HQNN) and hybrid quantum RF (HQRF) models used.	Cleveland and Statlog HD dataset	Detection	For Cleveland dataset AUC 96.6% accuracy obtained, for HQNN model 94.3%, and for HQRF and statlog model 97.7% and 90.5 respectively%.	Iran
2022	U.Ullah et al. [74]	Wrapper and Filter technique used for pre-processing; a Fully Convolutional Neural Network (FCQ-CNN) is taken into consideration	IHD dataset	Classification	Obtained testing accuracy of 84.6% and testing loss of 0.28.	Spain
2021	MS.Ishwarya et al. [75]	Quantum inspired approach with ensemble learning used.and also object encoding with RF.	PIMA Indian diabetes dataset	Classification	Obtained testing accuracy of 90.5% for proposed model.	India
2021	H.Yano et al. [76]	QRAC is used to reduce the number of qubits for pre-processing; an f fold cross validation with VQC model and ZZ-featureMaping is taken into consideration.	Heart disease dataset	Classification	Obtained testing accuracy of 85.1%, 83.3% and 84.2% respectively in the case of various pre-processing techniques.	Japan
2021	D.Maheshwari et al. [77]	Important features selected using the intersection of RF, LR and SVM; a VQC model with amplitude encoding and QSVM Model used.	Diabetes dataset	Classification	Obtained maximum accuracy of 68.7% for VQC and 74.1% for QSVM model.	Spain
2021	D.Pomarico et al. [78]	10-fold cross validation used for pre-processing; a QSVM model used to reduce complexity	Breast cancer dataset	Classification and detection	Obtained maximum accuracy 69.5% for VQC and 69.2% for QSVM model.	Italy
2020	S.Saini et al. [79]	A QSVM and a kernel-based QSVM algorithm used; a quantum simulator and realtime quantum process used.	Breast cancer Wisconsin dataset	Classification	Obtained maximum accuracy of 85% for KQSVM and 80% for QSVM model.	India
2020	S.Chakraborty et al. [80]	Hybrid feature selection technique used for quantum oracle operation, amplitude amplification, and amplitude estimation.	Breast cancer dataset	Classification	Obtained maximum accuracy and F1-score of 95%, Recall 94% and precision score 95.3% for HQFSA model.	India
2020	D.Maheshwari et al. [81]	Ensemble learning using various models DT, RF, Adaboost, Qboost voting model 1 and voting model 2.	Type 2 diabetes mellitus dataset	Classification	Obtained maximum accuracy. Recall and specificity 69% .	Spain
2020	D.Sierra-Sosa et al. [82]	The importance of state preparation for VQC model researched; stock parameters used to solve the NISQ device problem	Diabetes dataset	Classification	Obtained maximum accuracy of 70% and 72% for 2 qubit and 3 qubit respectively.	USA
2019	S.Mardirosian et al. [83]	Classical quantum hybrid algorithm used; VQC model with 2 qubit and 3 qubit is taken into consideration.	UCI breast cancer dataset	Classification	Obtained maximum accuracy of 91% and 73% for 2 qubit and 3 qubit respectively.	Netherlands
2019	ZY.Chen et al. [84]	VQC model used; various optimisers used to reduce loss for back propagation.	MNIST breast cancer dataset	Classification	Obtained maximum accuracy 87% with -1 loss.	China
2019	K.Benlamine et al. [85]	Three quantum distance prototype-based clustering models analysed, where K-means outperforms than other clustering approaches.	UCI breast cancer dataset	Classification		France
2019	OM.Parkash-Patel et al. [86]	A quantum inspired neural network based on fuzzy logic is taken into consideration; Fuzzy C-Means (FCM) clustering also used for learning.	UCI breast cancer, diabetes, heart dataset	Classification	Obtained maximum accuracy of 99.85%, 98.1% and 94.44%.	France

retinopathy estimated, with the model rendering promising results. A quantum clustering technique is described in [95] to identify prostate cancer using an MR image brain tumor dataset. For classification purposes, a prostate radiation protocol with 100 to 170 slice images per patient, minimum pixel sizes between 256 × 256, a resolution plane of less than 1 mm, and slice thickness ranging from 1 mm to 2 mm were taken into consideration. Reference [96] used conventional methods to undertake image processing and feature extraction operations on the data, and then train a VQC model with a 4-qubit quantum processor in order to recognise CT images of COVID-19-healthy and infected patients. The results demonstrated that the quantum computer provided a competitive edge in COVID-19 images with classification accuracy of 90.9% - 97.7%. In order to expand the size of the dataset and improve accuracy, Amin et al. [97] first used a Conditional-GAN (CGAN) to create CT images, whereby two models - CML and QNN - were described for classification of Covid-19, with different layers, sets of parameters and activation functions. Both the models performed well and obtained maximum accuracy of 93% and 80% in the case of the UCSD-AI4H and POF hospital dataset. Reference [98] used quantum circuits to train a classical neural network termed quantum-assisted NN (qNN), where QNN was executed in parallel by a quantum circuit and was discovered to be significantly faster. Furthermore, orthogonal weight matrices were developed to train quantum orthogonal networks (qOrthNN) in order to avoid gradient explosion and improve accuracy. Chest X-ray images were also used from PneumoniaMNIST and RetinaMNIST and maximum accuracy of 86% and 78% obtained respectively. For its part, a locally order-less tensor network model (LoTeNet) with fewer computational resources using few model hyper parameters and GPU memory is described by Selven in [99], with accuracy of the experimental results for binary classification experiments on the PCam and LIDC datasets of 94.3% and 87.4% being obtained, respectively. Reference [100] developed a quantum based on variational algorithms in order to categorise data by employing quantum feature mapping with a significantly smaller number of training parameters. The breast cancer datasets were used to train the classifier, and the results (93.7%) showed that it performed better in binary and multi classification than the conventional neural network model, whether using linear or non-linear separable data. QNN implementation is the best solution for the purpose of identifying some specific diseases. Reference [101] demonstrated that there are two distinct components of QML: 1) adding quantum data to neural networks; and 2) utilising hybrid MIA technology to complete information about disease identification. For classification and detection of medical CT Scan images maximum accuracy of 94.3% and 87% was obtained, respectively. In order to conduct quantum feature selection, [80] suggested a hybrid quantum feature selection algorithm (HQFSA) that made use of graph theory. The suitability for dimensionality reduction was ascertained, and then an important set of features extracted using the Grover algorithm and amplitude amplification method, using the UCI breast cancer dataset and with the greatest accuracy of 96% being obtained. Reference [102] used BQ-CNN, a quantum particle swarm optimisation technique that evolves CNN structure based on binary coding for image classification tasks. On the MNIST images dataset, experiments showed that the technique improved performance with an accuracy of 96% and 85% in the case of the CS and MDRBI dataset. The quantum SVM algorithm, which is claimed to offer exponential speedup for least squares SVM (LS-SVM), was described with a view to addressing the big-data challenge [103], and the classification task was accelerated exponentially, demonstrating the algorithm's feasibility. The proposed model was evaluated by taking two privet datasets into consideration with an accuracy of 84.9% and 91.4% respectively. Practical applications for NISQ computers are also possible thanks to hybrid quantum-classical algorithms. Additionally, the data drive quantum circuit learning (DDQCL) approach is provided in [104] and can be used to train shallow circuits for generative applications as well as help characterise the quantum devices. The three Synthetic datasets with 1000 data points sample has been taken into consideration and get good results other than architectural circuit design obtained, while a new quantum-based autonomous perceptron model (APM) was developed by Sagheer et al. [105] to address categorisation issues and boost learning effectiveness. Furthermore, for pattern classification purposes, research was conducted into synthetic and breast cancer datasets, which demonstrated benefits in terms of computing speed and maximum accuracy of 99% and 98% respectively, and described in 4.

C. BIOMEDICAL SIGNAL DATASETS

In the healthcare industry, biosignals play an important role in diagnosing some disorders. The term ''biosignal'' refers to electrical impulses generated by brain neurons, tissues and muscles, and monitored by biomedical sensors [106]. The brain's activity can be monitored by a computer with the use of a BioSignal interface, which comprises hardware and software [107]. The four main components of the BioSignal system are filter, control devices, amplifiers and sensors. These signals come from the body and are enabled by the machine and encoded, decoded, and processed by body interfaces. Neurons in the human brain produce signals as a result of both reflexive and voluntarily performed actions [108]. Biosignal accretion methods are further classified as invasive and non-invasive. Invasive procedures such as electrocorticography (ECOG) [109] involve the insertion of sensors into the human body, while non-invasive data which does not involve the skin breaking involves an electrocardiogram (ECG) [110], magnetoencephalography (MEG) [111], electroencephalograms (EEG), and Functional Near-Infrared Spectroscopy (fNIRS) [112]. ECG examines the electrical activity of the heart and diagnoses cardiovascular disease, and EEG is used to identify disorders of the brain, such as Alzheimer's, while EOG is used to monitors the cornea-retinal of the front and rear of the human eye and conducts ophthalmological and eye movement diagnoses. Furthermore, electromyograms (EMG) [113] assess the

TABLE 4. Overview of imaging articles in healthcare.

Year Published	Author Citation	Methodology Used	Used Dataset	Task Targeted	Result	Country
2023	N.Alsharabi et al.. [87]	Classical AlexNet used with quantum VQC model to form a hybrid model in order to diagnose neuro-degenerative disease.	PPMI MRI, ADNI MRI dataset	Classification	Obtained 97% accuracy in the case of Parkinson's disease, and 96% in that of Alzheimer's disease.	Yemen
2023	S.Deshmukh et al. [88]	Improved hybrid model used including additional explainable strategy; a local interpretable model explanation is merged with quantum K-means algorithm.	Breast cancer MRI, Knee MRI dataset	Quantum clustering	Obtained 92.6% accuracy in the case of breast cancer, and 93.7% in that of Knee disease.	India
2023	D.Konar et al. [89]	3D self supervised quantum inspired NN is taken into consideration; a quantum Fuzzy logic technique used	Brain MR and liver tumor dataset	Segmentation	Maximum accuracy of 99% and 98.9% obtained for both datasets respectively.	India
2023	AK.Mishra et al. [90]	mining lambda (λ_0). Gabor filtering is taken into consideration for pre-processing while feature extraction using DCNN is based on the SqueezeNet approach, with a deep variational autoencoder being used	Cervical cancer image dataset	Classification	Obtained 99.07% accuracy.	India
2022	S.Moradi et al. [91]	Two QML models used: a quantum distance classifier (qDS) and simplified quantum kernel SVM (sqkSVM),	Breast cancer and Heart failure dataset	Binary classification	Obtained maximum accuracy of 91% and 87% for both datasets.	Austria
2022	EH.Houssein et al. [92]	A hybrid quantum-classical convolutional neural network (HQ-CNN) model, quantum layer, two convolutional layers, three maximum pooling layers, and two fully connected layers used	Covid-19 X-ray dataset	Classification	Obtainedmaximum 98.6% accuracy, 99% and recall respectively in the case of the proposed model.	Egypt
2022	J.Amin et al. [93]	Proposed 2 qubit QCNN model, data encrypted and decrypted is held using the SHA-256 algorithm, with two dense layers, a Keras layer and Softmax activation function	BraTS2019, BraTS2020, BraTS2021 brain MRI	Semantic segmentation	Obtained greatest accuracy of 98%, recall 99%, F1-score 98%, and precision 99%.	Pakistan
2022	S.Toledo-Cortes et al. [94]	Quantum-inspired deep probabilistic learning ordinal regression model, using Deep Quantum Ordinal Regressor (DQOR)	Eye fundus, Prostate cancer images	Diagnosis	Obtained testing accuracy of 58.7%, MAE 69.5%	Colombia
2021	J.Reyes Bruno et al. [95]	Quantum clustering technique used, with prostate radiation protocol with 100 to 170 slice images per patient being taken into consideration.	Brain tumor MRI	Diagnosis	Obtained good results in terms of diagnosing brain tumor.	Colombia
2021	E.ACAR et al. [96]	Conventional method used for feature extraction, then a VQC model trained with a 4-qubit quantum processor, and quantum transfer learning used.	COVID-19 image dataset	Classification	Obtained testing accuracy of 90.9% and 97.7% respectively.	Turkey
2021	J.Amin et al. [97]	Conditional-GAN (CGAN) used to create CT images, then two models, CML and QNN, were described using different sets of parameters and activation functions.	Covid-19 CT Scan Images	Classification	Maximum accuracy of 93% and 80% obtained for two Covid-19 datasets.	Pakistan
2021	N.Mathur et al. [98]	Quantum circuits used to train a classical neural network termed quantum-assisted NN (qNN); orthogonal weight matrices were developed for training of quantum orthogonal networks (qOrthNN).	PneumoniaMNIST, RetinaMNIST Chest X-ray	Classification	Obtained maximum accuracy of 86% and 78% for both datasets respectively.	France
2020	R.Selven et al. [99]	Locally order-less tensor network model used (LoTeNet) to reduce computational resources with GPU memory	PCam and LIDC thoracic CT, MRI	Classification	Obtained maximum accuracy of 94.3% and 87.4% for both datasets.	Denmark
2020	S.Adhiksry et al. [100]	Quantum based on variational algorithm developed for data categorisation, using quantum FeatureMapping to reduce training parameters.	Breast cancer dataset	Binary and Multi Classification	Obtained maximum accuracy of 93.7%.	India
2020	V.Dutt et al. [101]	QNN model implemented, using hybrid MIA technology to complete information about disease identification.	Medical CT Scan Images	Classification and Detection	Obtained maximum accuracy of 94.3% and 87% respectively .	Spain
2019	LI.Yangyang et al. [102]	CNN and binary encoding strategy used; a quantum particle swarm optimisation technique is also taken into consideration.	CS and MDRBI Images	Classification	Performed well with 96% and 85% accuracy for CS and MDRBI datasets.	China
2019	C.Ding et al. [103]	Quantum SVM taken into consideration for big-data challenges using least squares SVM (LS-SVM) with matrix sampling.	Two privet medical image datasets	Classification	Obtained maximum accuracy of 84.9% and 91.4% respectively.	China
2019	M.Benedetti et al. [104]	Data drive quantum circuit learning (DDQCL) approach implemented; shallow quantum circuit used to reduce the number of training parameters.	Synthetic dataset	Classification	Model confidence of 95% obtained.	UK
2019	A.Sagheer et al. [105]	Quantum-based autonomous perceptron model (APM) developed; non-linear classification model.	Synthetic and UCI Breast cancer	Pattern recognition and Classification	Obtained maximum accuracy of 99% and 98% respectively.	Saudi Arabia

TABLE 5. Overview of biosignal articles in healthcare.

Year Published	Author Citation	Methodology Used	Dataset Used	Task Targeted	Result	Country
2023	N.Baygin et al. [114]	LOSCO CV and K-fold CV are taken into consideration for pre-processing, using feature selection techniques based on quantum computing.	Mental Arithmetic EEG Dataset	Classification	Obtained accuracy of 93.40% and 97.88%, with geometric means of 88.44% and 96.42% respectively.	Turkey
2022	M.Sameer et al. [115]	Feature extraction using quantum algorithm; hybrid classical-quantum layers with 1D CNN model; model training hyper parameters reduced.	Bonn EEG Dataset	Binary Classification	Maximum accuracy and specificity obtained of 100%.	India
2022	T.Koike-Akino et al. [116]	Hybrid quantum classical QNN model implemented, using a VQC model with classical DNN model,	Stress, RSVP, MI, EEG, EMG, ECOG Dataset	Signal Processing	Obtained maximum accuracy of 87.23%, 95.12%, and 60.22%, respectively.	USA
2022	A.Padha et al. [117]	Hybrid quantum model used, with learning capacity increased using a parameterised quantum circuit and a classical LSTM Model taken into consideration.	SWELL-KW Stress EEG Dataset	Classification	Obtained maximum accuracy of 87.67%.	India
2022	S.Sridevi et al. [119]	Hybrid quantum classical model taken into consideration, using a quanvolutional neural network and 2D scalogram technique, with desecrate wavelet transformation	MIT-BIH arrhythmia ECG Dataset	Classification	Accuracy and operating curve score of a publicly accessible physio net MITBIH arrhythmia database recorded as 98% and 100% respectively.	India
2021	R.Kumar Nath et al. [120]	Quantum annealing is taken into consideration for important four feature selection; a Pearson correlation coefficient among the attribute variable and target variable used	Respiration, ECG, foot EDA, hand EDA Dataset	Classification	Quantum annealing obtained more promising results than with the classical technique in optimising training phase.	USA
2020	S.Aishwarya et al. [121]	Various QML models taken into consideration, using the VQC model, quantum annealing, hybird quantum classical NN model	Cognitive stae of mind EEG Dataset	State mind Prediction	Obtained greatest validation accuracy of 61.53%.	India
2020	Li.YaoChong et al. [122]	A hierarchic quantum mechanics-based architecture taken into consideration for feature selection, using a random nonlinear kernel from the modified QSVM model.	EEG signal Dataset	Classification	Obtained maximum accuracy of 95.14%	China
2018	S.MR Taha et al. [123]	Hybrid method and auto regressive model used; quantum recurrent neural network (QRNN), with model proposed compared to QNN and Quantum Wavelet NN.	Biomedical EEG signal Dataset	Classification	Obtained maximum accuracy of 88.28% with the fastest processing time of 6 seconds.	Iraq

electrical activity of prosthetic function as well as the ability of skeletal muscles. For their part, quantum sensors are devices that exploit quantum effects in order to achieve enhanced sensitivity and precision in measuring physical quantities. Integrating quantum sensors with ECG or EEG monitoring systems could enable more accurate and detailed data to be gathered. The high sensitivity and noise reduction capabilities of quantum sensors may contribute to improved biosignal analysis in QML models, mitigated through the use of silico tests, where quantum computers simulate human beings. ECG and EEG data include useful information that can be retrieved and used in ML models as features. One approach in the context of QML is to use quantum algorithms or quantum-inspired techniques to extract features from biosignal data, which can then be supplied to QML models to be analysed and classified. In contrast to MHR and Image datasets, the majority of researchers working on QML also use biosignal data to identify specific diseases. A paradigm for feature engineering based on QC was proposed in [114], by employing LOSO and K-fold cross validation, whereby a publicly available EEG dataset measuring the performance of a mental arithmetic activity including 20-channel EEG signal segments is taken into consideration. The data was collected from 36 healthy right-handed volunteers separated into two groups containing 10 bad counters and 26 good counters. Using LOSO and 10-fold CVs, the model obtained accuracy of 93.40% and 97.88%, with geometric means of 88.44% and 96.42% respectively. A new approach for feature extraction and classification that involves a 1D CNN model using the hybrid classical-quantum layers was proposed in [115]. In the Bonn EEG dataset for the binary classification task, the proposed model obtained maximum accuracy and specificity of 100% while reducing model complexity with the least learning parameters. Additionally, by introducing Gaussian noise into the EEG signal, the proposed technique's robustness was also assessed. Reference [116] offers a hybrid quantum-classical NN model for EEG, EMG, and ECOG analysis that combines a VQC model with a DNN model. Additionally, it also shows that the proposed QNN delivers state-of-art performance while maintaining a small number of trainable parameters for VQC. The model was evaluated using a variety of EEG data sets - stress, RSVP, and MI - and obtained maximum accuracy of 87.23%, 95.12%, and 60.22%, respectively. A parameterised quantum circuit is merged with a traditional LSTM model in [117] to increase the learning capacity and accuracy of predictions, and on a variety of sensor data from the SWELL-KW [118] dataset, the efficiency of the proposed method was evaluated with 87.67% accuracy. The time series dataset includes data from worker information interactions with computers, facial expressions, body postures, heart rates (variability), and skin conductance, which were captured under various working environments. According to Sridevi et al. [119], discrete wavelet transform is suggested for decomposing ECG signals, and this is followed by computing a 2D scalogram in order to acquire time frequency features and by applying a quanvolutional neural network to categorise the scalogram images in order to detect arrhythmia. The accuracy and operating curve score of a publicly accessible physio net MITBIH arrhythmia database were recorded as 98% and 100% respectively. Quantum annealing (QA) is an innovative method that was introduced in [120] for important feature selection using physiological signals, whereby four features are extracted from the signal source - respiration, ECG, hand and foot EDAs - for the purpose of stress detection. The Pearson correlation coefficient among the attribute variable and the target variable is used to calculate the bias of feature variable, with results demonstrating the promise of quantum annealing in optimising the training phase of a ML classifier, particularly under situations involving data uncertainty. The cognitive processes of human behavioural outcomes were taken into account by Aishwarya et al. [121], taking into consideration different QML classifiers, i.e, VQC, QA classifier and hybrid quantum classical NN. These models were compared, and predictions of upcoming cognitive responses made using EEG data. The preliminary findings of these approaches are shown, and they are quite positive, with up to 61.53% validation accuracy. Reference [122] describes hierarchic quantum mechanics-based architecture for implementing feature extraction and classification in EEG signals, whereby a quantum state was formed via the quantum wavelet packet transformation (QWPT) after the classical EEG signal dataset was created as a quantum state. The random non-linear kernel from the modified QSVM model is used to predict the label of the EEG signal and obtained maximum accuracy of 95.14%. Another novel hybrid method for classifying two types of EEG signals using an auto regressive model was also described in [123], whereby the key features from EEG data were extracted using two distinct element extraction approaches. Back propagation is utilised to train the proposed QRNN model, which is then compared to QNN and Quantum Wavelet NN. As demonstrated in Table 5, the experimental results show that the proposed model obtained maximum accuracy of 88.28% with a fastest processing time of 6 seconds.

VIII. DISCUSSION

The aim of this section is to address the responses of all the potential research questions outlined in Table 2. This involves summarising and evaluating the records selected from the state of the art, which will serve as a guideline for future researchers working on QML in the healthcare domain. The quality of each article was ensured after analysing and evaluating each article based on the information provided in Table 1. The study encompasses a comprehensive analysis of 49 recent articles published between 2018 and 2023, and evaluation was conducted by constructing a set of quality metrics as shown in Table 6.

How QML algorithms can be utilised to enhance medical data analysis, such as improving disease segmentation, classification, or anomaly detection: As discussed briefly in the state of art, QML algorithms have the potential to enhance medical data analysis in several ways, including improving disease segmentation, classification, and anomaly detection. The quantum-enhanced feature selection technique is an important step in medical data analysis, whereby relevant features are selected with a view to building accurate models. Quantum machine learning algorithms can assist in identifying the most informative features from complex medical datasets, leading to improved disease segmentation and classification. Moreover, QSVM [124], QRF [125], QKNN [126], QNN [127], VQC [57], and QCNN [128] are the popular algorithms for classification tasks, and these algorithms can leverage the power of QC to enhance classification accuracy, enabling diseases or medical conditions based on patient data to be better identified. Quantum algorithms, such as quantum k-means [129] or quantum spectral clustering [130], can aid in grouping similar data points together, allowing for better disease segmentation, which can be particularly helpful in medical imaging analysis, where accurate segmentation of organs or tissues is crucial for diagnosis and treatment planning. Detecting anomalies in medical data is vital for early diagnosis and treatment of diseases. Quantum machine learning algorithms can assist in identifying abnormal patterns or outliers in large-scale medical datasets, enabling early detection of diseases or unusual patient conditions. By using the unique quantum effects, such as quantum superposition and entanglement, these networks can potentially provide enhanced capabilities for medical data analysis and improve pattern recognition, feature extraction, and classification tasks in medical data analysis.

How QML models can be integrated with classical machine learning approaches in order to leverage the strengths of both in healthcare data analysis: Integrating quantum machine learning models with classical machine learning approaches can potentially leverage the strengths of both in healthcare data analysis. A hybrid quantum-classical machine learning model combines classical machine learning algorithms with QC techniques in order to leverage the power of both paradigms. QC has the potential to process information exponentially faster than classical computers in certain scenarios, which makes it an exciting field for various applications, including healthcare and disease diagnosis. The working process for the quantum model uses the same classical classical algorithms, the only difference being the data encoding technique. The classical model uses the classical input information of 0 or 1, known as bits,

TABLE 6. Content of evaluated research articles taken into consideration based on merit points.

		Content of paper					Additional Quality Measures						
Sr No	Reference	1	2	3	4	5	6	7	8	9	10	Merit points	Quality
1	D. Maheswari et al. [67]	9	10	18	8	10	9	0	4	15	4	87	Better paper
2	B.Prakash et al. [68]	8	9	17	8	10	6	0	4	14	0	76	Average paper
3	G.Abdulsalam et al. [69]	9	9	16	9	8	9	0	4	14	5	83	Good paper
4	S.Diaz-Santos et al. [70]	8	8	16	9	8	9	0	0	14	5	77	Average paper
5	U.Ullah et al. [71]	10	10	16	9	9	9	0	5	13	3	84	Good paper
6	H.Gupta et al. [72]	10	10	18	9	10	10	0	5	14	5	91	Best paper
7	H.Heidar et al. [73]	9	9	15	8	9	10	0	5	14	2	81	Good paper
8	U.Ullah et al. [74]	10	9	19	8	9	10	0	5	14	3	87	Better paper
9	MS.Ishwarya et al. [75]	9	9	19	10	10	10	0	5	15	5	92	Best paper
10	H.Yano [76]	10	10	18	10	10	10	0	5	15	5	93	Best paper
11	D.Maheshwari et al. [77]	10	10	18	9	10	9	0	5	14	5	90	Best paper
12	D.Pomarico et al. [78]	8	9	16	9	8	9	0	5	13	5	82	Good paper
13	S.Saini et al. [79]	9	10	18	10	9	9	0	5	13	5	88	Better paper
14	S.Chakraborty et al. [80]	10	9	17	10	10	10	0	5	14	5	90	Best paper
15	D.Maheshwari et al. [81]	8	8	16	9	8	10	5	5	13	5	87	Better paper
16	D.Sierra-Sosa et al. [82]	9	8	17	8	8	9	0	5	13	4	81	Good paper
17	S.Mardirosian et al. [83]	8	8	16	8	8	9	0	5	13	1	76	Average paper
18	ZY.Chen et al. [84]	9	8	17	9	8	9	5	5	13	5	88	Better paper
19	K.Benlamine et al. [85]	7	8	17	9	8	9	5	5	13	5	85	Better paper
20	OM.Parkash-Patel et al. [86]	8	9	18	8	9	8	0	5	13	5	83	Good paper
21	N.Alsharabi et al. [87]	9	9	17	8	10	8	0	5	12	3	81	Good paper
22	S.Deshmukh et al. [88]	9	9	15	8	9	10	0	5	14	4	83	Good paper
23	D.Konar et al. [89]	10	10	18	9	10	9	0	5	14	5	90	Best paper
24	AK.Mishra et al. [90]	10	10	19	10	10	9	0	5	15	5	93	Best paper
25	S.Moradi et al. [91]	9	10	18	9	9	10	0	5	13	5	88	Better paper
26	EH.Houssein et al. [92]	10	10	20	10	10	10	0	5	15	5	95	Best paper
27	J.Amin et al. [93]	9	10	19	9	10	9	0	5	15	5	91	Best paper
28	S.Toledo-Cortes et al. [94]	10	9	19	9	9	10		5	14	5	90	Best paper
29	J.Reyas Bruno et al. [95]	8	8	16	9	8	10	0	5	13	1	78	Average paper
30	E.Acar et al. [96]	8	9	15	9	8	9	0	5	12	5	80	Average paper
31	J.Amin et al. [97]	10	10	19	10	10	9	0	5	15	5	93	Best paper
32	N.Mathur et al. [98]	9	9	15	8	9	10	0	5	14	5	84	Good paper
33	R.Selven et al. [99]	9	10	18	10	9	9	0	5	13	5	88	Better paper
34	S.Adhiksry et al. [100]	10	10	18	9	10	9	0	5	14	5	90	Best paper
35	V.Dutt et al. [101]	8	9	18	9	10	9	0	5	14	5	87	Better paper
36	S.Chakraborty et al. [80]	10	10	18	10	10	10	0	5	15	5	93	Best paper
37	LI.Yangyang et al. [102]	10	10	20	10	10	10	0	5	15	5	95	Best paper
38	C.Ding et al. [103]	9	10	18	10	10	10	0	5	15	5	92	Best paper
39	M.Benedetti et al. [104]	10	10	20	10	10	10	0	5	15	5	95	Best paper
40	A.Sagheer et al. [105]	9	10	18	9	9	10	0	5	13	5	88	Better paper
41	N.Baygin et al. [114]	10	10	18	9	9	10	0	5	14	5	90	Best paper
42	M.Sameer et al. [115]	8	9	19	9	10	10	0	5	13	5	88	Better paper
43	T.Koike-Akino et al. [116]	8	8	16	8	8	9	0	5	13	2	77	Average paper
44	A.Padha et al. [117]	8	10	17	8	9	9	0	5	14	3	83	Good paper
45	S.Sridevi et al. [119]	9	10	17	8	9	9	0	5	14	3	84	Good paper
46	R.Kumar Nath et al. [120]	10	9	17	8	8	8	0	4	14	3	81	Good paper
47	S.Aishwarya et al. [121]	8	9	18	9	10	9	0	5	14	5	87	Better paper
48	LI.Yao-Chong et al.. [122]	9	9	19	8	10	10	0	5	15	5	90	Best paper
49	S.MR Taha et al.. [123]	9	8	13	8	9	10	0	4	14	5	80	Good paper

and processes this data using a classical ML algorithm, providing two exclusive possible states. In the case of the quantum model, the classical one is first converted into a quantum state known as qubits using Feature-Mapping through a unitary gate operation. A quantum feature map utilises a quantum circuit based on the conventional machine learning kernel method in order to represent classical data within the quantum state domain. In order to classify non-linear data by locating distinct hyperplanes, the data is then transformed into a higher-dimensional Hilbert space. The feature map encodes classical input into a quantum variable by employing N unitary gates in order to undertake a ground state transformation. A quantum model contains a quantum layer, quantum circuits, quantum gates, and quantum registers, where the quantum parameters are used for computation. At the output of the quantum model, a measurement circuit is used to decode the quantum variable back into classical data. QML models can be used to optimise complex healthcare systems, such as drug discovery, treatment planning, or resource allocation, by finding the most efficient solutions more quickly than the CC method.

What the fundamental limitations and advantages of QML models are in handling healthcare data compared to classical machine learning models: Researchers often encounter the persistent challenge of isolation, which stems from various factors. Quantum decoherence, triggered by heat and light, poses a significant threat: when qubits are exposed to such conditions, they may lose their quantum properties, including entanglement, resulting in data loss stored within these qubits. Additionally, rotations in logic gates of quantum computers are susceptible to errors. Furthermore, the field of quantum machine learning relies on the utilisation of computers with extended circuit length and error correction, which entails redundancy for each qubit. QML also faces a limitation concerning the utilisation of a limited number of data samples relative to the number of qubits available. To accommodate larger datasets and additional qubits, QC devices necessitate an increased number of logic gates which, in turn, means that the computational cost escalates and prolongs model execution time. These limitations can potentially impact the quantum states, as an incorrect rotation may lead to errors in the final results. Developers of algorithms for quantum computers must pay close attention to the underlying physics - unlike classical algorithms that can be developed following the principles of the Turing machine, designing an algorithm for quantum computers requires a foundation based on the intricacies of raw physics. There are no straightforward formulas that can directly relate it to logical operations, making the development process more nuanced and complex. QML enhances computational speed and facilitates data storage undertaken by algorithms within a programme - it expands learning validation by executing machine learning algorithms on emerging computing devices known as quantum computers. The processing of information relies on the principles of quantum physics, which significantly diverge from traditional computer models.

What the considerations and methodologies for evaluating the robustness and generalisability of QML models are when applied to diverse healthcare datasets, including data from different hospitals, regions, or demographic groups: Evaluating the robustness and generalisability of QML models when applied to diverse healthcare datasets, including data from different hospitals, regions, or demographic groups, requires careful consideration of several factors. The first step is data representation, because QML often involves mapping classical data into quantum states. The choice of data representation can impact the model's ability to generalise across diverse datasets, and so it is crucial to select a representation that preserves the relevant features of the data and is robust in terms of variations in data sources. Secondly, to evaluate generalisability, it is essential to gain access to diverse datasets that encompass different hospitals and regions, which ensures that the model's performance is not limited to specific subsets of the data and can handle any inherent variations in healthcare data. A proper pre-processing of healthcare data is then also important, standardising and normalising the data to remove any biases or inconsistencies. Additionally, missing data needs to be handled appropriately to prevent any bias in the model's performance, and ensemble methods employed by combining multiple QML models trained on different datasets or with varied initialisations. Ensemble methods can enhance robustness and generalisability by reducing the impact of individual model biases and errors. The presence of such biases and errors to ensure fairness in predictions across diverse groups also needs to be analysed, and the model's performance evaluated separately for different groups of datasets in order to identify any discrepancies or disparities. Performance of the QML model on any external datasets that were not used during training or model development also needs to be validated, as this helps assess the model's ability to generalise completely unseen data sources. Finally, model interpretability and explainability can be taken into consideration, these being crucial, especially in healthcare applications. Techniques used to explain the model's predictions also have to be developed, providing insights into how the model incorporates different features and influences decision-making.

Which types of data can be used for adoption of a quantum predictive model, and is it feasible to use open access datasets for evaluating such models? Additionally, what specific quantum computing devices are applicable for evaluating QML models using healthcare data: Evaluation of QML models can be conducted using various types of healthcare datasets. These datasets can be categorised into two main types: private datasets [67], [71] [74], [77] and publicly available open access datasets [69], [72] [75], [84]. Private datasets are collected from multiple sources such as hospitals, healthcare facilities, and clinical centres, and these datasets comprise healthcare images, electronic healthcare records, or biomedical signals. They contain sensitive and confidential information and are typically not accessible to the general public. On the other hand, publicly available datasets are openly accessible to anyone interested in using them for research or analysis. These datasets also consist of healthcare images, electronic healthcare records, or biomedical signals, but they do not contain sensitive patient information - they are specifically created and made publicly available for research purposes, allowing researchers and developers to test and evaluate their QML models.

There are various QC systems used for executing QML models. For instance, IBM Qiskit [131] is an open-source QC framework developed by IBM, providing a set of tools, libraries, and APIs that allow users to create, compile, and run quantum programs on IBM's quantum systems. IBM has a collection of quantum processors with varying numbers of qubits, which are the basic units of quantum information. For its part, Qiskit supports a range of quantum algorithms and provides a high-level interface for developing quantum machine learning models, being widely used by researchers, developers, and enthusiasts in the QC community. There is also D-Wave quantum annealing [132], which is a specialist approach to QC that focuses on solving optimisation problems, while Google Cirq [133] is an open-source QC framework developed by Google that is designed to create, control, and simulate quantum circuits on both universal and adiabatic quantum systems. Adiabatic QC is another approach to quantum computation, where the system slowly evolves from an initial state to a target state that represents the solution to a problem.

IX. CONCLUSION

This work is based on a systematic review, where various QML algorithms that take healthcare datasets into consideration are reviewed and analysed. Initially, we gathered a total of 2038 articles from four distinct databases - namely, Web of Science, Scopus, IEEE Digital Library, and Springer Link. These articles covered the specific field of study and were published between 2018 and 2023. A meticulous evaluation process was then conducted to ensure impartiality and eliminate any biases. To streamline the research, we employed several criteria to remove duplicate articles and applied various elimination measures and quality assessments. As a result, we successfully reduced the initial pool of articles and ultimately identified 49 articles that were deemed highly relevant to our study, and these selected articles served as the primary focus and foundation for our research. All articles that fit the criteria for this review include those that (a) concentrate on learning patient representations, (b) use patient data, such as EHR, images, and ECG signals, and (c) employ quantum machine learning and quantum deep learning models. This systematic review is divided into two parts: creating a potential research questionnaire and defining quality criteria for the records selected, which will serve as a framework for future research and development at the interface of QC and machine learning. Based on the analysis of these papers, we identified several distinct QML designs and implementations, with the primary focus notably seeming to be on applying neural networks within the quantum realm. Among the prominent QML models, we encountered various quantum networks, each serving specific purposes. These included QSVM, QRF, QKNN, QCNN, QLSTM, and VQC algorithms. Interestingly, these quantum algorithms were extensively explored and tested in the context of EHRs, medical images, and biosignal healthcare datasets, which indicates a significant interest in leveraging QC with a view to addressing critical challenges in the healthcare domain, potentially unlocking new avenues for medical advancements and diagnostic improvements.

One of the possible limitations of this study is the difficulty in identifying all the relevant papers that meet our inclusion criteria. The challenge arises from the wide variety of methods used in healthcare, making a comprehensive search using automated keyword queries complex. Furthermore, it is important to highlight the fact that most existing QML algorithms are presently being assessed in classical environments rather than genuine quantum settings. This limitation is attributed to the scarcity of quantum-ready data for conducting QML experiments and the substantial effort involved in converting classical data into quantum data. Consequently, a promising direction for future research involves the development of more efficient encoding methods in order to tackle this issue.

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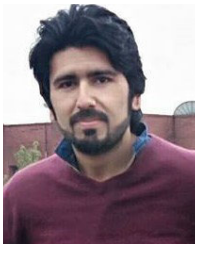

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