



A Review on Artificial Intelligence and Quantum Machine Learning for Heart Disease Diagnosis: Current Techniques, Challenges and Issues, Recent Developments, and Future Directions

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Abstract

This study presents a comprehensive analysis of the existing techniques and applications of artificial intelligence (AI) to cardiovascular disease diagnosis. The application of AI to the diagnosis of cardiac diseases can enhance diagnostic precision, diagnostic throughput, and patient outcomes. This literature survey analyzes state-of-the-art AI-based methods, rates their efficiency, examines potential future research and development avenues, and finds challenges and limitations, providing a foundational overview of main developments in AI, machine learning, deep learning, and quantum computing in relation to heart disease prevention. This study seeks to guide the use of AI-based techniques for heart disease detection, having an ultimate objective of enhancing patient outcomes through research and development. This review mainly emphasizes the significance of further studying and advancing AI for its ability to revolutionize the diagnosis and management of heart diseases.

Keywords: Artificial intelligence; heart disease diagnosis; deep learning; quantum computing; machine learning; cardiovascular disease; Cleveland dataset.

1. Introduction

Diseases of the heart and blood vessels are categorized as cardiovascular diseases. Genetics, unhealthy lifestyle choices (e.g., smoking, poor diet, and lack of exercise), and preexisting medical conditions are some of the potential drivers of cardiovascular diseases (such as diabetes and high blood pressure). Serious complications can be prevented, and patient outcomes can be improved through the early detection and management of cardiovascular diseases. These patients account for more than 17.9 million deaths annually, making cardiovascular diseases the leading causes of death worldwide [1] [2]. Caused by heart attacks and strokes. This study highlights the importance of the early detection and management of cardiovascular diseases to contribute to the prevention of serious complications and improvement in patient outcomes. Cardiovascular disease risk factors comprise smoking, high blood pressure, obesity, high cholesterol, physical inactivity, and unhealthy diet, which can be modified through lifestyle changes. The early detection and management of cardiovascular diseases involve regular checkups and screenings, lifestyle changes, and medical treatments [3].

More than 17 million people per year lose their lives to cardiovascular diseases, which includes heart diseases. The AI has the probable to revolutionize the field of cardiology by allowing for earlier and more precise diagnosis, which is essential for successful therapy and administration. The diagnosis of heart diseases (HD) can benefit from the ability of AI-based techniques to sift through mountains of data, find trends, and make forecasts [4]. A number of recent studies and advancements have shown that AI can be useful in the diagnosis of heart disease. There are, however, obstacles and constraints that must be overcome. The aim of this study is to presents a synopsis of the status of AI in the detection of heart diseases, including its history, present methods, challenges, advancements,

performance, and potential future paths. The application of AI to the diagnosis of heart diseases can enhance diagnostic precision, diagnostic throughput, and patient outcomes. The following are the major contributions of this study:

- Comprehensive analysis of the current state of AI in heart disease diagnosis is provided, evaluating current approaches, assessing progress made in the field, identifying challenges and limitations, highlighting recent developments, evaluating the performance of AI-based methods, and discussing future directions for research and development.
- Thorough examination of the current state of AI in heart disease diagnosis is conducted, and areas where further research and development is needed are identified.
- Insights into the use of AI-based methods for heart disease diagnosis is provided, which are useful to accuracy, speed and efficiency of diagnosis, ultimately leading to better outcomes for patients.
- The performance of AI-based methods for heart disease diagnosis is compared with that of traditional diagnostic methods.
- This study serves as an introduction to major advancements in AI, machine learning (ML), deep learning (DL), and quantum computing (QC) for cardiovascular disease prevention and the potential impacts of these advancements on clinical practice.

The rest organization of this study is as follows: Section 2 discusses the importance of AI in heart disease diagnosis. The main challenges in and limitations of using AI for heart disease diagnosis are presented in Section 3. Section 4 presents the recent developments in AI for heart disease diagnosis, particularly novel methods, applications, and datasets, and evaluate the performance of AI-based methods. Future directions for research and development in the field of AI for heart disease diagnosis in Section 5. Finally, Section 6 summarizes the main findings of the review and provides recommendations for future research.

2. AI importance in heart disease diagnosis

By aiding physicians and other healthcare workers in making informed choices, AI potentially improves the diagnosis and management of cardiovascular diseases. EHR and medical images are just two examples of the massive amounts of data that can be analyzed by AI systems to reveal trends and risk factors that humans might miss. This can aid physicians in determining whether or not a patient actually has heart disease and, if so, at what stage of the illness they are. AI can also be used to track patients' progress and make course corrections as needed. The use of AI in cardiology potentially enhances diagnostic precision and therapy efficacy, ultimately benefiting patients [5]. Heart disease research requires ML and DL methods. ML can uncover trends and risk factors in medical images and digitized health records and can detect heart illness [6]. Convolutional neural networks (CNNs) can detect early heart disease signs in X-rays, CT scans, and magnetic resonance imaging (MRI). CNNs can recognize heart disease signs, including heart muscle loss and structure abnormalities. DL can assess medical history, age, sex, and family history to predict cardiovascular diseases [7]. DL allows doctors to monitor patient decline and adjust care. ML and DL can detect early heart disease signs from wearable devices, such as heart rate gauges. ML and DL can improve heart disease diagnosis accuracy and throughput, which are crucial to patient results. Precision medicine will increasingly use AI. ML and DL are categorized by learning processes and extensively used in medicine [8].

2.1 Heart disease diagnosis based on ML techniques

ML is a technique for processing data that allows the robotic development of analytical models. It is a subfield of AI, the central tenet of which is that computers can learn to reason autonomously by analyzing large amounts of data and recognizing trends. Supervised, unsupervised, and reinforcement learning are variations of ML [9]. ML facilitates the automatic analysis of large quantities of data and the discovery of patterns that may not be instantly evident to a person, thus playing an essential role in heart disease diagnosis. Educated medical decisions can be made with the aid of these methods' ability to anticipate patient outcomes and the effects of various treatments [10].

- Predictive modeling: To forecast results, such as hospitalization and mortality, in individuals with heart disease, predictive models can be developed using ML methods.
- Image analysis: The analysis of images, such as electrocardiograms (ECGs) and echocardiograms, by ML algorithms can help physicians diagnose heart diseases.
- Risk assessment: To calculate an individual's chance of getting cardiovascular diseases, ML algorithms can examine demographic information and clinical details, such as cholesterol level, blood pressure, age, and previous medical conditions.
- Personalized medicine: Individual patients' treatment responses can be predicted using ML to create subsets of patients with comparable traits.
- Electronic health records (EHR): To facilitate simpler access to and analysis of patient data, ML can be used in deriving pertinent information from EHR.

Multiple ML approaches can be used in heart disease diagnosis [11] :

1. In supervised learning, a model is trained to make forecasts by means of annotated data. A supervised learning program might be educated using a medical information database containing data from healthy and heart disease patients. The algorithm would be trained to recognize data patterns that are indicative of heart diseases and then use these patterns to make predictions about new cases. The result or goal variable is known during training. Supervised learning methods include logistic regression (LR), decision trees (DTs), random forests, and support vector machines (SVMs).
2. In unsupervised learning, a program learns without being fed with classified data. It autonomously learns to recognize trends and organize data. Patient subgroups sharing risk factors for a cardiovascular illness can be identified using unsupervised learning methods. Methods that can be trained with data where the result or goal variable is unknown. Unsupervised learning strategies include clustering and dimensionality reduction methods.
3. Semi-supervised learning refers to a method that learn from identified and unstructured examples. This method may be helpful in settings where collecting annotated data is challenging or costly. In a medical imaging application, for instance, obtaining a large number of labeled images of heart disease can be challenging. A significant number of unlabeled pictures might be obtained with little effort. Semi-supervised learning algorithms can then use identified and unlabeled pictures to improve performance and ultimately, diagnostic accuracy [9].
4. Reinforcement learning uses environmental data to make decisions and manage issues. Reinforcement learning addresses decision-making and managerial issues instead of classification or regression. Reward and discipline teach reinforcement learning algorithms. The RL has been used in many contexts, but detecting heart disease with it is rare. Robotics and control systems use reinforcement learning for dynamic decision-making. Heart disease prognosis is usually a one-time call based on static inputs (such as patient data, imaging, or test findings) [10-[12]].

Medical records and MRI studies are just two examples of data that can be analyzed using ML methods for the diagnosis and management of heart diseases. The term “machine learning” refers to a technique that employs quantitative and statistical techniques to draw inferences from datasets [13]. For example, one study used IQR and discretization filters to enhance the efficiency of a hidden naive Bayes classifier for heart disease detection and tested it on a heart stalog dataset [14]. Another study provided a method for tuning artificial neural network (ANN) parameters to identify optimum parameters for heart disease classification and used ANN as a decision support tool for heart disease detection [15]. Different ML methods for forecasting cardiac conditions were compared using various standard datasets [16]. Intelligent systems for forecasting the probability of getting a heart illness with ML algorithms have been developed and analyzed [6]. SVM, K-nearest neighbors (KNN), DT, and tensor flow ML techniques were used to analyze a heart illness dataset [17]. To detect heart illness, researchers used naive Bayes, LR, KNN, SVM, DT, and random forest ML algorithms on a variety of feature sets. Ensemble methods, such as bagging and boosting, have been used in forecasting cardiovascular diseases by merging multiple basic ML models to operate as a single entity [18]. Other studies used ML algorithms like KNN, naive Bayes, SVM, LightGBM, XGBoost, and random forest to classify heart illnesses and build hospital heart disease predictive models [19]. Furthermore, CNN and SVM have been used in identifying heart failure from ECG signals [20]. Various ML algorithms have been suggested and evaluated for heart disease detection, and some studies have emphasized the significance of feature selection techniques in improving model accuracy. Table 1 summarizes the use of ML methods in the HD diagnosis.

Table 1: Summary of ML methods used in heart disease diagnosis

Author, Year, and Reference	Method	Dataset	Strength	Weakness
Sarra et al. (2023) [12]	Artificial neural network (ANN)	Cleveland dataset	The ANN prediction model developed had an accuracy of 93.44%, which was 7.5% greater than that of SVM. Based on the outcomes of the study, the amount of time required for training and classification was reduced to less than one minute as a result of the utilization of a straightforward neural network.	The study did not provide information about the robustness and generalization capabilities of the proposed model, and thus understanding how well the model will perform on new and unseen data is difficult.

Yaqoob et al. (2022) [13]	PSO optimizer algorithms	Cleveland dataset	Accuracy increased by 2.6%, classification error decreased by 7%, and sensitivity increased by 7.1%. Thus, accuracy increases while few rounds were simultaneously fired.	The study did not consider the number of IOMT client sites, rate of learning solutions, or privacy of patient information.
Arif Ullah et al. (2022) [14]	SVM, artificial bee colony, bat algorithm, and memory-based learner	UCI	SVM was the most accurate classifier, with an accuracy of 97.90%, sensitivity of 90.96%, and specificity of 98.83%.	The study should have looked at how well inferential algorithms work with small data and data classification in the healthcare industry.
Sara et al. (2022) [15]	Support vector machine (SVM) algorithm	Cleveland and Statlog	The SVM's accuracy increased from 84.21% to 89.47% in the Cleveland and Statlog datasets after a study showed that the two feature selection methods played a critical role in enhancing its accuracy.	The research did not explain why the huge number of genes, which are difficult to detect through machine learning and make the tasks more complicated, influences performance.
BORA et al. (2022) [11]	Logistic regression (LR), SVM, random forest, naïve Bayes (NB), KNN, gradient boost	UCI and Kaggle	The SVM achieved the highest level of accuracy, whereas random forest showed the best accuracy, and random forest delivered the highest accuracy. These models can be used in monitoring patients in real time and provide reliable references to medical practitioners.	Combining two classes simultaneously increases the likelihood of making mistakes and having poor accuracy, requiring mastery of the training for both combined classes.
Karthick et al. (2022) [16]	SVM, gaussian NB, LR, Light GBM, XG Boost, and random forest algorithm	UCI	The accuracy of predictions made by the random forest algorithm was the highest, followed by those made by SVM and LR.	The study did not attempt to combine different plausible reasons for heart diseases to better comprehend sickness.
Rahma and Salman. (2022) [10]	SVM, NB, K-nearest neighbors (KNN).	UCI	NB was the most effective ML algorithm for predicting heart disease, achieving 96.9% accuracy.	Although numerous diseases can be diagnosed without UCI, this study did not elaborate the traits used to do so (heart valve disease, pericarditis, Wolff Parkinson-White syndrome, and congenital heart disease).
Prajapati and Singh (2022) [9]	SVM, NB, KNN, linear regression, and logical regression	UCI	Machine learning is a good way to find or predict diseases because it uses mathematical computations and ensemble methods.	This work did not provide justifications for the arbitrary use of training datasets and feature selection because of the lack of standards and the vagueness of custom-built algorithms.
Hriday et al. (2022) [21]	SVM, KNN, decision tree (DT), and tensor flow machine learning methods.	UCI and Kaggle	KNN has the best performance when it comes to datasets, with a 96.42% success rate.	The most recent statistics on cardiovascular disease do not include features that contribute to the range's diminished capacity.

Al Bataineh and Manacek. (2022) [7]	PSO algorithm.	Cleveland.	The MLP-PSO model can help medical professionals make accurate diagnoses and provide better treatment recommendations, with an accuracy of 84.61%.	Manually determining the optimal neural network architecture for a particular task is a time-consuming process and should only be attempted by highly qualified industry professionals.
Jayasree and Usha (2022) [6]	SVM, KNN, and DT	UCI	ML algorithms can increase the efficiency of healthcare practitioners by helping them forecast and process time series. Increasing performance is a goal of DL implementation across many different business sectors.	Improved predictions of heart disease's early phases require multi-modeling and models with a higher level of complexity. Owing to the sheer volume of data that hospitals and the healthcare business acquire, this task is extremely difficult.
Ali et al (2022) [8]	NB, logistic regression, KNN, SVM, DT, and RF	Kaggle	The random forest algorithm achieves the highest accuracy possible, 72.59%, when configured with features in the optimal way.	This research needs to be expanded to look at more factors, such as how a person's heart condition changes over time, in order to make better predictions.
Khalid Amen et al. (2020) [17]	Random forest, gradient boosting machine, extreme random forest, LR, and SVM	Cleveland	LR method is superior to other algorithms in accuracy, improving precision medicine by reducing errors.	The study's findings were inaccurate due to the limited size of the dataset.
Abu Yazid et al. (2018) [18]	ANN	Cleveland and Statlog.	The suggested framework is capable of achieving high classification accuracy, with 90.9% accuracy on Cleveland and 90% accuracy on Statlog datasets.	The majority of the tuning of parameters is performed through a process of trial and error; tuning the parameters of a classifier does not guarantee the highest level of accuracy that can be achieved.

The issues that may be present when using ML techniques for heart disease diagnosis are as follows:

- The richness and variety of the data used for training ML methods is crucial to models' final performance. A model's effectiveness drops dramatically if it cannot generalize to new instances, and effect likely occurs in the absence of data variations.
- Overfitting: This problem arises when a model is overly complicated and matches the training data, leading to subpar results on novel and unknown data. Approaches, such as regularization and cross-validation, are useful.
- Data bias: if data are biased, resulting algorithms may perform well with some populations but badly with others. Methods, such as resampling, data enrichment, and the use of data from a wider range of sources are useful.
- Some ML techniques, such as deep neural networks, can be challenging to interpret, making it hard to grasp how the model arrived at a specific choice.
- Some ML techniques can be thought of as black boxes, making comprehending how they reach specific conclusions difficult.
- Important private and ethical concerns, such as the security of patient data and the potential for discrimination, are raised by the use of ML techniques for medical diagnosis.
- Reliance on ML techniques, which can only evaluate data in the context of what they are provided

and cannot read a patient's emotions or interpret their motivations, and human interactions are consequently limited.

2.2 Heart disease diagnosis based on deep learning methods

Deep neural networks analyze data trends. Image and vocal detection are their strengths [22]. DL methods include CNNs commonly used in image and video recognition. CNNs learn local trends in images and are good at identifying objects and other features. The second form of neural network, the recurrent neural network (RNN), is used for sequential data tasks, such as audio recognition and natural language processing. RNNs can contextualize and predict new inputs because they can remember and apply learned data. Adversarial generative networks (GANs) are used for image creation and data improvement. GANs use two neural networks—a generator and a discriminator—to make fake data that look and act like real data. Autoencoder neural networks are taught to recreate data. Autoencoders can identify anomalies and reduce complexity. Fifth, Transformer, a neural network used in natural language processing for translation and text summarization, uses a fixation gadget to focus on specific inputs and improve accuracy.

A DL can rapidly, accurately, and automatically study vast datasets and can revolutionize heart disease diagnosis. DL systems can assess ECGs and echocardiograms for cardiac abnormalities. CNNs can obtain local image features, making them ideal for this. DL can predict cardiovascular disease risk according to demographics, health state, and medical history, and DL systems can find data trends that humans might miss, making them useful for this. Personalized medicine: DL can classify people into similar groups with different drug reactions. DL can extract relevant data from digital health records to simplify patient data access and research. Predictive modeling: Using DL algorithms, researchers can build models to help doctors select the best treatments for individual patients and identify those at high risk for heart disease-related events, including illness or death. DL may improve heart disease diagnosis by discovering novel markers and drug targets. However, DL models are complex and require a large amount of data. To increase confidence in these models' predictions, clinical expertise should verify their results.

Over time, scholars and practitioners have shown interest in using DL to build heart disease detection models. For heart disease diagnosis, a DL structure was proposed for information age and coronary disease likelihood [23]. A one-dimensional CNN and a bidirectional long short-term memory were their DL models (Bi-LSTM). Using dual event-related moving average (DERMA) and fractional Fourier-transform (FrIFT) in detecting aberrant and normal morphological events in ECG data was proposed [20]. Real data were used in diagnosing some heart cases with a new PNHs-set context [24]. Fuzzy scaled fuzzy hyper soft set (D-set) and Riesz Summability were used to blend these traits. Their method automatically diagnosed heart insufficiency [34]. Another study suggested using DL to detect heart diseases in various ways [25]. CardioXNet, a low-power and end-to-end CRNN, detects five kinds of cardiac auscultation from raw PCG data [36]. An end-to-end process was proposed for disease class prediction through Unet CNN segmentation and a classifier ensemble [26]. An automatic heart disease detection system that combines a binary CNN with a new multiagent feature wrapper (MAFW) model and a smartwatch and heart device was proposed [27]. Moreover, a study [28] presented a smart healthcare monitoring framework that uses ensemble DL models and feature fusion to help doctors quickly and accurately diagnose heart problems and increase the accuracy of heart disease prediction. These studies have shown that DL-based heart disease diagnostic systems can be superior to traditional methods and improve the accuracy of medical practitioners' heart disease prognosis. They proposed designs, models, and methods for heart condition detection. Table 2 describes heart disease DL methods.

Table 2: Summary of deep learning algorithms in heart disease diagnosis

Author, Year, and Reference	Method	Dataset	Strength	Weakness
Sarra et al. (2022) [19]	Generative adversarial network (GAN) model	Cleveland Statlog	HL-based heart disease diagnostic frameworks improved accuracy, specificity, sensitivity, and F1 score compared with those of previous generations.	The data used in the models were limited and unequal, resulting in lower accuracy.
Mastoi et al. (2022) [26]	KNN and SV	MIT-BIH and Ningbo People's	KNN machine and ECG vector machine trained to detect cardiac diseases with	Baseline wandering and powerline interference can cause spikes in ECG data.

		Hospital (SPNH)	99.99% accuracy.	New information was not provided in this study.
Atiqe Ur Rahman et al. (2022) [20]	Modified Sanchez's method	Cleveland	The research developed a framework for medical diagnostics to reduce computer complexity, which can be extended to other uncertain circumstances.	The study did not explain how to manage situations with periodic or rough information and data, such as those with attributes, sub-attribute values, and opinions of decision-makers.
Botros et al. (2022) [27]	CNN-SVM Model.	MIT-BIH and the BIDMC	According to the study's authors proposed paradigm can be applied to portable devices to enable real-time patient monitoring and provide trustworthy information to medical experts.	Figuring out what an ECG signal means in real time was difficult.
Atiqe Ur Rahman et al. (2022) [26]	D-set and other for Riesz mean)	Cleveland	By placing the emphasis on various characteristics, algorithms equip decision-makers with the ability to arrive at better and more trustworthy conclusions.	Additional avenues of opting out of participation or unclear grading need to be explored in this research.
SHUVO et al. (2021) [22]	Convolutional neural network (CNN)	PCG	This model is ideal for embedded system applications because of its small number of parameters and potential for clinical diagnosis.	More PCG datasets with a wide variety of cardiovascular disease annotations are needed.
Ammar et al. (2021) [23]	CNN	150 patients Dijon Hospital	The approach produces a mean dice overlap coefficient of 0.92 for the entire cardiac structure, making it easy to understand and categorize.	MYO's segmentation is affected when the accuracy of MYO segmentation decreases. This result is in contrast to the LV and RV structures, which only have a single barrier between them.
Mohamed Elhoseny et al. (2021) [28]	CNN and MAFW model	Cleveland	Hybrid model has best recall (98.4%), accuracy (90.1%), and precision (88.9%), making it more accurate than classical benchmarking.	Additional classification testing is needed to reduce the cost and complexity of computation.
Ayoub Khan. (2020) [24]	CNN	UCI	The proposed MDCNN-based system for predicting heart disease is superior to other classifiers in terms of accuracy, with 98.2% precision.	In the course of the work, the training and testing of the projected task should be carried out with hardware that is currently available in the market.
Ali et al. (2020) [25]	SVM, MLP, RF, and NB.	Cleveland	The system proposed has an accuracy of 98.5%, making it superior to other cutting-edge technologies in predicting heart disease.	Missing values and noise in wearable sensors can lead to inaccurate findings and confusion, making the identification of useful and relevant data items difficult.
Ganorkar and Kute (2018) [29]	Neural network SVM	ECG signal	The procedure is completely automated and contributes to the accurate	Real-time prediction does not explain complexity, nonlinearity, or

			and identification of cardiac insufficiency.	unpredictability.
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When applied to vast amounts of medical data, such as EHR and images, DLs can help physicians to conduct heart disease diagnosis by spotting trends and deducing patients' prognoses. DLs can aid in enhancing diagnostic precision and early detection of individuals at risk for heart disease. However, DL faces a number of significant issues when applied to heart disease detection.

- The quantity and quality of data are crucial to the training of heart disease algorithms. Gathering and organizing medical data can be challenging and time consuming.
- Bias in training data can have an effect on the results of a DL method. A model can underperform on novel and unseen data when the data used to train it is not indicative of the community it will be used on.
- Results interpretation: Owing to the complexity of DL methods, how a given prognosis is reached is often unclear. This limitation can hinder physicians' confidence in a model's findings, and conveying to patients why they are given a heart disease diagnosis is difficult.
- Moreover, the collection and use of data required to train models is subject to stringent laws governing the use of DL in medical applications and can be viewed as an invasion of privacy. In addition, safety issues related to the use of DL when dealing with confidential medical data have been found.
- Achieving good results by using small datasets or restricted computational resources in training DL techniques is challenging because of the large amount of data and computational capacity. In addition. The model's results might not perform well when it is applied to novel data or when it is subjected to subtle shifts in the data's distribution.

2.3 Heart disease diagnosis based on quantum machine learning techniques

In quantum machine learning (QML), QC and ML are combined to enhance performance. The ultimate goal is to create novel algorithms and techniques that can take advantage of the peculiarities of quantum systems to address issues that are intractable with traditional processing methods [30]. Potentially reducing the time required to teach ML models is a significant benefit of QML. Some tasks can be accomplished by quantum algorithms, including quantum gradient descent and quantum SVMs at a significantly higher rate than their conventional equivalents. QML can be useful in areas where significant quantities of data need to be processed, such as voice and image recognition, natural language processing (NLP), and drug finding. Given that QML can possibly expedite the analysis of massive amounts of medical data and make precise forecasts about a patient's health. It has the potential to become an essential instrument for diagnosing heart disease. To increase the precision of diagnostics and immediately find people at risk of contracting heart diseases, QC can be used because it can perform some tasks considerably quicker than conventional computing. In addition, QML algorithms can evaluate physiological data from wearable devices or other tracking systems to keep monitor patients' health in real time and ward off cardiovascular diseases. QML offers a novel approach for data analysis, in which the quantum states themselves serve as the data, thereby mitigating the problem of data bias.

QML techniques have recently been suggested for the early diagnosis of heart illness. Hybrid quantum neural network and hybrid random forest quantum neural network are possible alternatives to QML [31]. Predictions of heart illness can be made more quickly and accurately with these techniques because they take advantage of QC's unique characteristics. Another research suggested various ways to prepare quantum data and convert regular data into quantum states [32]. This paves the way for the implementation of quantum methods, such as the fully convolutional quantum neural network (FCQ-CNN). The research presents a baseline comparison of this algorithm's performance in managing categorization tasks using classical data, emphasizing its potential for the early diagnosis of heart diseases. Moreover, a recent study [33] suggested modifying the FCQ-CNN algorithm by designing parameterized quantum circuits, quantum filters, pooling operators, conventional data preparation techniques, quantum feature mapping, optimizers, and cost functions. This approach can boost the algorithm's efficiency in terms of forecast accuracy and other metrics. [34]. In addition, a quantum feature importance selection method was suggested, which uses a quantum-enhanced SVM to determine which features are the most important for quantum classifiers. The precision of predictions for a growing set of characteristics improved. Another study explored QML techniques for detecting cardiac problems before they become serious [35]. For better results with less expensive training, another research suggested using mixed quantum-classical ML. They introduced a novel variational quantum classifier that encodes data in N dimensions with just one quantum device and a "single-shot training" method. A different study [36] suggested a QML classifier-based ensemble ML model for predicting cardiovascular disease risk. For early heart disease diagnosis, two QML

methods: the hybrid quantum neural network and the hybrid random forest quantum neural network were proposed [37]. In addition, FCQ-CNN, a quantum version of the classical CNN, was assessed, and a number of techniques for prepping quantum data to convert conventional data into quantum states were suggested [38]. In addition, a quantum-enhanced SVM was used in selecting the most pertinent characteristics for quantum classifiers [39].

QML potentially provides novel approaches for assessing medical data and forecasting patients' health outcomes and thus has the power to significantly alter the healthcare system. These findings show that QML can be useful in detecting heart illness at an early stage and call attention to the need for more study in this field. Interest in QML has grown in recent years as researchers from different disciplines have demonstrated its high performance. The exponential rise in speed and computational capability offered by quantum computers can revolutionize the healthcare sector. Table 3 presents a summary of how QML can be applied to the heart disease detection.

Table 3: Summary of QML techniques on heart disease diagnosis

Authors, year, Reference	The method used	Dataset	strengths	The Weaknesses
Abdulsalam et al. (2023) [36]	SVC, ANN, QSVC, QNN, and VQC.	Cleveland	QML classifiers are better at predicting cardiac disease than classical classifiers but are less accurate than Bagging QSVC model.	Traditional computers are extremely expensive to solve classical SVC problems in more-dimensional space.
Heidari and Hellstern. (2022) [31]	. of HQNN, HQRf	Cleveland and Statlog	QML can reduce the time needed for processing, making them suitable for the early prediction of cardiac disease.	Traditional methods of machine learning lead to the inefficient use of resources, thus increasing expenses.
GROSS et al. (2022) [34]	QSVM's	real-world payment transactions the European cross-border processing portfolio	The QSVM facilitates the exploration of the feature space and increases the accuracy of the combined quantum-classical method.	QML needs to reduce dimensionality and optimize performance because of finite number of qubits and error rates.
Kavitha and Kaulgud (2022) [32]	K-means clustering method.	UCI	Quantum computers are faster than classical ones because of the Qasm simulator's clustering-specific quantum circuit and k-means.	Quantum decoherence and quantum gate rotations make solving problems with precision difficult.
UBAID ULLAH et al. (2022) [33]	(CNN).	UCI	The FCQ-CNN model showed the best testing accuracy of 84.6% for cardiovascular datasets, outperforming CNN and FCNN models.	Quantum computers require a large number of qubits to be resilient to errors.
Gabriel Silva (2021) [37]	PHM algorithms	MFPT	This research aims to identify how existing PHM approaches can be improved by quantum computing.	Programs must be improved to guarantee the security and availability of hardware-ready NISQ computers through the use of cloud services.

3. Main challenges and limitations

The application of AI techniques to heart disease diagnosis faces a number of challenges and limitations.

1. **Data availability and quality:** To build and verify AI techniques for heart disease diagnosis, obtaining enough high-quality data is a major problem. EHR, imaging tests, and physiological readings are examples of such diverse datasets. Given that accurate and dependable forecasts depend heavily on the quality and amount of data used in training and verifying models, data availability and quality are the major obstacles and constraints when AI techniques are used in heart disease diagnosis

[40]. Underfitting, in which the model does not transfer to new data, and overfitting, in which the model closely matches the training data and performs badly on new data, are the consequences of a lack of appropriate high-quality data. Thus, the model's predictions may not be precise or dependable when used with actual data. Data availability and quality can impact the variety and representativeness of the data, both of which minimize bias in forecasts. Some groups may not be correctly predicted by the model when data used in training it is not indicative of the community it will be used on [41]. If the data have low quality, the model may be impacted by noise, which makes comprehending the decision-making process of the model difficult and can affect interpretability. The availability and quality of data have a significant impact on the accuracy, reliability, and interpretability of predictions and can lead to bias and unfairness in the predictions when data are not representative of the population it will be used on. Thus, it is an important consideration when employing AI methods for heart disease diagnosis.

2. **Data bias and interpretability:** Data bias can affect the accuracy or fairness of AI algorithms and can then affect the forecasts they make. In the context of heart illness diagnosis, where erroneous conclusions can have dire effects, this effect can be a significant issue. Furthermore, many AI models are “dark boxes,” making comprehending a model's decision-making process difficult and thus the model's results [42], [43]. In the diagnosis of a heart illness with AI, two major hurdles and constraints are data bias and interpretability. The term “data bias” describes the existence of inherent inaccuracy in information used in constructing and testing AI algorithms. When data used in training a model does not adequately reflect the community it will be used on, incorrect or unjust forecasts may result. For instance, a model's predictive efficacy may be diminished if data used in training it is not broadly indicative of the population or is limited to a single area. To interpret means to comprehend the process by which a model generates its forecasts. Deciphering the decision-making process of many AI models, especially DL models, is difficult. Thus, comprehending why a model makes a particular forecast and pinpointing and fixing model errors are extremely challenging [43]. Given the gravity of a misdiagnosis, data bias and interpretability take on added significance in the context of cardiac illness detection. Poor patient outcomes can result from a model's inaccuracy in predicting results for certain populations or from the complexity of understanding a model's reasoning behind a given forecast.
3. **Lack of domain knowledge:** Building an AI model takes knowledge of the medical field and ML. The development and interpretation of AI models for cardiac disease diagnosis can be hindered by this limitation as medical specialists may lack the technical background, and ML experts may lack medical expertise [42]. Expertise in the medical realm and the technological elements of ML is required in the development of AI models for the detection of cardiac diseases. Medical professionals are well versed in a condition's signs, causes, and therapy options, but they may lack the requisite expertise to build and understand AI models. Experts in ML may be able to build AI models, but they may lack the medical knowledge necessary to fully grasp the complexities of a disease and how to best implement those models in the healthcare setting. A number of issues that can arise from a dearth of subject expertise, including the selection of inappropriate data or features, inability to comprehend the context of predictions, and incorrect interpretation of findings. This can reduce the likelihood of the models being trusted and adopted by the medical community because practitioners may struggle to comprehend the model's logic and apply its findings to their practice.
4. **Privacy and security:** The development of AI models for the detection of heart disease requires careful attention to privacy and security issues, as the models may need to handle confidential personal information, including medical records. Given that AI techniques for heart disease diagnosis require the processing of personally identifiable information, such as medical data, privacy and security concerns must be addressed. EHR, imaging tests, and physiological metrics can be useful for AI models and the diagnosis of cardiac illnesses. Such information can be compromised by hackers, stolen, or misused if not secured properly [44]. Concerns about data security and the likelihood of data leaks have grown alongside the popularity of EHR and remote surveillance. Thus, people may lose faith in the healthcare system, and this situation can contribute to problems with the law and government. Moreover, AI models may be susceptible to adversarial attacks, and a model or data may be altered to make false or misleading forecasts. This issue are especially concerning in the context of cardiac illness diagnosis, and a misdiagnosis can have devastating effects.
5. **Regulation:** However, regulations for regulating the creation and use of AI models for heart disease diagnosis are few, and the field of AI in healthcare is advancing at an extremely fast pace. As a result, coders may find balancing legal and social concerns is challenging. Few laws that control the creation and use of AI models have been formulated. This situation presents one of the primary challenges and constraints when using AI techniques for heart disease detection. When developing and implementing these models, developers may find negotiating legal and ethical considerations challenging [45]. With regard to patient data, healthcare AI algorithms must adhere to laws, such as HIPAA and the EU's General Data Security Regulation. Verifying and testing the accuracy, reliability, and security of AI

models can be time consuming and expensive. In addition to being used in highly-regulated domains, such as mental health, AI models in healthcare are frequently used in making pivotal choices, such as diagnoses and therapy plans. Developers face challenges in understanding and adhering to these regulations because they can differ by area and region. The pace of development in AI is outpacing the ability to control it, and thus supervision and responsibility are reduced. In the medical field, a wrong prognosis or therapy can have devastating effects.

6. **Algorithms:** Using AI techniques in diagnosing heart illnesses is difficult and are limited by many factors, one of which is a dearth of high-quality and diverse data. Data for heart disease detection are often sparse and skewed, and algorithms depend on these large datasets to learn trends and make forecasts. Variance in the presentation of cardiac symptoms is considerable, and thus algorithms for correctly recognizing and diagnosing heart illnesses are challenging. Another difficulty is that AI models may not be able to describe how they arrive at a certain diagnosis [46], so human specialists must verify and understand the findings.

Quantum computing: Many of the suggested algorithms and techniques have not yet been applied to or tried on real-world issues; the field is still in its infancy. Owing to the novelty and fast development of QC, it presents one of the primary difficulties and restrictions in applying AI techniques to the detection of cardiac diseases. A number of obstacles must be addressed before QC can be used in actual contexts despite the fact that it potentially enhances the performance of AI models [43]. The efficiency of algorithms and the precision of predictions can be impacted by noise and errors in quantum systems and noise and errors are the major obstacles of QC. Furthermore, conducting complicated computations or managing large datasets on current quantum computers is challenging because of the restricted number of qubits (units of quantum information). Another difficulty in developing AI models for heart disease detection is the absence of software and development tools for QC. This situation increases the difficulty in creating and implementing these models in practice because of a dearth of knowledge and expertise in the area. However, research into QC is still continuing, and the hardware is not yet ready for large-scale applications [43]. Moreover, QC is still in its infancy, and the technology is not yet available for commercial use.

4. Datasets used in heart disease diagnosis

The Heart Disease Collection is a trove of health records concerned with cardiovascular diseases. Many forms of cardiac illness are categorized by this system [44], including atherosclerosis, tachycardia, and congestive heart failure. Age, gender, chest discomfort type, resting blood pressure, and serum cholesterol are just some of the 13 characteristics in datasets [45]. These characteristics are utilized in determining whether or not a person has a cardiac illness. Predictive algorithms built from this data collection can aid doctors in the early detection and diagnosis of cardiac issues. Patterns and connections between various characteristics and the existence of cardiac disease can be discovered using this method. The Heart Disease Dataset is a gold mine of information for doctors trying to crack the code on heart disease. In the categorization studies, heart disease and prediction is the framework for a part in a review article that focuses on datasets used in AI-based heart disease diagnosis. Four different libraries for ML at UCI have been established. Some examples of such datasets are the “Cleveland,” “Hungary,” “Switzerland,” and “Long Beach” datasets, as well as the “As ECG signal incorporates PCG recordings,” “MIT-BIH,” and PTB datasets. One more group of things, such as a database of MRI scans. Many researchers have compiled sensitive information or data they have collected, for example, the Ibn Al-Bitar Hospital and the Dijon Ningbo People’s Hospital. A variety of healthcare services can be found within hospitals (SPNH). Table 4 provides information about the dataset, including the amount of samples, the research that used the dataset, and a connection to the dataset itself.

Table 4: Heart Disease Dataset sources

Dataset Type	No. of samples	Used by	The dataset source link
Cleveland	303	[15][46][11][13][46][37][20]	https://archive.ics.uci.edu/ml/datasets/heart+disease
Hungary	294	[46][11]	https://archive.ics.uci.edu/ml/datasets/heart+disease
Switzerland	123	[11], [46]	https://archive.ics.uci.edu/ml/datasets/heart+disease
Long Beach	200	[18][19]	https://archive.ics.uci.edu/ml/datasets/Statlog+Heart
Statlog	270	[5], [15]	https://archive.ics.uci.edu/ml/datasets/Statlog+Heart

			+%28Heart%29
MIT-BIH	109446	[21][39][27], [46]	https://physionet.org/content/mitdb/1.0.0/
PTB	14552	[21]	https://www.kaggle.com/datasets/bjoernjohn/ptbxi-electrocardiography-database

• Cleveland Dataset

Composed of 303 individuals, the Cleveland data collection was compiled using medical records. The participants' ages, peak heart rates, gender, cholesterol levels, blood pressure levels, and diagnoses of cardiovascular illnesses are included. Computer learning researchers have access to the Heart Disease Archive. Only 14 out of the 76 characteristics in the Cleveland Heart Disease Index have been used by researchers. The next stage after a dataset has been preprocessed is data cleaning, which includes fixing any errors in the data's structure or display and removing or rectifying any incorrect, outdated, redundant, or useless information [10]. This happens after data processing is completed and the procedures include the MinMax scalar method, the normal scalar technique, and the missing value method. Splitting a dataset 80:20 between a training dataset and a testing or validation dataset with the train test split tool has been recommended, and the divisions are determined by a random state. A dataset is split into a training set and a testing set, or validation data collection is conducted. These procedures have been suggested. If the amount of data collected are lower than that of all data, the collected data should be divided equally between testing and training [10]. Multiple ML methods, including LR, DT, and random forest, have been used to assess the value of the Heart Disease UCI dataset. Three metrics—accuracy, precision, and recall—were used in evaluating the study's findings. An unprecedented precision of 88.7% was achieved by a random forest algorithm. To date, DL only had access to Cleveland [17]. The HDPM process was carried out in QML, a train/test division of 70/30 was achieved, and the dataset A was subjected to feature selection, outlier identification, and data balancing. In this case, we assume a train-to-test ratio of 90/10 and a mistake rate of less than 0.01% [36]. The details of Cleveland dataset with the types, and description presented in Table. 5.

Table 5: Cleveland dataset

Name	Description	Type
Age	Age in years	Numeric
Sex	0 = Female or 1 = male	Categorical
Cp	Type of Chest pain (1 = typical angina, 2 = atypical angina, 3 = non anginal pain, 4 = asymptomatic)	Categorical
Trestbps	Resting blood pressure (mm hg)	Numeric
Chol	Serum cholesterol (mg/dL)	Numeric
Fbs	Fasting blood sugar > 120 mg/dL (0 = false, 1 = true)	Categorical
Restecg	Resting electrocardiography results (0 = normal, 1 = ST-T wave abnormality, 2 = probable or definite left ventricular hypertrophy)	Categorical
Thalach	Maximum heart rate achieved during the thallium stress test	Numeric
Exang	Exercise-induced angina (1 = yes, 0 = no)	Categorical
Oldpeak	St depression induced by exercise relative to rest	Numeric
Slope	Slope of peak exercise ST segment (1 = upsloping, 2 = flat, 3 = down sloping)	Categorical
Ca	Number of significant vessels colored by fluoroscopy	Categorical
Thal	Thallium stress test result (3 = normal, 6 = fixed, 7 = reversible defect)	Categorical
Num	Heart disease status (0 = < 50% diameter narrowing, 1 = > 50% diameter narrowing)	Categorical

• Statlog Dataset

The Statlog (heart) collection contain 270 unique cases and 14 distinct features. A total of 120 healthy

people and 150 individuals with cardiac disease are included in the Statlog dataset. Thus, the sample has a uniform distribution of goal output, which is useful in preventing overfitting. Thalidomide, the number of major vessels, ST depression, exercise-induced angina, maximal heart rate, and chest discomfort are the characteristics with the closest association with the goal in the Statlog dataset. Classification accuracy was enhanced by 6.25 percentage points on the Cleveland dataset and 5.17 percentage points on the Statlog dataset in the suggested SVM model. This result is crucial to making correct diagnoses and reducing erroneous predictions. By using a set of 13 factors, one can decide whether or not an individual has heart disease as an outcome of the prediction method. All of the characteristics are listed in one convenient location.

- **Hungary dataset**

The Hungary dataset contains 2294 specimens. Given that the Cleveland and Hungarian datasets share many characteristics, they were merged during the data integration procedure. The dataset is not particularly large or complex, and it pertains to a subject of great interest to many people: cardiovascular illness. The spaces were filled with the norm. All the classified variables had a value of 0. After these three characteristics were discarded, the residual data collection contained 596 rows, and the final ML models used 11 characteristics. As mentioned in the division of training and testing data, the train-test split library was used in the data splitting process, and 80:20 data segments were obtained. A random state was used to ensure that each iteration dividing the data was the same. Through grid search parameter optimization, a rise in precision of 83% was observed.

- **PCG record Dats**

The collected PCG data from a variety of patients hospitalized at the Rawalpindi Institute of Cardiology in Pakistan. Subjects with autism spectrum disorder, those with visuospatial dissociation, and healthy controls all provided PCG data. Five-second audio were made in a medical setting while a specialist listened. PCG captures have a broad application range. A total of 1000 PCG recordings in WAV format were obtained from various sources, including books and webpages. These sounds were classified as “normal,” “aortic stenosis,” “mitral regurgitation,” “mitral stenosis,” or “mitral valve prolapse” (MVP). Each clip used an 8 kHz sampling rate. This approach ensured that the messages were comparable to one another [22]. Temporal characteristics were merged with the extracted MFCC features for precise signal depiction. When all PCG impulses were resampled at a rate of 2 kHz, it not only lowers the processing time but also protects the vital frequency components of the heart sound. Table 6 provides a summary of the dataset according to each class, and samples of signals gathered from normal, ASD, and VSD individuals are shown.

Table 6: Description of the PCG dataset

PCG data	No. of Signals	No. of Subjects	Male	Female
Normal	140	28	17	11
ADD	85	17	12	5
VSD	55	11	7	4

- **Kaggle dataset**

The Kaggle dataset is a cardiac disease-related dataset acquired through the Kaggle platform. Accessible via the IEEE-data port website, it is the most complete of its kind. A total of 1190 entries are included in the collection, and each record has 11 features. In deployed state, information takes the form of (1190, 12). `isnull()` was used in detecting absent numbers and other garbage during the data cleaning process. With a testing accuracy of 94.12% and a training accuracy of 94.12%, random forest outperformed other algorithms by a wide margin. Notably, 92.86% precision was displayed by XGBoost. Other strategies produced excellent results. One of the most important factors used was hyperparameter adjustment [11]. Researchers and medical professionals can use this dataset to identify individuals at high risk of getting heart disease and provide them with preventative treatment to reduce that risk. The quality of the dataset was determined by measuring the model’s ability to accurately forecast testing results. Separate training and test sets were created, and several ML methods were used in evaluating the efficacy of the Heart Disease UCI dataset. The model’s efficacy was measured in terms of its accuracy, precision, and recollection. The results showed that the random forest method had the best performance, with a precision of 88.7%. The most popular data collection for diagnosing heart illness is shown in Figure 1.

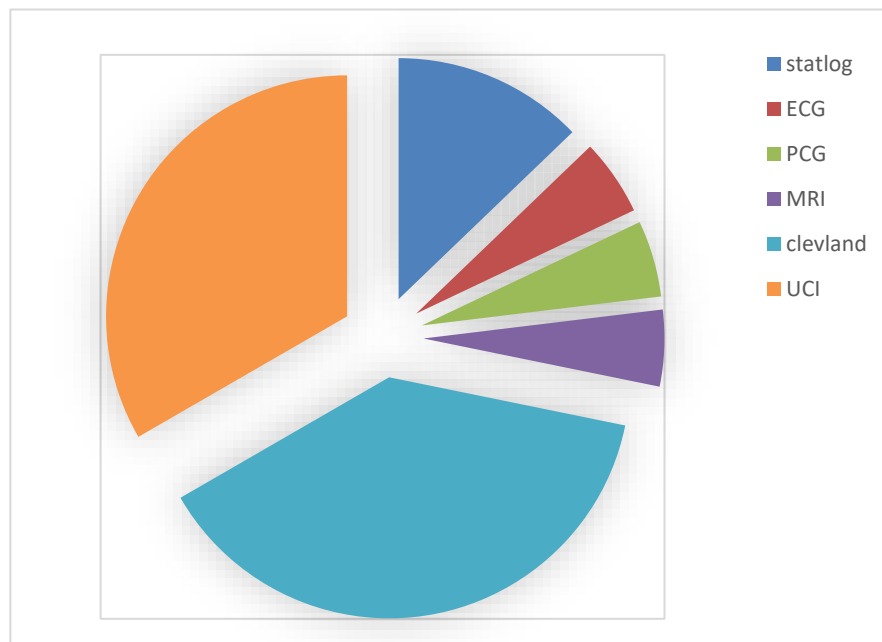


Figure 1: Most frequently utilized dataset for heart disease diagnosis

5.Future Directions

Researchers have used a broad range of approaches to address these issues, and while some have produced promising results, their studies have drawbacks. We have provided some recommendations for where attention should be focused in the future. Newcomers to the field who are attempting to plot the course of their projects will benefit from these suggestions.

1. Some studies used inadequate data, while others had to deal with a data mismatch issue. Both problems can be traced back to the fact that the topic of data imbalance has not yet been fully addressed in all relevant studies. For this reason, we proposed performing data augmentation and using augmented data for groups with few participants. This approach ensures balance among various classifications.
2. Hybrid learning techniques, such as SVMs, random forests, DTs, and optimization approaches or hybrid methods can be trained to diagnose heart diseases and analyze large amounts of patient data, involving test results, medical histories, and demographic information.
3. Image analysis: Medical images, such as ECGs and echocardiograms, can be analyzed by AI, which spots heart abnormalities and estimates the likelihood of heart disease.
4. Predictive modeling: Risk factors for cardiovascular diseases can be identified and used in predictive models. These variables include family history, gender, age, and lifestyle choice.
5. Wearable devices: Integrating AI into wearable devices to track heart health and identify early warning signs of heart disease is a promising area of research. We recommend developing AI techniques with cloud, edge, and fog computing.
6. Clinical decision support systems: These support systems driven by AI can be used to advise cardiologists on the most up-to-date methods for diagnosing and treating heart diseases.
7. Integration with EHR: Heart disease diagnosis and management can be aided by integrating AI with EHRs for the analysis of data from multiple sources, such as, medication records, laboratory results, and hospital admissions.
8. Large-scale data analysis: Large-scale data analysis can be performed to identify patterns and trends in heart diseases and provide novel insights into their causes and risk factors.
9. Collaboration with medical scientists: Working in tandem with the medical community, AI can help uncover the root causes of cardiac illnesses, from which novel therapies and treatments can be developed.
10. Reinforcement learning: To teach agents to make choices in response to incentives, reinforcement

learning is used as a method of ML. Based on a patient's unique symptoms and reactions to therapy, this method can be used in determining the most effective course of action.

11. Principal component analysis (PCA): To aid in heart disease diagnosis, PCA can be used in isolating the most pertinent features of medical images, such as ECGs.
12. NLP: Medical records and doctors' notes are two examples of unstructured data sources that can benefit from the NLP application. As a result, the likelihood of a misdiagnosis of heart disease may decrease and the diagnostic accuracy may increase.
13. ECG Analysis: CNNs are types of DL models and can be trained on the large datasets of ECG recordings to detect patterns and anomalies indicative of heart diseases. Having this information can aid in the early diagnosis of heart illness sometimes even before any sign appears. Echocardiograms and MRI scans are two examples of medical images that can be analyzed using DL models detecting heart abnormalities and assessing cardiovascular disease risk. The CNNs can be taught to recognize structural alterations in the heart, particularly those associated with disease, such as valve defects and thickened heart walls. Predictive models utilizing DL methods, such as RNNs, can be used to forecast the probability of cardiac diseases according to socioeconomic and lifestyle variables, medical histories, and test findings. In this approach, people at high risk of developing heart diseases can be prioritized for preventative measures. Integrating DL algorithms into wearable devices, such as smart watches and fitness trackers, allows the continuous monitoring of cardiac function. One application of DL models is the analysis of ECG signals from wearable devices for diagnosing heart disease and notifying patients and their doctors.
14. QC: QC is an emerging field that can have far-reaching effects in many sectors, including healthcare. It offers a number of benefits and has advantages over conventional computing methods in heart disease diagnosis. QC aids in the creation of novel treatments for heart diseases. By simulating drug and protein interactions at the molecular level, QC helps scientists learn more about how these drugs affect conditions. Patient outcomes may be enhanced if these data are used in developing novel medications or enhancing existing treatments. Moreover, QC has potential applications in predictive modeling. ML algorithms can be trained on the large datasets of patients with heart diseases by using QC, allowing the identification of patterns and risk factors that can be used in predicting the outcomes of individual patients. The accuracy of treatment decisions and the efficiency of heart disease management can be enhanced by these data. The analysis of X-rays and MRI scans can benefit from the application of QC. Healthcare workers can benefit greatly from the information provided by algorithms taught to recognize specific patterns in pictures that are suggestive of cardiac diseases. Understanding quantitative learning is the first step toward integrating QML with other AI-related technologies, which can then be put into practice and combined with various AI-related technologies, such as NLP, ML, and computer vision. Engaging in in-depth research using AI tools that are far superior to current methods is recommended. An error-free quantum computer is necessary for solving complex problems, including integer factorization, and searching unstructured databases. Millions of low-error and long-coherent-time qubits are needed.

6. Conclusion

This review concludes with a thorough evaluation of where AI stands in its ability to diagnose heart disease. It discusses what has been tried so far, how far the field has come, what obstacles remain, what is new, how well AI-based methods perform, and where the field should go from here in terms of research and development. The application of AI to the diagnosis of heart diseases may dramatically enhance diagnostic precision, turnaround time, and efficiency. This research provides a primer on the state of the art in AI, ML, DL, and QC as they are related to lowered risk of cardiovascular diseases and how that might affect clinical practice. The primary objective of this study is to improve patient results through the use of AI-based techniques for heart disease detection, and the areas where further research continued research into the role that AI in transforming the diagnosis and treatment of heart diseases.

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