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Recent Developments in Quantum Machine Learning-Based Detection of Diseases: A Systematic Review

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Abstract*— Quantum computers are a new technology with a strong computational power to solve complicated issues. Quantum computing has evolved into strong tools for a wide range of application disciplines, including chemistry, agriculture, natural language processing, and healthcare, as computer power has increased exponentially and machine learning algorithms have advanced. When conventional data and machine learning methods are processed using quantum computing, new domains emerge, such as quantum machine learning. Quantum machine learning offers great performance and computational capabilities, making it helpful for solving computing jobs. Quantum machine learning has several use cases in the field of medical science. Quantum machine learning analyses and classifies massive datasets using quantum computing techniques and algorithms to detect invisible trends and forecast disease development or progression. This method has the potential to bring novel understandings into complicated biological systems, allowing for the creation of treatments that are more efficient and personalized. It allows medical professionals to diagnose diseases quickly and accurately. In this research, we examined the work done in the field of disease prediction in the biomedical domain using quantum machine learning by analyzing the research papers of various researchers, including the performance of each method and approach employed, as well as their accuracy.

***Index Terms*— Disease detection, disease prediction, Machine Learning (ML), Quantum Machine Learning (QML).**

I. INTRODUCTION

Within the field of artificial intelligence, machine learning creates algorithms by understanding hidden patterns in datasets and using that knowledge to predict future data of a similar nature without the need for explicit programming for every job. Conventional machine learning predicts an output that may be utilised to get useful knowledge by combining data with statistical approaches. With rapidly expanding computer capacity and advances in machine learning techniques, quantum technologies have become useful instruments for a wide range of application disciplines, from chemistry to agriculture, natural language processing, and healthcare.

In recent times, Quantum technologies have seen remarkable growth. Quantum computers (QC) have the potential to completely change computation. Quantum computers employ qubits, which can represent both 0 and 1 values, compared to traditional computers that only represent either of them [1]. Quantum-enhanced machine learning has several applications in healthcare, including research, medical trials, patient management, and chronic illness diagnosis. The healthcare sector is using quantum computing to prioritise patient-centred treatment.

The Moore Law is used to revolutionise QML algorithms' performance and speed. "Quantum computation" is the term for a computational standard derived from the rules of quantum physics. In the current era of informatics development, quantum information and artificial intelligence (AI) are hot topics. QC is crucial for healthcare due to the growing volume and diversity of health data. During the COVID-19 pandemic, medical professionals faced challenges in analysing the genome of the virus using standard computational techniques due to the development of new variations. To effectively manage future pandemics, it's important to find innovative approaches to accelerate healthcare analysis and monitoring. QC offers a novel method to enhancing healthcare technology. Previous research has shown that quality control (QC) can enhance complex healthcare computations. However, the existing literature on QC for healthcare is unstructured and only addresses a small number of disruptive use cases [2].

A. Quantum computing

Quantum computing is the manipulation of quantum systems to process information. Quantum states' superposition can significantly accelerate processes. Complexity of computation arises from the ability to conduct actions on multiple states simultaneously [3].

In comparison with mainstream computers, which are based on the physical representation of the two states '0' and '1', quantum computers use qubit's superposition of two quantum states 0 and 1 to perform many different types of computation at once.

With its foundations in quantum physics, QC has the potential to become the backbone of the ultra-powerful computing infrastructures of the future, facilitating the real-time processing of massive volumes of data. Researchers that want to advance computing beyond the Moore's law period have lately been more interested in quantum computing; still, a thorough, systematic review is required to outline the opportunities, drawbacks, and difficulties.

B. Quantum bits

The basic building block of quantum computing and information is a Quantum bits or qubit, which functions similarly to a bit in conventional computers. Present-day quantum computers, with their noisy and imprecise quantum gates, can only implement a few tens of qubits in practice.

Three fundamental quantum characteristics may be seen in the behaviour of a spinning of electron surrounding the nucleus of an atom: quantum superposition, quantum entanglement, and quantum interference. These behaviours are intimately related

to the behaviour of qubits [4].

C. Quantum superposition

A fundamental idea of quantum mechanics is known as "quantum superposition," which states that a system or particle can exist in several states concurrently until it is measured or observed. This indicates that the particle is simultaneously in a composite of several states as opposed to being in a single, distinct state like position or momentum. Quantum bits, or qubits, are capable of representing both 0 and 1 simultaneously. This property makes quantum computing possible and may enable parallel processing, which might result in the solution of some problems far more quickly than with traditional computers.

D. Quantum Machine Learning

Quantum machine learning techniques utilize quantum computing performance to solve common machine learning challenges. Typically, traditional algorithms or expensive subroutines are adapted to work on quantum computers. These machines are expected to become widely available in the near future, helping in the processing of increasing global data. The new field combines known machine learning methods with quantum information theory to enhance its capabilities [3].

E. Comparing traditional and quantum computing process

The fundamental building blocks of a quantum computer are known as quantum bits, or "qubits," which have dual states or levels, i.e., they may concurrently represent one single bit in both "1" and "0," compared to traditional computers that work in terms of bits [2]. Quantum bits, or qubits, which depend on the spin electron, are the foundation of QC storage. It may convert more complicated data, including negative values, in addition to simple readings of 0 and 1[1].

II. QUANTUM MACHINE LEARNING ALGORITHMS

The different types of quantum machine learning models are:

A. Quantum k-nearest neighbour

Different distance metrics are used in quantum variants of the k-nearest neighbours (k-NN) approach, including the Euclidean distance. These quantum variations frequently employ a quantum encoding that might be helpful for implementation since it only needs a small number of qubits and a straightforward quantum circuit. The computation of Euclidean distances in the context of the article's proposed quantum k-NN algorithm relies on a unique quantum encoding with minimal qubit needs and a straightforward quantum circuit. If a quantum random access memory (QRAM) is available for data retrieval, this solution may be able to provide an exponential speedup over classical computations. The Jaccard index is used to assess the algorithm's performance in terms of classification accuracy and the accuracy of the nearest neighbours that are discovered.

B. Quantum support vector machines

Quantum SVM, or Quantum Support Vector Machine, is a quantum computing-based method for implementing the conventional Support Vector Machine (SVM) algorithm. It performs the SVM's computations using quantum circuits and operations, which may provide advantages such as decreased computational complexity and higher processing speed. Typically, the Quantum SVM method encodes the training data into a quantum state before calculating the inner products between the quantum states using a quantum kernel function. The quantum kernel function is then applied to create a quantum version of the classical SVM optimization issue, which can be addressed using quantum optimization methods. The resultant quantum SVM model may then be used to forecast new data in the same way that a conventional SVM would.

C. Quantum algorithm for clustering

Quantum clustering algorithms are a type of machine learning technique which is used to categorize data. These methods use the nearest-neighbour learning algorithm and are broken into two parts. The first stage is to divide data in the similar category into smaller groups with sublabels, which helps to set boundaries between data with distinct labels. The subsequent stage involves creating the quantum circuit for categorization, which contains many control gates. This method has successfully classified random data and entanglement for various Werner states, predicting test data

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labels. Algorithms for quantum clustering may prove beneficial in a variety of categorization scenarios, especially when building distinct phases in materials.

D. Quantum Neural Network

Quantum Neural Network (QNNs) are a kind of quantum computing paradigm that employs quantum circuits to accomplish calculations. QNNs compute using quantum gates rather than conventional activation functions. Quantum Neural Networks (QNNs) are a sort of quantum computing model that uses ideas from quantum physics and neural networks to conduct calculations. QNNs, like traditional neural networks, are made up of input, hidden, and output layers. The input layer of a QNN is made up of qubits that have been initialized to represent the input data. The hidden layers are made up of quantum gates that perform calculations on qubits to extract features from the incoming data. The output layer is made up of quantum gates that execute calculations on qubits to generate the final output. QNNs do calculations on numerous inputs at the same time using a concept known as quantum parallelism. This is conceivable because qubits may exist in a superposition of states, allowing them to represent several inputs simultaneously. Quantum neural networks may also use entanglement to execute calculations on correlated inputs, making them more efficient than conventional neural networks for certain applications.

E. Quantum Decision Tree

A quantum decision tree is a quantum computing-based variant of conventional decision trees, which are widely used machine learning techniques for classification and regression problems. In a quantum decision tree, internal nodes represent quantum tests or measurements of the quantum state, while branches indicate the results of these tests. The tree’s leaves reflect class labels or projected values in regression tasks. Quantum decision trees may be created using a variety of techniques, including the Quantum Decision Tree Learning (QDT) algorithm. QDT is a quantum variant of the classical ID3 method that creates decision trees by iteratively picking the optimal characteristic to split the data depending on a certain criterion, such information gain. The QDT method starts by creating a quantum superposition of all conceivable decision trees. It then iteratively measures the quantum state to generate a decision tree and updates the superposition based on the measurement results. This operation will continue until a termination condition is reached, such as reaching a maximum depth or obtaining the specified accuracy.

F. Hidden quantum Markov models

Hidden Quantum Markov Models (HQMMs) are a variant of conventional Hidden Markov Models (HMMs) that use quantum mechanics concepts to improve processing efficiency. HQMMs, like classical HMMs, are made up of hidden states and observable outputs. However, in HQMMs, quantum states reflect the hidden states, and quantum operations drive state transitions. HQMMs may be utilized for a wide range of applications, including classification, regression, and sequence prediction. To apply an HQMM to a specific job, the model is first trained on a collection of labeled or unlabeled data. During training, the model’s parameters are changed to increase the probability of the observed data. Once trained, the model may make predictions based on fresh data.

III. LITERATURE REVIEW

H Yano [5] The study describes a unique method for efficient discrete feature encoding designed specifically for variational quantum classifiers. Variational quantum classifiers show promise in machine learning problems because they can handle complicated data distributions and perform classification tasks using quantum computing resources. However, the efficacy of these classifiers is strongly dependent on the conversion of classical input into a quantum representation. The authors offer an effective approach for encoding discrete features, with the goal of reducing computational cost and improving classification performance. The method is intended to handle discrete feature spaces often found in machine learning applications. The suggested method efficiently represents discrete characteristics by utilising quantum systems’ intrinsic qualities and applying techniques such as amplitude encoding and phase encoding. Experimental results show that the suggested encoding approach improves the performance of variational quantum classifiers across several datasets. The strategy improves classification accuracy while using less computer resources, making it a potential step in quantum machine learning research. The study makes a substantial addition to the field of quantum machine learning by developing an efficient encoding strategy specifically designed for variational quantum classifiers. The approach tackles the issues of encoding discrete characteristics into quantum states, improving classification accuracy while lowering computing cost. The authors confirm the suggested scheme’s efficacy through rigorous testing, emphasising its practical applicability in quantum-enhanced machine learning. Further study should focus on applying the suggested technique to other types of quantum classifiers and undertaking theoretical analysis to gain a better grasp of its underlying principles. It was accurate with VQC = 66.1.

Amin [6] The research proposes a quantum machine learning architecture for COVID-19 classification that uses synthetic data generated by a conditional adversarial neural network (CANN). With the continuing epidemic, prompt and correct classification of COVID-19 infections is critical for effective containment and management strategies. Traditional machine learning algorithms may have problems in managing complicated data distributions and obtaining high classification accuracy, especially in the medical area, where data availability is frequently limited. The authors overcome these issues by combining quantum computing techniques and synthetic data synthesis via a CANN. This method enables the generation of different and representative datasets for training COVID-19 classification algorithms. Using quantum machine learning capabilities, the proposed architecture attempts to improve classification accuracy and generalization performance. Experimental assessments using COVID-19 datasets show that the suggested architecture achieves accurate classification results. The combination of quantum computing techniques and synthetic data creation using CANN improves performance when compared to regular machine learning approaches. The article emphasizes quantum machine learning's potential to address crucial healthcare concerns, including infectious illness categorization. Finally, the article makes a substantial addition to quantum machine learning and healthcare analytics by introducing a revolutionary architecture for COVID-19 classification. The suggested strategy improves classification accuracy and resilience over standard approaches by combining quantum computing techniques with synthetic data creation using a conditional adversarial neural network. The findings emphasise quantum machine learning's potential in tackling major healthcare concerns, as well as prospects for future study in illness detection and treatment using sophisticated computational approaches. On the POF hospital dataset, they achieved 0.94 precision, accuracy, recall, and F1-score, compared to 0.96 precision, 0.96 accuracy, 0.95 recall, and 0.96 F1-score on the UCSD-AI4H dataset.

Dang [7] The study provides on highlighting the growing relevance of picture categorization in a variety of disciplines, including medical, security and surveillance. It overcomes the issues that classic picture classification algorithms have, notably when dealing with huge datasets and obtaining high accuracy. The introduction lays the groundwork for investigating quantum computing approaches as a possible option to improve picture categorization efficiency. The paper describes the experimental setup used to assess the performance of the QKNN algorithm for picture classification tasks. It provides the picture datasets utilised for experimentation, as well as the performance criteria used to evaluate the method, such as classification accuracy and processing efficiency. The authors cover the QKNN algorithm's implementation specifics, as well as any adjustments required to adapt it to quantum computing platforms. The results of experiments to compare the QKNN algorithm's performance against classical KNN algorithms and other cutting-edge image categorization techniques. The authors evaluate the QKNN algorithm's classification accuracy, computational efficiency, and scalability, emphasizing its strengths and limits. They examine the ramifications of the experimental results, as well as the QKNN algorithm's potential real-world applications. The report finishes by summarizing the research contributions and major conclusions on the QKNN algorithm's effectiveness for picture categorization. The author applied the quantum K-nearest-neighbour approach to improve picture classification efficiency, achieving 83.1.

R. Narain [8] They compare the classic Framingham risk score to a unique approach using quantum neural networks. The Framingham risk score is a well-established approach used by clinicians to assess the likelihood of cardiovascular events in individuals over a given time period. However, the authors propose employing a quantum neural network, a cutting-edge approach influenced by quantum physics and neural network principles, to make more accurate predictions. The study is likely to collect data from patients, including age, gender, cholesterol levels, blood pressure, and smoking status. These data are then utilized to train both the Framingham and quantum neural network models. They employed 689 heart disease datasets for model training and 5,209 Framingham study datasets from the University of Washington in Seattle, WA, USA, for validation. QNN training involved identifying optimal weights for each layer through various trials. The QNN design has 7 input nodes, 85 hidden nodes, and one output node. Overall obtained accuracy of 98.57.

Gupta [9] This research investigates at the use of machine learning for diabetes prediction, comparing two approaches: deep learning (DL) and quantum machine learning (QML). The researchers created two prediction models, one using DL and the other using QML approaches. Both models used attributes from the PIMA dataset. To increase model performance, data preprocessing methods such as outlier removal, missing value imputation, and normalisation were used. The models were assessed using a number of tests, including accuracy, precision, recall, F1 score, and others. The performance was also measured against existing cutting-edge models. The DL model outperformed the QML model across all measures. The DL model attained an accuracy of 95.

S. Jain [10] The authors examine medical records pertaining to NSCLC patients using both quantum and traditional machine learning methods. They probably gather a variety of information, including treatment results, tumour characteristics, medical history, and patient demographics. It is likely that the paper will address the application and comparison of various machine learning models, including both classical algorithms (like random forests, support vector machines, or deep learning models) and quantum algorithms (which may make use of quantum-inspired techniques or quantum neural networks). It is probable that the paper gives the outcomes of the machine learning tests, encompassing the key metrics attained by both quantum and classical models in terms of accuracy, sensitivity, and specificity. They obtained a 95.24.

O. P. Patel [11] This paper explores the idea of stacked auto-encoders and explains how they are put together and operate. The authors then go on to explain how they created the Q-DNN algorithm by incorporating quantum-inspired methods into the auto-encoder design. To assess how well their suggested Q-DNN algorithm performs, the researchers have run tests. They have put the algorithm to the test on a variety of datasets and contrasted the outcomes with those from more conventional deep learning techniques. The outcomes show that the Q-DNN method performs better, especially when it comes to decreased computational cost and increased accuracy. The study report concludes with the introduction of Q-DNN, a unique deep neural network method influenced by quantum mechanics. The authors have created an accurate and effective deep learning model by skillfully fusing the concepts of quantum physics with stacked auto-encoders. This discovery might have a big influence on machine learning and open the door to future developments in deep learning algorithms that are more sophisticated and effective. It obtained 95.66.

Taha [12] This study suggests a unique method for categorizing Electroencephalography (EEG) signals by combining intrinsically quantum recurrent neural networks (IQ-RNNs) with autoregressive (AR) modelling. The goal of the authors' work is to increase the precision of EEG signal categorization, which is crucial for a number of applications including cognitive status monitoring, brain-computer interfaces, and neurological disease detection. The authors use an EEG dataset that is available to the public to assess the effectiveness of their suggested method. The findings demonstrate that, in terms of classification accuracy, the suggested method performs better than conventional machine learning techniques like support vector machines (SVMs) and random forests. Their accuracy rate was 88.28.

Ishwarya M.S. [13] The authors suggest a quantum-inspired ensemble method to decision-making with several attributes and agents. The authors provide a unique quantum-inspired decision-making algorithm based on quantum computing principles and ensemble learning methods. The suggested technique is tested on different benchmark datasets, and the findings demonstrate that it outperforms standard decision-making algorithms in both accuracy and resilience. The work is well-organized, with a clear description of the suggested strategy. The authors give a full explanation of the quantum-inspired algorithm and ensemble learning techniques employed in the approach. The report also offers a thorough examination of the suggested technique, demonstrating its efficacy in solving decision-making difficulties. The findings reveal that the suggested technique has a high accuracy of 90.5.

IV. FUTURE SCOPE AND CHALLENGES

The area of detection of diseases is quickly growing, and quantum machine learning (QML) is predicted to play a significant role in the future. QML integrates quantum mechanics concepts with machine learning techniques, having the possibility to enhance disease detection quickly and precisely.

The capacity of quantum computing to process large amounts of data fast and effectively has the potential to revolutionize medical data analysis. For example, it might aid in the identification of patterns in genetic data that are suggestive of specific illnesses, allowing for earlier and more accurate diagnosis. Furthermore, QML could help in the creation of personalized medication. Quantum algorithms might anticipate a patient's reaction to various treatments based on their genetic composition and health history, allowing clinicians to personalize therapies to particular individuals. In the field of infectious diseases, QML might help us track and anticipate epidemics. Quantum algorithms might produce more precise forecasts by analyzing data on disease transmission, environmental conditions, and population changes, allowing public health personnel to respond more efficiently.

However, it is worth mentioning that quantum machine learning is still in its early stages of development. While the potential is immense, considerable technological obstacles must be solved before QML can be extensively applied in disease diagnosis. These include creating quantum algorithms appropriate for medical data, constructing quantum computers capable of producing higher accuracy, and protecting the confidentiality and privacy of sensitive medical information.

V. CONCLUSION

We have presented a comprehensive description of current quantum machine learning (QML) research. In this paper, we discussed different types of quantum machine learning algorithms and also assessed the work of several scholars and examined the various types of QML algorithms employed in the papers. Different authors applied different techniques to distinct datasets, resulting in varying data accuracy. The performance of multiple algorithms was compared using a variety of matrices.

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