Journal of Applied Artificial Intelligence
https://jaai.sabapub.com
ISSN: 2709-5908

2022 Volume 3, Issue 1 : 47 – 60
DOI : 10.48185/jaai.v3i1.446

Developing a Model for Predicting Lung Cancer Using Variational Quantum-Classical Algorithm: A Survey

Philip Adebayo[1, *], Frederick Basaky[2], Edgar Osaghae[2]

[1]Department of Computer Engineering, Scholl of Engineering, Kogi State Polytechnic, Itakpe, Nigeria.
[2]Department of Computer Science, Faculty of Science, Federal University Lokoja, Kogi State, Nigeria.

Received: 22.02.2022 • Accepted: 05.06.2022 • Published: 30.06.2022 • Final Version: 30.06.2022

Abstract: There are real life problems that currently proved hard for classical computers (even the best of supercomputers) to solve-the so called computationally intractable problems. Computers and computing devices are limited, by virtue of the fact that they cannot perform certain complex problems. For example, modern cryptography assumes that it is impossible to factorize a large number as the complexity of solving this problem increases exponentially. Even the best supercomputers of today cannot sufficiently find the prime factors of a number with 700-1,000 digits. With quantum computing, however, Shor's algorithm proved that in principle, a quantum computer can be used to break the security of conventional cryptosystems. Quantum computing also promises exponential improvements for many optimization problems. Lov Grover algorithm was also designed to search for an element in unstructured database. Effort is currently on to leverage quantum computing and quantum mechanical phenomena to tackle complex machine learning problems. Using machine learning algorithm to solve problems is common place. What is however new is using quantum machine learning algorithm to solve problems such as detecting, classifying and predicting disease such as lung cancer. In this work, we highlight the limitations of classical computers to solve certain problems and then propose a hybrid model called the variational quantum-classical algorithm to predict the possibility of a patient developing lung cancer given a set of features which are spelt out in the dataset. The dataset is initially pre-processed, and made to pass through a Parameterized Quantum Circuit (PQC) and then post-processed. Finally, the output of the post-processing phase is used for prediction of lung cancer.

Keywords: Classical computers, Quantum computers, Quantum machine learning, Qubits, Qiskit.

1. Introduction

Before the advent of mobile phones and computers, it was difficult to believe that a time would come in the phase of technology transformation when users will literally move around with hand held devices. In the wee days of computer development, a single computer occupies an entire room and components inside failed every hour. More so, computers cost several millions of dollars. Miniaturization of components as well as devices led to the present crops of hand held devices that perform excellently better than their predecessors. Reduction in sizes was such that transistors replaced vacuum tubes, integrated circuits (ICs) replaces standalone transistors. Today, a single microprocessor can house billions of transistors.

Every two years or thereabout, the number of transistors inside a conventional microprocessor doubles and because of this trend of miniaturization, transistors are operated with lower and lower voltages. Conventional computers have reached the limit of computational capacity because when operated in circuits of very small size, the unpredictability of electrons is observed. They pass

[*] Philip Adebayo: philipadebayo41@gmail.com

through the boundary of conduction channels, a process known simply as ‘tunnel effect’. There are enough signs to prove that, after more than fifty years, Moore’s law is tending towards its physical limitations. It is as a matter of fact, not possible to decrease the size of the transistors any further. As it currently stands, it is difficult to build transistors much below 14nm. But new materials and methods are being sort to produce 1nm transistors en masse.

Computers, by virtue of their capacity and capabilities became an indispensable part of our daily lives- individuals and corporate organizations acquire them in their numbers to perform complex tasks that humans considered difficult or hard to accomplish. Trends in human history and development have been such that we cringe at the mention of the possibility of a new technological innovation. So much is expected from the quantum computing and quantum as a service model that will in the near term, drive the technological world making it possible to solve complex problems which may be impossible using conventional computers.

Future quantum computers will enter the race with disruptive potential to solve complicated challenges like comprehending photosynthesis, improving catalysts for the formulation of renewable fuels, and complex Artificial Intelligence (AI) systems [3]. This bears eloquent testimony to the assertion by [7] that Artificial Intelligence is used for augmenting human capacity in information and security activities. Google, Amazon, IBM, Microsoft, and Intel, among others, are already contending for a slice of the quantum computing pie. All of these progress and efforts have given fast conducting quantum computing a great future [13].

Biomarkers, which are collections of characteristics that can be assessed from a patient, such as gene expression or cholesterol level, were first employed in oncology, the branch of medicine that deals with cancer research and treatment, to make predictions about a person's health. To determine whether a patient is at risk for a future heart attack or malignancy, precision medicine, which is based on the idea of identifying a real subtype within which a patient falls and for whom a certain treatment may be most effective, and personalized medicine, which is a treatment meant for an individual, are two examples. Machine learning comes readily handy at the precision level.

Our research, which aims to construct a model for predicting lung cancer using a variational quantum-classical method, falls at the intersection of three fields: medicine, machine learning, and quantum computing. Quantum bits, or qubits, can be used to encode information in quantum machine learning. The counterpart of classical bits is a qubit. We can encode a single state out of 2^n potential states with n bits, but we can encode 2^n states simultaneously with n qubits. This is made possible via superposition, a quantum phenomenon in which a quantum system can exist in numerous states at the same time. Quantum computers will be able expand the storage capacity of devices by storing staggering aggregate of data in a relatively small space.

As diverse and complex as the computers and mobile devices are, they are limited by virtue of the fact that they cannot perform certain complex problems. Classical computers may take several years to solve problems such as factorization of large numbers (like 800 digit number) which are considered intractable at the moment. Ease of computability made researchers to begin to explore possible ways of creating innovation that will make the seemingly hitherto intractable problems tractable. This is the beginning of a significant inroad into quantum computing and by extension, Quantum Artificial Intelligence (QAI) and Quantum Machine Learning (QML) leading to their ability to carry out profoundly fast linear algebraic terms on a state space that grows in size exponentially with the number of quantum bits or qubits. It is hope that in the near term, somebody could just walk up to you and ask: “Hello, Are you QC compliant?”

1.1. Quantum Computing and Quantum Machine Learning

The use of engineered quantum systems to perform complex computations is referred to as quantum computing. It is a form of problem solving that makes use of quantum-mechanical occurrence such as superposition, entanglement and interference to overcome limitations in conventional computers. Quantum systems use probability theory that allows behavior such as superposition and entanglement, which may prove difficult to simulate with a traditional computers [3].

Google was able to achieve quantum dominance almost immediately, signaling the start of a promised power. Quantum computers have significantly greater capabilities than classical computers, and they have a significant edge over their traditional counterparts. The processing speed of quantum computing isn't what makes it so powerful. It's a little slow. It isn't quantum computing's memory that makes it so powerful. It's really little, only a few quantum bits in size.

The algorithms that quantum computing enables are extremely powerful because they have different complexity characteristics than their classical counterparts. Quantum computers have a lot of processing power. At the outset of quantum computing's development, two major successes were recorded: the first was due to Peter Shor's quantum algorithm, which could be used to factor enormous numbers. Shor's technique proved that a quantum computer can theoretically be used to break the security of traditional cryptosystems.

A quantum search technique invented by Lov Grover in 1996 was the second quantum computer accomplishment. When compared to the best-known classical algorithm at the time, this technique, which was meant to search for an element in a disorganized database, was shown to yield a quadratic speedup. This means that if a conventional algorithm searches for an element in an unorganized database in at most n steps, the Grover method does it in at most $\sqrt{n}$ steps [16].

Small-scale quantum computers with limited or no error correcting capabilities are currently available. They're known as Noisy Intermediate-Scale Quantum (NISQ) computers, and they are used to show some of quantum computing's limitations. They aren't even close to being full-fledged quantum computers. Because of the nature of superposition, quantum computing theoretically reduces the resource complexity of classical approaches tenfold, providing shorter runtimes on larger data sets in machine learning [16].

Efforts such as this, to construct models, training strategies, and inference schemes based on parameterized quantum circuits (PQCs) is known as Quantum Machine Learning (QML). We can also define QML as the use of quantum computing for the computation of machine learning (ML) algorithms. As QML development progresses, high-tech startups like Google, IBM, Amazon, Microsoft and other companies are struggling to be the first to build and sell the much awaited quantum machine learning systems.

Today, it is possible to apply quantum computing to practical tasks like the use of machine learning approach to classify lung cancer and pancreatic cancer. QML techniques provide a performance speedup in contrast with their conventional counterparts. This attracted special interest in the design of ML algorithms that rely considerably on quantum behavior to accelerate performance. The truth, for now, is that quantum computers are at its infancy and may not be able to do much by virtue of hardware limitations and other challenges. However, it must be noted that all state-of-the-art technology starts with this kind of preliminary, proof-of-concept demonstrations and there is certainly a chance that quantum computers and by extension-quantum machine learning may eventually become commonplace [23].

Classical machine learning sits at the intersection of artificial intelligence and statistics. It investigates and develops algorithms for finding patterns in data and making predictions based on that data. Quantum machine learning is the quantum component of conventional machine learning (QML). Quantum machine learning, or QML, uses quantum mechanical concepts and notions like superposition, entanglement, and the quantum adiabatic theorem to evaluate data and create predictions based on it. [15] posited that the chief motive behind QML is to traverse and analyze the possible advantages quantum calculations could offer to ML compared to classical ML algorithms.

1.2. Statement of the Problem

There are existing machine learning efforts to solve lung cancer problem and nib it in the bud. One solution that has not been leveraged is the use of quantum machine learning algorithm to predict the likelihood of a patient developing the disease thereby preventing it from spreading. Once a patient is aware of the possibility of him/her developing the disease in future, he/she makes decisions on lifestyle modifications which are clearly spelt out as features in the dataset.

1.3. Aim and Objectives

The aim of this work is to develop a model for predicting lung cancer disease using Variational Quantum-Classical algorithm.

The objectives of this work are:

1. Use of quantum machine learning algorithm to identify a person at risk of lung cancer and nib the deadly disease in the bud.
2. To evaluate the efficiency and accuracy of the proposed model.

1.4. Significance of the Study

More effort will be spent in the near future on getting the quantum computing environment to a more acceptable state, replete with the infrastructure and skill sets required to commercially utilise quantum computers via the cloud. In fact, certain businesses, such as healthcare, online gaming, education, financial services, insurance, transportation, energy exploration, and airplanes, are already using quantum computers to solve problems that are too hard for current systems.

2. Literature Review

A review of underlying fundamental principles of quantum computing is necessary to commence discussion on quantum machine learning. The binary digit (bit) is the fundamental unit of information in traditional information processing. The quantum bit (qubit), on the other hand, is the quantum information unit. A qubit, exists in a superposition of the two distinct states. A bit exists in either of two states: 0 or 1. Despite the fact that a qubit can be made up of a linear combination of basis states, the measurement compels the qubit to be either state 0 or state 1. We can write a qubit state as a superposition of the 0 and 1 state. The mathematical representation of a qubit, $|\psi\rangle$ (psi) is as shown in equation (1):

$$|\psi\rangle = \alpha|0\rangle + \beta\,|1\rangle = r\alpha ei\Phi\alpha|0\rangle + r\beta ei\Phi\beta|1\rangle \tag{1}$$

where α and β are complex numbers that have been appropriately normalized. As a result, given complex numbers and the normalizing requirement $\langle\psi|\psi\rangle = 1$, it is necessary that:

$$|\alpha|2 + |\beta|2 = 1 \tag{2}$$

It should be noted that α and β are probability amplitudes not probabilities. They can be positive or negative. But their squares- α^2 and β^2 represents the probabilities and their probabilities must add up to 1. As α increases, the likelihood of measuring the qubit as 0 also increases. More so, as the value of β increases, the probability or likelihood of measuring the qubit as 1 also increases. The qubit is in a state of superposition of the states $|0\rangle$ and $|1\rangle$ until we measure it. When we measure it, it will be either 0 or 1. However, if we measure 100 qubits in the same state one hundred times, we will not receive the same result. The quantum bit has two basis vectors. This is shown in equation (3):

$$|0\rangle = \begin{bmatrix}1\\0\end{bmatrix} \text{ and } |1\rangle = \begin{bmatrix}0\\1\end{bmatrix} \tag{3}$$

The quantum superposition is the addition of the two basis states as seen in equation (4).

$$|\psi\rangle = \alpha|0\rangle + \beta\,|1\rangle = \begin{bmatrix}\alpha\\\beta\end{bmatrix} \tag{4}$$

There are a few noteworthy caveats to quantum computing:

1. You must verify reversibility when transforming qubits.
2. A qubit cannot be copied in any condition.
3. A qubit's state of superposition cannot be measured without collapsing.

A qubit, on the other hand, can perform tasks that a standard bit cannot. The value of a qubit is not limited to 0 or 1. It could be a mix of the two states. You can also entangle two qubits so that they share a superposition state [12].

Now lung cancer is one of the most expensive diseases in the world, according to [22]. With a mean life expectancy of fourteen months from the momentof diagnosis, the cost of getting chemotherapy and radiation therapy is around $4000-$8000 per month. Doctors are subjected to intense daily workloads and are at danger of burnout, which can lead to mental health problems. This work analyzed the performance of 4 distinct AI models in lung nodule cancer diagnosis, with their performance compared to physicians/radiologists reading accuracy, in order to alleviate this burden.

Two seasoned physicians with over ten (10) years of expertise in the domains of pulmonary critical care and hospital medicine selected a total of 648 papers. The abbreviation for the PICO framework, which is a generally accepted standard in the research sector, is used in this method:

1. **Problem:** Lung cancer is the subject of this narrative review.
2. **Intervention:** In addition to assessing the performance of each research team's AI deep learning prototype, this review delves deeper into the artificial intelligence (AI) application.
3. **Comparison:** This evaluation compares the performance of the four research groups' standard machine learning classifiers with the deep learning ensemble convolutional neural network approach (CNN).
4. **Outcomes:** Performance of AI model outcomes is measured for each research team's model performance sensitivity, which measures how good the algorithm accurately identifies the type of lung nodule.

The algorithm's ability is measured by the model specificity to eliminate false positives, and a high specificity number indicates low rate of lung cancer misdiagnosis. In addition, the accuracy of the model in this study refers to the percentage of data that was correctly classified. The area under the curve (AUC) curve and the receiver operator characteristic (ROC) curve were used.

[2] presented a review of the Variational Quantum Classifier (VQC), a classical-quantum hybrid algorithm, and the procedures for implementing it as part of Quantum Circuit Learning. The paper showed that Quantum Circuits and output dependent functions based on parameters that are iteratively executed determines the behavior of a Variational Quantum Classifier, as opposed to classical execution that is iteratively executed to minimize the function's outcome, making it fault tolerant. Gradient descent was the traditional method of execution, which aimed to identify a function's local minima.

Differential programming is used to create Variational Algorithms and State Preparation, which turns traditional datasets into amplitude and rotations of Quantum bits that Quantum hardware can understand. The resulting quantum bits are then processed using parameterized Unitary Operations, the output of which is a classification of a piece of data that can be changed according to preset criteria.

A Quantum circuit (QC) is at the core of Quantum hardware, and it manages execution in a sequential style using Quantum Gates set in a continuous structure, according to the research. The outputs were extrapolated and manipulated using the Quantum Mechanical Phenomenon, and the state was obtained using Quantum Entanglement and Quantum Tunneling. This allows Quantum Hardware Devices to simultaneously explore various states at a fast rate. Quantum Machine Learning entails classical algorithms that, when implemented, aid in the solution of issues. This procedure makes use of Quantum Hardware, which necessitates the conversion of a classical algorithm into a Quantum intelligible format. This makes the training and testing for labeling the Iris Flower data set faster and more accurate. At the end of processing, the qubits are measured which gave classification of the Iris Flower. The entire work was divided into three stages:

State Preparation: The static state circuit converts the traditional dataset into various quantum bits understood by the quantum circuit and operated in the initial ground state to encode an initial input, x, into amplitude encoding of quantum bits. The Iris flower classification prediction was then determined by measuring the output qubits. Some of the encoding processes are as follows:

i. Basis Encoding

ii. Amplitude Encoding

iii. Products Encoding

Model Circuit: The author created criteria for parameters that will be picked up during the optimization phase and learned how to train their Variational Quantum Circuit model, which had an impact on the cost function's shape.

Measurement: The authors take the output qubits from the previous processing phases and use them to make the necessary predictions about which genus the Iris flower belongs to.

[7] proposed an end-to-end framework for executing clique problems in polynomial time, thereby solving the problem of the clique, particularly the k-clique problem, with a quantum algorithm, demonstrating that quantum algorithms are more organized in terms of computation than their classical counterparts by virtue of quantum mechanical attributes. Quantum circuit design was also proven for the k-Clique problem.

Due to the computational difficulty of this problem of the k-clique, circuit designing in a quantum environment for a variant of the k-clique problem where the answer lists all cliques of size k is substantially more challenging in practice. They use Grover's technique to solve a variant of the k-clique problem, which lists all the cliques of size k, to gain the instant advantage of tackling numerous modern-day applications such as community discovery, data mining in bioinformatics, and disease categorization. They created the circuit for a specific form of the k-clique problem to solve the engineering obstacle of implementing such a variation of the k-clique problem.

They went on to prove that the graph is substantially larger for small values of k. In terms of quantum cost per qubit and circuit depth, their method for building circuits for the k-clique problem exceed the performance of the existing state-of-the-art. They also suggested a generalized strategy for the maximum clique problem (MCP), which lists all the greatest cliques among all the cliques for a given graph, using this provided way to address the k-clique problem. Here's a rundown of their most noteworthy contributions: The researchers developed an automated end-to-end methodology for translating the clique problem to any accessible quantum computer.

1. For the first time, a quantum search method was used to implement a form of the k-clique problem.
2. As n >> k, n being a large number of nodes in a given graph and k is very small, an approach to figure out the k-clique problem that exceed the performance of the state-of-the-art approach in terms of qubit cost and circuit.
3. They also demonstrated the triangle finding issue, which is a type of k-clique problem with k = 3 to 6.
4. They also used a classical-quantum hybrid computing to solve the maximum clique problem, extending their method to addressing the k-clique problem.
5. Finally, they used a python-based programming interface called QISKit to implement the generalized algorithm on arbitrary graph instances and simulate it in the QASM simulator as well as in actual quantum devices (IBMQX architecture).

[21] studied a novel computational paradigm: a cloud, which is quantum-classical, in which quantum computers (QPUs) work side-by-side with conventional computers (CPUs) via a shared cloud architecture to x-ray the concept of variational quantum-classical algorithm. They used the benchmark to measure the dramatic reduction in latency achieved by the Rigetti Quantum Cloud Services (QCS) platform with the aid of special methods for quantum program compilation and qubit register reset.

Compilations together with qubit reset were recognized as possible impediments for cloud architecture, and they walked over particular modifications taken to decrease their contributions to Rigetti's quantum cloud platform's latency budgets. They demonstrated that colocation, active qubit reset and parametric compilation provided significant improvements over the early generation of quantum cloud offerings, but they also pointed out that these are just a handful of the many likely platform optimizations for speeding up industry progress and sanctioning quantum advantage.

The authors used pyQuil, a Python tool for developing and executing Quil programs, to implement hybrid algorithms with parametric compilation in three instances. These are the following:

1. Readout error symmetrization and mitigation, which required the use of a confusion matrix to describe measurement flaws.
2. Bell state tomography is a single-qubit gate U that can be decomposed into an Euler angle decomposition at any time.
3. The variational quantum eigensolver, which used the approaches used in the previous two examples to run a full variational algorithm using only one parametric binary.

A variational circuit was proposed by [9] to classify a data set with four attributes using a variational circuit. The operations performed in the circuit are as follows:. The four qubits in the circuit are all set to the state of $|0\rangle$. After that, the Hadamard gate was applied to each qubit separately to place them in a superposition of $|0\rangle$ and $|1\rangle$. Using a unitary square matrix built for state preparation, each qubit is subjected to a unitary operation. In this technique, traditional data (bits) are encoded into qubits. After state preparation, the variational circuit is built using multiple layers of interleaved rotational gates.

According to [8], gains in processing power and data acessibility, as well as algorithmic developments, have resulted in good results for ML techniques in data generation, regression, classification and reinforcement learning tasks. The emphasis was on demonstrating the limitations of quantum algorithms and how they can be contrasted with their best classical equivalents, and why quantum resources are anticipated to benefit learning challenges. Both learning in the midst of noise and other computationally demanding machine learning problems have been recommended as research topics.

Train PQC models for the diffusion and oracle operators in Grover's technique [20]. Grover's technique can identify new enhanced operators for the special scenario of three and four qubits, according to the authors, who also note that it is optimal up to a constant. To solve Simon's hidden subgroup problem, [24] build a PQC model (1997). In their simulations, they got the original Simon's algorithm with the same results. [5] used well-known approaches to convert integer factoring to an Ising Hamiltonian, then train a parameterized Quantum circuit (PQC) model to find the ground state, which leads to factor discovery. [10] created circuits that can run the SWAP test and find solutions with less components.

According to the work of [18], titled An Efficient Cancer Disease Prediction System through Quantum Computing Technique; the majority of malignancies are caused by uncontrolled cell proliferation. Tobacco, user food, alcohol, some illnesses, radiation, inadequate physical activity, environmental contaminants, and a combination of genes leading to malignant mutations are some of the causes of cancer. Hierarchical Clustering Explorer (HCE) is the method used here. HCE is a visualization tool for exploring and studying multi-attribute datasets interactively. Users can put their own datasets into the program and study them using various visualization and statistical tools. An overview of data is displayed in the form of a color mosaic, allowing the authors to drill down into the data and manipulate multiple views as needed. Clustering results were displayed in a dendrogram form in the form of a color mosaic view.

Hybrid systems centered on PQC offer a foundation for gradual algorithm evolution. In the not too distant future, however, hybrid algorithms will depend heavily on traditional resources and infrastructures. As quantum technology improves, traditional resources will be increasingly supplanted by quantum resources and general approaches. [25] present an interpolation approach between near-term VQE and long-term quantum phase estimation. In a similar vein [19], non-destructive SWAP and Hadamard tests could eventually replace destructive SWAP and Hadamard testing. Hardware-efficient circuits will be replaced with new parameterizations based on tensor network theory. These higher-level structures will be able to be implemented on existing hardware thanks to quantum compilers [11, 14].

There are existing machine learning efforts to solve lung cancer problem and nib it in the bud. One common denominator in the forgoing literatures is the fact that quantum machine learning effort has not been used. We intend to leverage this gap to predict the likelihood of a patient developing the disease thereby preventing it from spreading. Once a patient is aware of the possibility of him/her developing the disease in future, he/she makes decisions on lifestyle modifications and early and committed treatment of chronic diseases, some of which are clearly spelt out as features in the dataset.

3. Materials and Methods

Our study focused majorly on, but is not limited to the years 2017 to 2021, when quantum machine learning was at its apex. This is because it marks the start of quantum devices' emergence and growth, as well as the employment of noisy intermediate-scale quantum (NISQ) devices. Our goal is to come up with a model for predicting lung cancer using variational quantum classical algorithm. The methodology adopted is the Cross Industry Standard for Data Mining (CRISP-DM).

We adopted the methodology by virtue of the following:

a. The CRISP-DM methodology encourages best practices.

b. It gives room for this work to be replicated.

c. It can be implemented in any data science project.

Business Understanding: Here we tried to understand the overall objectives of Quantum Computing and Quantum Machine Learning and how it can be applied to solve lung cancer problems.

Data understanding: During this phase, we try to identify the requirements relevant to the objectives. We carried out certain activities to understanding the data gaps and the relevance of the data to identify a person at risk of lung cancer and nib the deadly disease in the bud.

Data preparation: We carried out preprocessing activities which included checking for inconsistencies and discrepancies (since unclean data can disrupt the mining procedure) so as to avoid invalid outputs. The preprocessed data is a refined quality of the raw data from Kaggle. The features or variables in the dataset include: gender, age, smoking, alcohol, coughing, shortness of breath, yellow finger, swallowing difficulties, chronic disease, fatigue, allergy, wheezing, anxiety, peer pressure and chest pain.

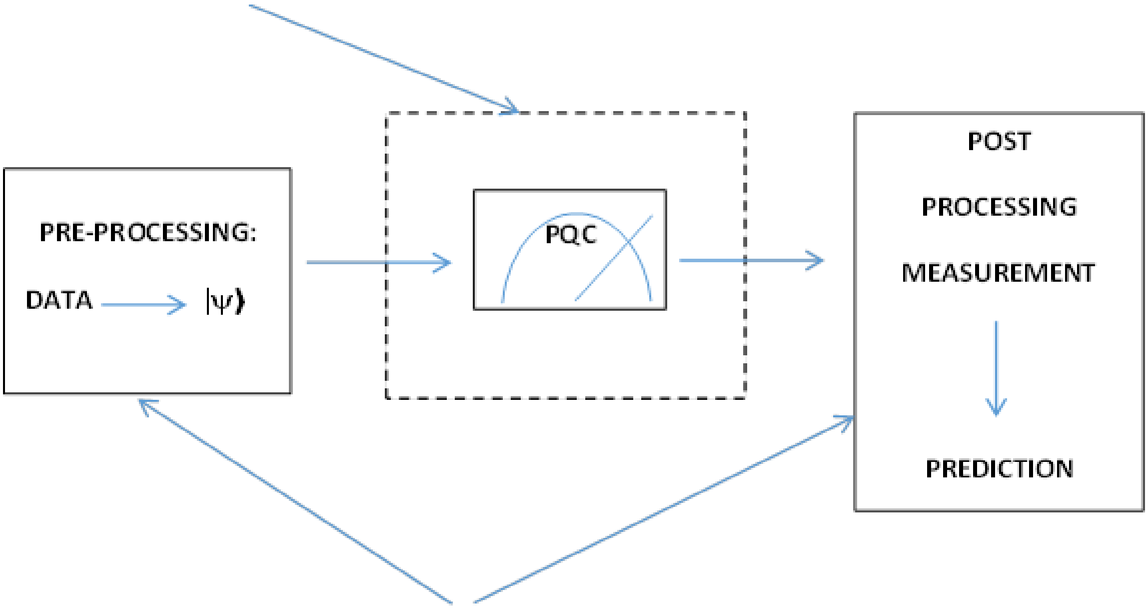
Modeling: This is where we applied the variational quantum-classical algorithm. It consists of three parts:

ii. We pre-process the data on our classical computer to determine the modifiers and create the final quantum state.

iii. We applied the modifiers in a quantum circuit to measure the qubits.

iiii. Finally, we post-process the measurement and transform it into a prediction.

Running At Quantum Computer



Running at Classical Computer

Figure 3.1 architectural design of variational quantum-classical algorithm. Source: [12]

Evaluation: Here, we focused on interpreting the mined patterns to make them understandable by way of summarization and visualization. This pattern or models are then interpreted. Jupiter notebook kited with python Qiskit will be used for coding.

4. Results and Discussion

Many quantum algorithms have been run on Near-Term Quantum Devices, which are basically Application Specific IC devices or Field Programmable Hardware. Because full-fledged Quantum Hardware is still a long way off, we won't be able to discuss Quantum Advantages until then. As a result, encoding conventional data into amplitudes of Quantum states, which can then be processed using Quantum Circuits, is the best practice or logical method to performing Quantum Algorithms.

The outside structure of this program runs on a conventional computer, while the inner component runs on a quantum computer. It's called a Variational Quantum-Classical Algorithm, and it's a favored strategy for quantum devices in the near future. A closed-loop between the classical and quantum components makes up the overall algorithm. We employ classical datasets on quantum computers in the Classical Quantum method.

Hybrid Quantum algorithms are based on the dual nature concept, which asserts that a Quantum Circuit updates the parameters according to some rule based on the outcome and performs the algorithm with the parameterized requirements, according to [17]. These circuits operate in an iterative manner, which means that after producing an output, the circuit strives to improve itself by modifying its parameters according to a set of rules.

A variational quantum-classical model based on a PQC is shown in Figure 3.1. We began by taking a data vector from the training set and applying traditional pre-processing on it. The parameters of an encoder circuit $U_{\varphi(x)}$ are transferred to the pre-processed data point (x). The model's main functionality is then implemented using a variational circuit U_{θ}. Following that, measurements are used to estimate a set of expectation values $\{(MK)_{x,\theta}\}^{k}_{k=1}$. In order to give an appropriate output for the task, we applied a post-processing function f to this set.

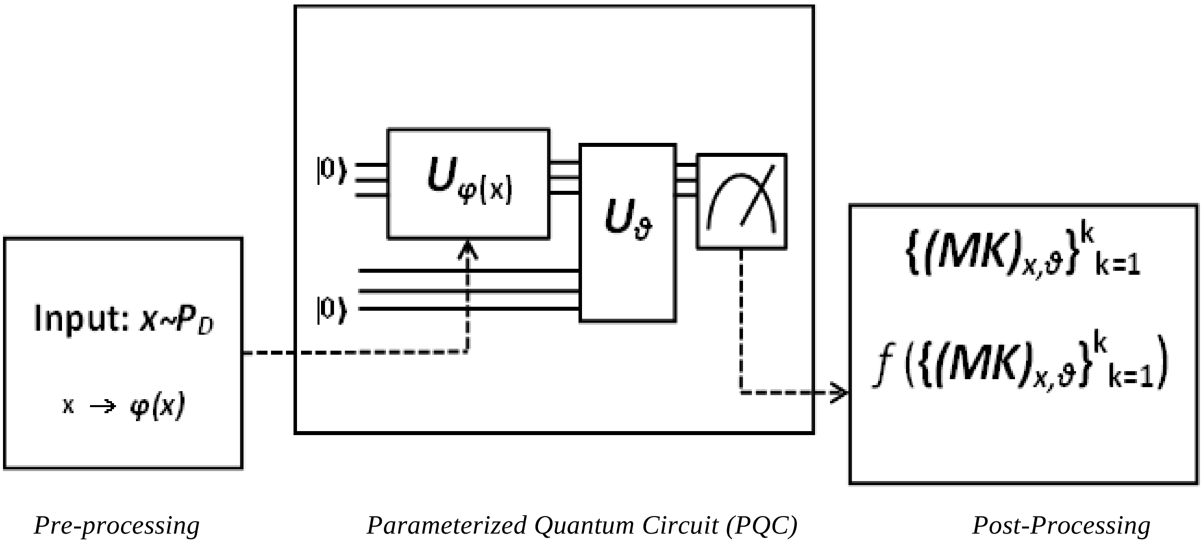


Figure 3.2 A model of Variational Quantum-Classical Algorithm. Source: [17].

We employed the kernel approach to encode the data. Kernel methods are a well-refined field with the purpose of embedding data into a higher-dimensional feature space where a specific problem can be solved more easily. Nonlinear feature maps, for example, alter the relative position of data points, making it easier to classify a dataset in the feature space. Similarly, encoding conventional data into a quantum state can be thought of as a feature map $x \rightarrow U_{\varphi(x)}|1\rangle^{\otimes n}$ to the high-dimensional vector space of n qubit states. Here, φ which turns the data vector into circuit parameters, is a user-defined preprocessing function.

The main goal of a variational quantum-classical model is to show that the Noisy Intermediate Scale Quantum (NISQ) devices have a quantum super-advantage. Computational load is split between a classical computing unit and a quantum processing unit in this model. In most cases, the classical-quantum paradigm is used to solve optimization problems.

Quantum mechanical systems can also benefit from PQC models. A classical model cannot learn to recreate the statistics of quantum supremacy systems unless it uses exponentially growing resources. PQC models will provide a distinct advantage over classical methods for quantum learning problems if we can quickly load or prepare quantum data in a qubit register.

4.1 Detection of Lung Cancer Using Quantum Computing

Cancer diagnosis is a difficult and time-consuming process. Traditional diagnostic approaches appear to be time consuming and inaccurate. To achieve the desired results, a more accurate, rapid, and trustworthy procedure as well as diagnostic tool is required. In this work, we utilize Python-based package called Qiskit which allowed us to create quantum circuits and run them on hardware or simulators. Circuit-based platforms such as the IBM Quantum Network, Rigetti, and IonQ run Qiskit.

We started by performing data cleaning on the lung cancer dataset to ensure that it is fit for the mining process. We applied the variational quantum-classical algorithm to extract data patterns. This consists of three steps:

i. We pre-process the data on our classical computer to determine the modifiers and create the final quantum state.

ii. We applied the modifiers in a quantum circuit to measure the qubits.

iii. Finally, we post-process the measurement and transform into a prediction.

The final quantum state was created using the pre-processing. There are fifteen different aspects in the lung cancer dataset. All features were converted to numbers between 0 and 1. Here, we pre-process our lung cancer data so that it may be processed by a quantum computer. The preprocessing objective is to convert these fifteen numbers into a quantum state vector with a probability that corresponds to the patient's actual chance of getting cancer.

The PQC is then wrapped in a traditional pre- and post-processing process. The PQC is a quantum circuit that accepts all of the information it requires as input parameters. As a result, its name has been parameterized. Based on these parameters, it estimates the thing's label. The outside structure of this program runs on a conventional computer, while the inner component runs on a quantum computer. It's called a Variational Quantum-Classical Algorithm, and it's a favored strategy for quantum devices in the near future. As a result, our post-processing consists solely of changing the output format and entails converting the quantum circuit's output into a usable prediction.

5. Conclusion

In this era of Noisy Intermediate-Scale Quantum (NISQ), a Variational Quantum Classifier (VQC), a combination of Quantum and Classical algorithms, is capable of handling issues that are well beyond the capabilities of ordinary computers. However, one potential drawback is that as circuits become more expressive, the optimization environment may become more difficult to explore. At this point, it should be emphasized that real-world datasets of sufficient size could provide answers to these issues and should thus be prioritized. However, in some third-world nations, obtaining datasets of this nature is difficult due to data that has not been properly curated.

Our research delves into the basics of quantum computing and quantum machine learning in a fascinating way. We investigated a hybrid quantum-classical algorithm, primarily the Variational Quantum Classifier (VQC), and the steps required to implement it as part of Quantum Circuit Learning. This research will serve as a foundation for future research in the fields of Quantum Computing and Quantum Machine Learning. To get a prediction of lung cancer sickness, we really assessed the Qubits received from prior processes. This is a hybrid algorithm that combines quantum hardware with traditional machine learning algorithms. As a result of the above, it's easy to deduce that my team and I were able to implement classical Machine Learning that can be interpreted by quantum hardware.

We conclude that it is high time we embrace a new paradigm (such as quantum machine learning) to solve problems like predicting lung cancer and carving a niche for the field of medicine, quantum computing and machine learning.

Conflicts of Interest: The authors declare no conflict of interest.

References

[1] Aaronson S. (2015). Read the fine print. *Nat. Phys.* 11, 291–293 DOI 10.1038/nphys3272.

[2] Amogh A., Dhruv S., Pratyanush G., & Madhavi R. (2020). A Review of Supervised Variational Quantum Classifiers. *International Journal of Engineering Research & Technology (IJERT) 9(4), 574-576.*

[3] Amoldeep S., Kapal D., Harun S., Hem D., Maurizio M. (2021). Quantum Internet- Applications, Functionalities, Enabling Technologies, Challenges, and Research Directions

[4] Ananya, M., Bernard R., Audrey B., Stephen P., Laura M. (2021). Can we screen for pancreatic cancer? Identifying a sub-population of patients at high risk of subsequent diagnosis

[5] Anschuetz E, Olson J, Aspuru-Guzik A & Cao Y (2019). Variational quantum factoring *International Workshop on Quantum Technology and Optimization Problems* (Berlin: Springer) pp 74–85

[6] Arpita S., Amit S.,Debasri S., Banani S., Amlan C. (2021). Circuit Design for Clique Problem and its Implementation on Quantum Computer, *ResearchGate.*

[7] Basaky F., Oladipe E., Adebayo P., Hussein U., Sani G. et al. (2021). Artificial Intelligence and Robotics: A Cloud Based Secured Surveillance System and Reduced Human Influence, *American Journal of Computer Sciences and Applications* 29(02)

[8] Carlo C., Mark H., Alessandro D., Massimiliano P., Andrea R., Simone S. and Leonard W. (2018) Quantum machine learning: a classical perspective. https://doi.org/10.1098/rspa.2017.0551 (Accessed 10th January, 2022).

[9] Chalumuri A., Kune R., Manoj B. (2021). A hybrid classical-quantum approach for multi-class classification, Quantum Information Processing 20(3) doi:10.1007/s11128-021-03029-9.

[10] Cincio L, Subaşı Y, Sornborger A. & Coles P J (2018). Learning the quantum algorithm for state overlap *New J. Phys*. 20 113022

[11] Cowtan A., Dilkes S., Duncan R., Krajenbrink A., Simmons W., Sivarajah S. (2019). On the qubit routing problem *arXiv*:1902.08091

[12] Frank Z. (2021). Hands-on Quantum Machine Learning with Python.

[13] Huang H., Wu D., Fan D., et al. (2020). Superconducting quantum computing: a review. Sci China Inf Sci, 63(8): 180501, https://doi.org/10.1007/s11432-020-2881-9.

[14] Iten R., Reardon-Smith O., Mondada L., Redmond E., Kohli R., Colbeck R. (2019). Introduction to universal qcompiler *arXiv:*1904.

[15] Kashif M., Al-Kuwari S. (2021). Design Space Exploration of Hybrid Quantum–Classical Neural Networks. Electronics, 10, 2980. https://doi.org/10.3390/electronics10232980 (Accessed 20th January, 2020)

[16] Kok D. (2021). Building a quantum kNN classifier with Qiskit: theoretical gains put to practice.

[17] Marcello B., Erika L., Stefan S., Mattia F. (2019). Parameterized quantum circuits as machine learning models. *Quantum Science and Technology. 4 043001.* https://doi.org/10.1088/2058-9565/ab5944.

[18] Milan J., & Setu K. (2013). An Efficient Cancer Disease Prediction System through Quantum Computing Technique, *International Journal of Computer Applications 81(3).*

[19] Mitarai K. & Fujii K. (2019). Methodology for replacing indirect measurements with direct measurements *Phys. Rev. Res*. 1 013006

[20] Morales M., Tlyachev T & Biamonte J (2018). Variational learning of grover's quantum search algorithm *Phys. Rev*. A 98 062333

[21] Peter W. Shor. (1997). Polynomial-time algorithms for prime factorization and discrete logarithms on a quantum computer. *SIAM Journal on Computing*, 26(5):1484 1509.

[22] Sathyakumar K., Munoz M., Singh J, et al. (2020). Automated Lung Cancer Detection Using Artificial Intelligence (AI) Deep Convolutional Neural Networks: A Narrative Literature Review. Cureus 12(8): e10017. DOI 10.7759/cureus.10017. *Springer Nature Singapore Pte Ltd.* techniques. *Journal of Software Engineering and Applications* 69–77 (2014).

[23] Stephens R. (2019). Essential Algorithms, A practical Approach to Computer Algorithms using Python and C#. *Indianapolis: John Wiley and Sons, Inc.(Pp 572).*

[24] Wan K., Liu F., Dahlsten O. & Kim M. (2018). Learning simonas quantum algorithm *arXiv*:1806.10448

[25] Wang D., Higgott O. and Brierley S. (2019). Accelerated variational quantum eigensolver *Phys.Rev.* Lett. 122 140504