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Title:

Leveraging Quantum Computing to Revolutionize Deep Learning: A Focus on Hybrid Algorithms for Medical Image Classification

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Dedication

I dedicate this achievement to you as a token of my deepest gratitude for the countless sacrifices you made to help me pursue my dreams.
At this meaningful moment, I find myself filled with sincere appreciation for each and every one of you who contributed to my academic journey.
These past years have been marked by challenges and accomplishments, but also by moments of laughter, encouragement, and shared growth.
Thank you for every effort, every word of motivation, and for standing by me through both triumphs and trials.
I hope you will continue to share in the successes and joyful moments yet to come. I am proud to call you my friends, and I am truly grateful to you from the bottom of my heart.
To my esteemed professors, whose knowledge and guidance played a vital role in the completion of this project—I dedicate this work to you as a sincere expression of my appreciation for the wisdom and experience you generously shared. *To my dear parents, who never spared any effort or support—your unwavering presence has always been my source of strength and inspiration.*
I dedicate this achievement to you as a token of my deepest gratitude for the countless sacrifices you made to help me pursue my dreams.
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Abstract

This thesis investigates the amalgamation of quantum computing and deep learning to mitigate computational constraints in image classification tasks. As deep learning models get more complicated, classical computing methods have a lot of problems with resources, energy use, and scalability. Quantum computing, with its built-in parallelism and ability to solve problems in more than one dimension, could help get around these problems. This study concentrates on the advancement of hybrid quantum-classical algorithms capable of functioning efficiently within the limitations of contemporary Noisy Intermediate-Scale Quantum (NISQ) devices while improving the precision and efficacy of image classification tasks. The goal of the work is to close the gap between the theoretical benefits of quantum computing and

the real-world problems that come up when using it in machine learning.

Quantum Learning (QL) has developed as a promising method for classifying medical images by using quantum mechanics to make machine learning algorithms work better and faster. This systematic review offers an extensive critical evaluation of the present state of QL techniques formulated for medical image classification, emphasising trends, methodologies, and prospective developments in this swiftly advancing domain. A comprehensive literature search was performed across five principal databases, yielding a total of 28 pertinent studies published between 2018 and 2024. The studies were examined and categorised according to the type of quantum algorithm, the medical imaging modality, and the performance metrics employed. The analysis identified quantum learning (QL) techniques, such as Quantum Support Vector Machines (QSVM), Quantum Convolutional Neural Networks (QCNN), and several hybrid quantum-classical methodologies. These methods have been utilised for various medical image classification tasks, including brain tumour classification, skin lesion classification, and COVID-19 detection, yielding encouraging outcomes regarding accuracy, sensitivity, and specificity. Nonetheless, various challenges were recognised, such as the preprocessing and encoding of medical images for quantum processing, the restricted scalability of existing quantum hardware, and the necessity for interpretable and explicable quantum learning models. This review highlights the significant potential of QL to transform medical image

classification while also stressing the importance of interdisciplinary collaborations and additional research to address current challenges and promote the incorporation of QL techniques into clinical practice.

General Introduction

In recent years, deep learning has revolutionized the field of image classification, particularly within medical diagnostics, where convolutional neural networks (CNNs) have achieved significant success in tasks such as tumor detection, anatomical segmentation, and disease classification. Nevertheless, these models typically demand substantial computational power, long training cycles, and extensive annotated datasets—making them challenging to deploy in constrained environments or complex medical scenarios.

Quantum computing offers a fundamentally new computational paradigm by leveraging the principles of superposition, entanglement, and quantum parallelism. Unlike classical systems, quantum computers can process high-dimensional input spaces more efficiently, making them theoretically attractive for learning tasks involving complex and high-dimensional data distributions [1, 2]. This potential has fueled the growing field of Quantum Machine Learning (QML), which aims to integrate quantum computing into classical learning pipelines to improve their expressivity, robustness, and scalability.

One of the most promising approaches in this domain is the development of hybrid quantum-classical models. These systems combine quantum variational circuits with classical neural networks to exploit the strengths of both paradigms while remaining compatible with today's Noisy Intermediate-Scale Quantum (NISQ) hardware [3]. Their application to vision-based tasks, such as medical image classification, remains an open frontier with substantial clinical relevance.

Research Problem

Despite the growing body of work on hybrid quantum-classical models, several fundamental challenges remain unresolved. Current quantum hardware faces notable limitations, including high error rates, limited qubit coherence, and restricted circuit depth. At the same time, integrating quantum circuits into classical deep learning workflows is still in its infancy, particularly in complex domains such as medical imaging.

This work seeks to address the following key research questions:

- Can hybrid quantum-classical algorithms be effectively designed to improve accuracy and efficiency in image classification tasks?
- How can these algorithms be optimized for deployment on existing NISQ hardware while maintaining clinical relevance?

These problems form the foundation for exploring whether practical quantum-enhanced learning can be achieved in real-world diagnostic systems.

Objectives

The main objectives of this thesis are as follows:

1. To establish a solid theoretical foundation in quantum computing and deep learning techniques.
2. To conduct an in-depth literature review of existing hybrid quantum-classical architectures, with a focus on variational quantum circuits (VQCs).

3. To propose and design a novel hybrid model that integrates quantum circuits into a classical image classification pipeline.

4. To implement and simulate the hybrid model using platforms such as TensorFlow Quantum and Qiskit on standard datasets (e.g., MNIST, CIFAR-10, BUSI).

5. To quantitatively compare the hybrid model's performance against classical benchmarks in terms of accuracy, efficiency, and scalability.

6. To identify future pathways for deploying such models on real quantum hardware and to propose strategies to overcome current technological barriers.

We will see in this chapters the work and the objectif about that .

Theoretical Foundations of Quantum Computing

1.1 Introduction

Quantum computing is rooted in the principles of quantum mechanics, a physical theory that describes the behavior of matter and energy at atomic and subatomic scales. The theoretical framework of quantum computing diverges fundamentally from classical computation, which is based on deterministic Boolean logic and the manipulation of binary bits. In contrast, quantum computation employs qubits—quantum bits—that can exist in linear superpositions of classical states. This superposition, along with entanglement and quantum interference, enables quantum systems to perform computations in ways that have no classical analog.[4]

The formal model of quantum computation is often described using the quantum circuit model, where quantum gates act on qubits to transform their states in accordance with unitary operations. This model is analogous to classical logic circuits but operates under the constraints and capabilities of quantum mechanics. Key gates include the Hadamard, Pauli, and controlled-NOT (CNOT) gates, which are used to construct complex quantum algorithms. [5]

Another theoretical cornerstone is quantum complexity theory, which studies the computational power of quantum machines relative to classical ones. Groundbreaking algorithms such as Shor's algorithm for integer factorization and Grover's algorithm for unstructured search demonstrated exponential and quadratic speedups, respectively, over the best-known classical counterparts (Shor, 1997; Grover, 1996)[6][7]. These results established the potential of quantum computers to solve specific problems more efficiently, providing a foundation for research in quantum algorithm design and quantum information theory.

Ultimately, quantum computing unites concepts from computer science, linear algebra, and quantum physics into a coherent framework that continues to evolve. As theoretical models mature, they guide the development of practical quantum algorithms and architectures tailored to the capabilities and limitations of real quantum hardware.

1.2 Classical vs Quantum Computing

The universal shift from classical to quantum computation models is one of the most significant changes that this century has undergone in matters of information, abstraction and technology. It involves a new way of thinking, far removed from the classical computer conception. It stands to generate a profound surprise in many areas of economic activity and even human imagination. From the designer's perspective, quantum algorithms can overtake classical ones for some problems. Computer scientists are being forced to draw new lines in their discipline as constraints on possible alternatives, while physicists must re-examine fundamental principles set since the inception of their science. Mathematicians need new paradigms to express problems and new logics to reason about them. Economists who shall revel in the plume of possibilities now unfold must address the very nature of information and the socio-logistical structures through which it can be processed. And most importantly, computer users, from those pondering commercial deals at the top of the economic ladder to those wondering about horoscopes at its bottom, find themselves on a rocky precipice needing new means of estimating the chances and pitfalls of computational endeavors.[8]

Most discussions surrounding quantum computation and algorithms assume some level of understanding of the underlying workings of quantum computers. However a clear, detailed and intuitive exposition of the basic principles at the foundation of quantum computing is not readily available to the average (computer) scientist. A necessary prerequisite is in knowing how these principles offer features and modalities distinct to classical computing. It can then be readily grasped and appreciated their ongoing ramifications, such as those in relation to quantum algorithms devised to leverage these properties, quantum game theory and possible future applications.[9]

1.3 Quantum Mechanics and Computation

The theoretical foundations of quantum computing rest on the principles of quantum mechanics, first articulated by pioneers such as Schrödinger, Heisenberg, and Dirac in the early 20th century. The application of these principles to computation was first envisioned by Richard Feynman in 1982, who proposed that quantum systems could be used to simulate other quantum systems more efficiently than classical computers.

1.3.1 Quantum Superposition and Entanglement

1.Qubit and Superposition

A qubit, or quantum bit, is the fundamental unit of quantum information. Unlike a classical bit, which can take on the discrete values 0 or 1, a qubit exists in a quantum state that can be a linear combination—or superposition—of both states simultaneously. Mathematically, the state of a single qubit can be expressed as:

$$\psi\rangle = \alpha|0\rangle + \beta|1\rangle \tag{1.1}$$

where $|0\rangle$ and $|1\rangle$ are the computational basis states, and $\alpha, \beta \in C$ are complex probability amplitudes satisfying the normalization condition [10]

$$|\alpha|^2 + |\beta|^2 = 1 \tag{1.2}$$

The principle of superposition allows quantum systems to represent and process multiple possibilities at once. When a qubit is in a superposition, it does not have a definite state until it is measured. Upon measurement, the qubit collapses probabilistically to one of the basis states $|0\rangle$ or $|1\rangle$, with probabilities $|\alpha|^2$ and $|\beta|^2$, respectively.

This property is central to the potential power of In a system of n qubits, the state space has 2^n dimensions.

basis states, enabling quantum computers to explore vast solution spaces in parallel. This exponential state space, combined with quantum entanglement and interference, forms the core of many quantum algorithms' advantages over classical counterparts. [5]

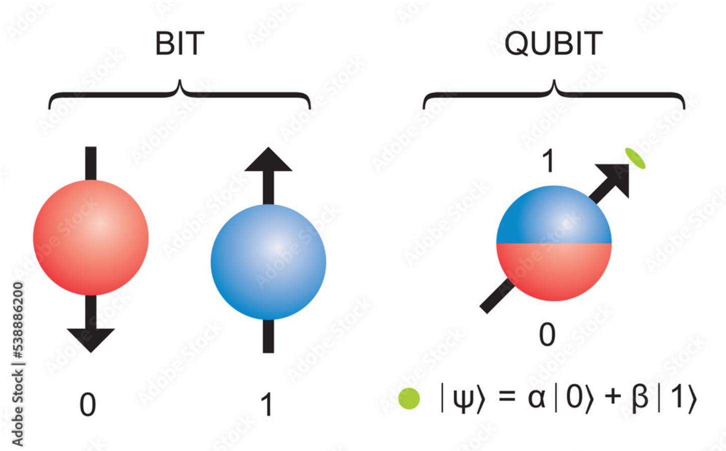

Figure 1.1: bit to qubit

2. Quantum Entanglement

Quantum entanglement is a fundamental phenomenon in quantum mechanics where the states of two or more particles become correlated in such a way that the state of each particle cannot be described independently of the state of the others, even when the particles are separated by large distances. This non-classical correlation defies the principles of local realism and has been experimentally validated through violations of Bell's inequalities. [11]

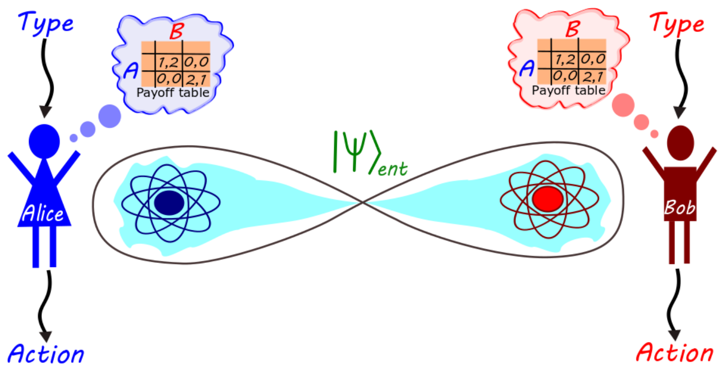

Figure 1.2: quantum entanglement for 2 qubit

In an entangled system, the measurement of one qubit instantaneously affects the state of its entangled partner, a feature that Einstein famously referred to as "spooky action at a distance." A common example is the Bell state:

$$|\Phi^+\rangle = \frac{1}{\sqrt{2}}(|00\rangle + |11\rangle) \tag{1.3}$$

This two-qubit state exhibits maximal entanglement, meaning that measurement outcomes on either qubit are perfectly correlated. Entanglement plays a crucial role in quantum information theory, enabling powerful protocols such as quantum teleportation, superdense coding, and entanglement-based quantum key distribution. [12]

Moreover, entanglement is considered a vital resource for quantum computation and quantum communication. It provides quantum systems with a computational advantage over classical counterparts by allowing for the creation of nonlocal correlations that classical systems cannot replicate.[13]

3.Quantum Measurement

In quantum mechanics, measurement is a non-trivial process that collapses a quantum system's state into one of the eigenstates of the measurement operator. A qubit, for example, may exist in a superposition:

$$|\psi\rangle = \alpha|0\rangle + \beta|1\rangle \tag{1.4}$$

Prior to measurement, the qubit does not have a definite value; instead, it is described by the probability amplitudes $\{|0\rangle, |1\rangle\}$. Upon measurement, the qubit collapses to:

- $|0\rangle$ with probability $|\alpha|^2$.
- $|1\rangle$ with probability $|\beta|^2$.

This collapse is inherently probabilistic and irreversible. The measurement not only retrieves information from the quantum system but also alters it—a phenomenon with no classical equivalent. This behavior is formalized in the Born rule, which links quantum states to measurement outcomes. [10]

Measurement is central to quantum computing, as it is the final step in most quantum algorithms and determines the classical output of quantum processes.

4.Quantum Gates and Circuits

Quantum gates are the quantum analogues of classical logic gates and serve as the fundamental units of quantum computation. Mathematically, they are represented by unitary matrices, meaning they preserve the norm of quantum states and are thus reversible. These gates operate on qubits, which unlike classical bits can exist in a superposition of basis states. The action of a quantum gate transforms the state vector of a qubit (or qubits) through matrix multiplication. [4]

a.quantum gates include

• Pauli gates (X, Y, Z): Perform rotations around different axes of the Bloch sphere.Acts like a classical NOT gate: it flips $|0\rangle$ to $|1\rangle$ and vice versa.

• Hadamard gate (H):Creates superposition: it maps $|0\rangle$ to $\frac{1}{\sqrt{2}}(|0\rangle + |1\rangle)$.

• CNOT gate(Controlled-NOT) flips the second qubit if the first qubit is $|1\rangle$,creates entanglement between qubits.

- Rotation gates (RX, RY, RZ): parameterised rotations used in variational algorithms.

Operator	Gate(s)	Matrix
Pauli-X (X)	$\boxed{X}$	$\begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix}$
Pauli-Y (Y)	$\boxed{Y}$	$\begin{bmatrix} 0 & -i \\ i & 0 \end{bmatrix}$
Pauli-Z (Z)	$\boxed{Z}$	$\begin{bmatrix} 1 & 0 \\ 0 & -1 \end{bmatrix}$
Hadamard (H)	$\boxed{H}$	$\frac{1}{\sqrt{2}}\begin{bmatrix} 1 & 1 \\ 1 & -1 \end{bmatrix}$
Phase (S, P)	$\boxed{S}$	$\begin{bmatrix} 1 & 0 \\ 0 & i \end{bmatrix}$
$\pi/8$ (T)	$\boxed{T}$	$\begin{bmatrix} 1 & 0 \\ 0 & e^{i\pi/4} \end{bmatrix}$
Controlled Not (CNOT, CX)		$\begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 \\ 0 & 0 & 1 & 0 \end{bmatrix}$
Controlled Z (CZ)	$\boxed{Z}$	$\begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & -1 \end{bmatrix}$
SWAP		$\begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}$
Toffoli (CCNOT, CCX, TOFF)		$\begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \end{bmatrix}$

Figure 1.3: Quantum logical gates.

b.A quantum circui

is a sequence of quantum gates applied to a register of qubits. The circuit evolves the quantum state through multiple gate layers. The process includes:

1.Initialization Set all qubits to a known state, usually $|0\rangle$.

2.Gate Application Apply a designed sequence of quantum gates to perform a computation or algorithm.

3.Measurement Collapse the quantum state to classical output values by measuring qubits in the computational basis.

4.Universal Gate Sets

A universal gate set is a collection of gates from which any quantum algorithm can be constructed. A typical universal set includes:

All single-qubit rotation gates (e.g., R_x, R_y, R_z).

One entangling two-qubit gate (e.g., CNOT).

Barenco et al. (1995) showed that such a set can approximate any unitary transformation on any number of qubits, which is foundational for quantum algorithm design.[14]

1.4 NISQ Devices: Noisy Intermediate-Scale Quantum Computing

The term Noisy Intermediate-Scale Quantum (NISQ) was introduced by John Preskill (2018)[15] to characterize the current stage of quantum computing hardware development. NISQ devices typically contain 50 to a few hundred qubits, which are not yet error-corrected, and are subject to significant noise due to decoherence, imperfect gate operations, and readout errors. These devices lie between small quantum prototypes and future fault-tolerant quantum computers.

1.4.1 Key Characteristics of NISQ Devices

1.Intermediate Scale

NISQ systems operate with tens to hundreds of qubits. While this scale is insufficient for fully error-corrected quantum computation, it allows for the exploration of complex quantum algorithms that are beyond the reach of classical simulations.

2.Noise and Decoherence

Qubits in NISQ devices are subject to environmental interactions that lead to decoherence. Gate operations are imperfect, and measurements are noisy. As a result, quantum computations must be completed before decoherence becomes significant, and algorithm design must account for this constraint.

3.Lack of Full Error Correction

NISQ devices cannot yet support quantum error correction at scale due to resource limitations. Quantum error correction requires encoding logical qubits into many physical qubits, which is currently infeasible on NISQ hardware.

4.Variational Algorithms for NISQ

To work within these limitations, researchers have developed variational quantum algorithms (VQAs) that rely on shallow circuits and classical optimization. Key examples include:

5.Variational Quantum Eigensolver (VQE) for quantum chemistry and optimization problems.

6.Quantum Approximate Optimization Algorithm (QAOA) for solving combinatorial optimization tasks. These algorithms are hybrid in nature, combining quantum circuit evaluation with classical feedback loops.

7.Quantum Advantage Potential

While general-purpose quantum computing is not yet achievable, NISQ devices may demonstrate quantum advantage in specialized domains, such as quantum simulation of many-body systems, approximate optimization, or even machine learning tasks, where classical resources scale poorly.

1.4.2 Hardware Architectures of NISQ Devices

The hardware architecture of NISQ (Noisy Intermediate-Scale Quantum) devices is foundational to understanding their capabilities and limitations. NISQ-era quantum computers aim to scale up to hundreds of qubits, but are still constrained by noise, decoherence, and limited connectivity. These architectures must balance qubit fidelity, coherence time, gate implementation efficiency, and system scalability.

1. Superconducting Qubits

One of the most mature and widely adopted technologies in NISQ hardware is based on superconducting circuits, particularly transmon qubits. These are fabricated using Josephson junctions and operate at millikelvin temperatures in dilution refrigerators.

Examples: IBM Quantum (e.g., IBM Eagle), Google Sycamore, Rigetti Aspen.

2.Trapped Ion Qubits

Trapped ions encode qubits in the electronic states of ions held in electromagnetic fields. Quantum gates are implemented using laser pulses.

Examples: IonQ, Honeywell Quantum, Alpine Quantum Technologies (AQT).

3. Spin Qubits in Quantum Dots

Spin-based qubits use the spin states of electrons or holes in semiconductor quantum dots.

Examples: Intel, QuTech (Delft), University of New South Wales.

4. Neutral Atom Qubits

Neutral atoms are held in place by optical tweezers and manipulated using Rydberg interactions.

Examples: QuEra, ColdQuanta, PASQAL

5. Photonic Qubits Photon-based qubits use polarization or path encoding of photons for quantum information.

Examples: Xanadu (Canada), PsiQuantum

1.5 Fundamental Quantum Algorithms

Quantum computing has introduced a new paradigm in algorithm design, offering the potential to solve certain computational problems with a significant advantage over classical approaches. Fundamental quantum algorithms exploit the unique principles of quantum mechanics—namely **superposition, entanglement, and quantum interference**—to achieve either polynomial or exponential speedups for specific tasks. These algorithms are not only theoretical milestones but also serve as essential building blocks for quantum software in the noisy intermediate-scale quantum (NISQ) era and beyond.

The first breakthrough came with the **Deutsch–Jozsa algorithm**, which demonstrated how a quantum computer could distinguish between constant and balanced Boolean functions using a single query, as opposed to the exponentially growing number required by classical algorithms. This was soon followed by **Shor's algorithm**, which provided an exponential speedup for factoring large integers—an achievement with profound implications for cryptography (Shor, 1994). In parallel, **Grover's algorithm** offered a quadratic speedup for unstructured search problems, enabling a marked reduction in the number of queries needed to find a target element in a dataset (Grover, 1996).[7][6]

Beyond these canonical examples, quantum algorithm development has expanded to include **Quantum Phase Estimation (QPE)**, a key component in many quantum simulations and eigenvalue problems, and hybrid algorithms such as the **Variational Quantum Eigensolver (VQE)** and **Quantum Approximate Optimization Algorithm (QAOA)**. These are designed specifically for NISQ devices, optimizing shallow quantum circuits in tandem with classical routines.

Quantum algorithms are increasingly being explored for a wide range of applications, including chemistry, machine learning, optimization, and materials science. While a general-purpose quantum advantage has not yet been universally established, the demonstrated efficiency of these foundational algorithms strongly suggests that quantum computing holds transformative potential for solving problems that are currently intractable for classical machines. [16]

1.5.1 Shor's Algorithm

Shor's Algorithm, proposed by Peter Shor in 1994, is one of the most celebrated quantum algorithms due to its ability to factor large integers exponentially faster than the best-known classical algorithms. This breakthrough demonstrated, for the first time, a clear quantum advantage in solving a problem of major practical and theoretical importance—specifically, one that underpins the security of widely used cryptographic protocols such as RSA.

1. Problem Addressed

The algorithm addresses the integer factorization problem: given a composite number N, find its non-trivial prime factors. Classically, this problem is believed to require super-polynomial time for large N, with the best algorithms (like the General Number Field Sieve) operating in subexponential time.

2. Quantum Advantage

Shor's algorithm factors integers in polynomial time, specifically in$O((\log N)^3)$, which constitutes an exponential speedup over classical approaches. The algorithm also solves the discrete logarithm problem in similar time complexity.

3. How It Works (Overview)

The algorithm reduces the problem of factoring to order-finding, which is then solved efficiently using a quantum subroutine:

1.Choose a random integer $a < N$ that is coprime with N.

2.Define a periodic function $f(x) = a^x \bmod N$.

3.Use Quantum Phase Estimation and the Quantum Fourier Transform (QFT) to find the period r of this function.

4.If r is even and $a^{r/2} \not\equiv -1 \bmod N$, then compute: $\gcd(a^{r/2} \pm 1, N)$ to obtain non-trivial factors of N.

The classical post-processing steps are simple, but the quantum subroutine that performs period finding is the key to the algorithm's power.

4. Impact and Applications

Shor's algorithm has major implications for cryptography, especially RSA, Diffie–Hellman, and elliptic curve cryptography (ECC), all of which rely on the classical hardness of factoring and discrete logarithms. A scalable, fault-tolerant quantum computer running Shor's algorithm could render many current cryptographic systems insecure, motivating the development of post-quantum cryptography.

5. Limitations Shor's algorithm requires a large number of coherent, error-corrected qubits, which current NISQ devices do not yet support.

Practical implementation on real quantum hardware remains a significant engineering challenge, though small-scale demonstrations (e.g., factoring 15 or 21) have been successfully conducted. [17]

1.5.2 Grover's Algorithm

Grover's Algorithm, developed by Lov Grover in 1996, is a fundamental quantum search algorithm that provides a quadratic speedup over classical methods for searching an unstructured database or solving a black-box function inversion problem. It is particularly notable because it demonstrates quantum advantage for a broad class of problems, even when the underlying function has no apparent algebraic structure.

1. Problem Addressed:

Grover's algorithm solves the following problem:
Given a function $f : \{0,1\}^n \to \{0,1\}$, where $f(x) = 1$ for a single unknown input $x = x^*$, and $f(x) = 0$ otherwise, the goal is to find x^* with high probability.
Classically, this problem requires $O(N)$ evaluations in the worst case, where $N = 2^n$. Grover's algorithm finds the solution in $O(\sqrt{N})$ steps, offering a quadratic speedup.

2. How It Works

Grover's algorithm begins with a uniform superposition over all possible inputs and then repeatedly applies the Grover iteration, which consists of two main operations:

Oracle O_f: A quantum subroutine that flips the sign of the amplitude of the solution state $|x^*\rangle$. The oracle acts as follows:

$$O_f\,|x\rangle = (-1)^{f(x)}\,|x\rangle$$

Diffusion Operator (or Inversion About the Mean): Amplifies the probability amplitude of the solution state by reflecting all amplitudes about their average.
After $O(\sqrt{N})$ iterations, the probability of measuring the correct result x^* approaches 1.

3. Applications

Grover's algorithm is applicable to a wide range of problems, including:

- Unstructured database search
- Inverting cryptographic hash functions
- Solving NP-complete problems in quadratically fewer steps (e.g., SAT, 3-SAT, clique detection)
- Estimating medians and finding minima

Though it does not offer exponential speedup like Shor's algorithm, Grover's quadratic advantage is significant in practice, especially for large datasets. [7]

1.6 conclution

The theoretical foundations of quantum computing offer a profound shift from classical computation by leveraging quantum principles such as superposition, entanglement, and unitary evolution. These concepts enable powerful models like qubits, quantum gates, and circuits that underlie algorithms with proven quantum speedups, such as Shor's and Grover's. While current implementations face practical challenges like noise and scalability, these foundational theories continue to guide the development of future quantum technologies with the potential to revolutionize fields like cryptography, optimization, and simulation.

Theoretical Foundations of Deep Learning

2.1 Introduction

In the realm of data science, deep learning has emerged as a transformative paradigm, fundamentally altering how complex and high-dimensional data are analyzed and interpreted. Unlike traditional machine learning approaches that rely heavily on manual feature engineering and struggle with scalability, deep learning models automatically learn hierarchical representations of data through multi-layered neural network architectures. This capability has led to significant performance advancements across a broad spectrum of tasks in computer vision, natural language processing, speech recognition, and beyond.

At the foundation of deep learning lie artificial neural networks—computational structures inspired by the interconnectivity of biological neurons in the human brain. Architectures such as Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and more recently, Transformers, have demonstrated exceptional versatility in processing diverse data modalities.

CNNs have revolutionized computer vision by leveraging spatial hierarchies in visual data, enabling high accuracy in image classification, object detection, and segmentation tasks. In contrast, RNNs are specifically designed for modeling temporal and sequential dependencies, making them well-suited for applications such as language modeling, speech recognition, and time-series analysis. Transformers, which utilize attention mechanisms rather than recurrence, have further advanced the field by offering superior scalability and performance in sequence modeling, especially in natural language understanding.

Together, these architectures illustrate the profound impact of deep learning in enabling systems to extract complex patterns from data, making it an indispensable tool in modern artificial intelligence.
[18, 19]

Additionally, we conduct a comparative analysis to evaluate the performance of deep learning models against traditional machine learning methods, providing insights into their efficacy and potential limitations. Through this comprehensive exploration, we aim to elucidate the significance of deep learning in data science and pave the way for further advancements in this rapidly evolving field. [20]

2.2 Principles of Deep Learning

Deep learning is founded on core principles that enable it to model complex, high-dimensional data. One key principle is representation learning, where deep neural networks automatically learn features from raw input across multiple layers of abstraction, reducing the need for manual feature engineering [21]. These models typically follow a hierarchical architecture, enabling them to progressively extract low-level to high-level patterns.

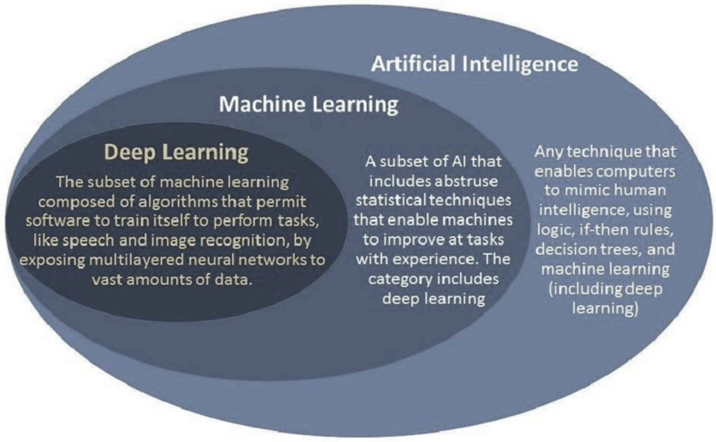

Figure 2.1: The relation between artificial intelligence, machine learning, and deep learning

Another core principle is end-to-end learning, which allows the entire model—from input to output—to be trained jointly for optimal performance. The backpropagation algorithm, combined with optimizers like Adam or RMSProp, enables effective training by minimizing loss through gradient descent. [22]

To improve generalization and mitigate overfitting, techniques such as dropout, batch normalization, and data augmentation are commonly used. Moreover, deep learning systems are highly data- and computation-intensive, often requiring large datasets and hardware acceleration (e.g., GPUs/TPUs) to achieve state-of-the-art results [23].

These principles make deep learning a foundational tool in modern AI applications, from image and speech recognition to medical diagnostics and quantum computing.

2.2.1 Artificial Neural Networks (ANN)

2.3 Artificial Neural Networks (ANNs)

Artificial Neural Networks (ANNs) are computational models inspired by the structure and functioning of the human brain. They serve as the foundational architecture in deep learning and are designed to recognize patterns and relationships within data. ANNs consist of layers of interconnected nodes or neurons, each of which performs a mathematical operation on its input to produce an output. These networks are particularly effective in learning complex functions through training on large datasets.

A typical ANN consists of three main types of layers:

- **Input Layer**: Receives raw data in vectorized form.
- **Hidden Layers**: Perform non-linear transformations of the input. These may include one or more layers, depending on the complexity of the task.
- **Output Layer**: Produces the final prediction or classification.

Each connection between neurons is associated with a weight, which determines the strength of influence one neuron has on another. During training, the network uses algorithms such as *backpropagation* and *gradient descent* to adjust these weights and minimize the loss function—a measure of how far the predicted output is from the actual target.

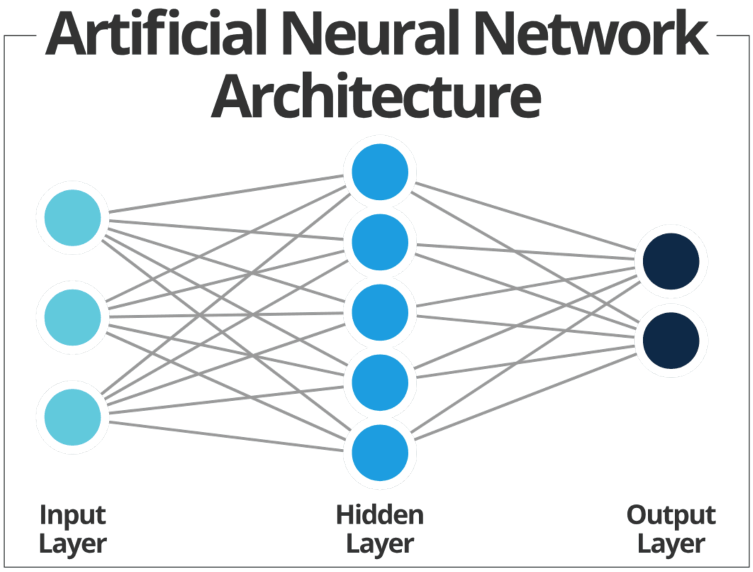

Figure 2.2: Architecture of a deep neural network.

ANNs are highly flexible and can approximate any continuous function under certain conditions, as stated by the *Universal Approximation Theorem*. Their applications span a wide range of domains, including image classification, speech recognition, natural language processing, and time-series forecasting.

Despite their strengths, traditional ANNs can be limited in depth and expressiveness. This limitation has led to the development of more advanced architectures such as **Convolutional Neural Networks (CNNs)** and **Recurrent Neural Networks (RNNs)**, which are specialized for handling spatial and sequential data, respectively.

2.4 Convolutional Neural Networks (CNNs)

Convolutional Neural Networks (CNNs) are a specialized class of deep learning models designed to process data with a grid-like structure, such as images. Inspired by the visual cortex in biological systems, CNNs are particularly effective at identifying spatial hierarchies and local patterns through the use of convolutional operations [21].

A typical CNN architecture consists of three main types of layers:

- **Convolutional Layers**: Apply learnable filters (kernels) to the input data to extract local features, producing feature maps that capture edges, textures, and shapes.
- **Pooling Layers**: Downsample the spatial dimensions to reduce computational load and mitigate overfitting, often using max or average pooling.
- **Fully Connected Layers**: Perform high-level reasoning based on the features extracted by previous layers and produce the final classification output.

The key advantages of CNNs include local receptive fields, shared weights, and spatial invariance, which make them more efficient and scalable than fully connected networks for image-related tasks. CNNs have achieved remarkable success in areas such as image classification, object detection, medical imaging, and facial recognition.

Recent developments have further improved CNN architectures by integrating mechanisms such as residual connections, attention modules, and hybrid structures that enhance depth and representation power [24].

2.5 Evolution of CNN Architectures

Over the years, several Convolutional Neural Network (CNN) architectures have been proposed to improve accuracy, efficiency, and training speed. Below are some of the most influential CNN architectures, arranged chronologically and categorized by their key innovations.

2.5.1 LeNet-5 (1998)

Purpose: Digit recognition (e.g., MNIST).
Key Features: Simple CNN with two convolutional layers followed by fully connected layers.
Impact: One of the first successful CNNs.[25].

2.5.2 AlexNet (2012)

Purpose: ImageNet classification.

Key Innovations:

- Deeper network (5 convolutional + 3 fully connected layers)
- ReLU activations
- Dropout regularization
- GPU acceleration

Impact: Revived deep learning; significantly improved ImageNet classification accuracy.[26].

2.5.3 VGGNet (2014)

Purpose: Object recognition.

Key Features:

- Small 3×3 filters
- Uniform architecture (VGG-16, VGG-19)
- Very deep networks (up to 19 layers)

Impact: Simplicity and depth; widely adopted for transfer learning. [27].

2.5.4 GoogLeNet / Inception (2014–2016)

Purpose: Reduce computation while maintaining network depth.

Key Innovations:

- Inception modules (parallel convolutions of varying sizes)
- Global average pooling
- Fewer parameters than traditional CNNs

Impact: Enabled efficient deep learning.[28].

2.5.5 ResNet (2015)

Purpose: Enable training of extremely deep networks (up to 152 layers).

Key Innovations:

- Residual connections (skip connections)

Impact: Solved vanishing gradient problem; became the new baseline for deep vision tasks.[29].

2.5.6 DenseNet (2017)

Purpose: Enhance gradient flow and parameter efficiency.

Key Innovations:

- Dense connections: each layer receives input from all previous layers

Impact: More compact and efficient than ResNet.[30].

2.5.7 EfficientNet (2019)

Purpose: Improve both accuracy and computational efficiency.

Key Innovations:

- Compound model scaling (depth, width, resolution)
- Neural architecture search (AutoML)

Impact: State-of-the-art performance with fewer parameters. [31].

2.5.8 Recent Advances (2023+)

Recent CNN research has focused on:

- Attention-enhanced CNNs
- Hybrid CNN–Transformer models
- Lightweight/mobile models (e.g., MobileNetV3, ShuffleNetV2) for edge devices[32]

2.6 Recurrent Neural Networks (RNNs)

Recurrent Neural Networks (RNNs) are a class of neural networks specifically designed to handle sequential data. By incorporating loops within their architecture, RNNs maintain information from previous time steps, enabling the learning of temporal dependencies and patterns. This makes them particularly effective for applications such as speech recognition, time-series forecasting, and natural language processing [33].

Traditional RNNs often encounter difficulties in learning long-term dependencies due to issues like vanishing or exploding gradients [34]. To overcome these limitations, advanced variants such as *Long Short-Term Memory (LSTM)* networks [35] and *Gated Recurrent Units (GRUs)* [36] have been developed. These architectures incorporate gating mechanisms to control information flow and improve memory retention over longer sequences.

Consequently, RNNs and their extensions play a critical role in modeling dynamic, context-dependent data across a wide range of modern deep learning applications.

2.7 Generative Adversarial Networks (GANs)

Generative Adversarial Networks (GANs), introduced by Goodfellow et al. in 2014 [37], are a class of generative models composed of two neural networks: a *generator* and a *discriminator*. The generator aims to synthesize data resembling the real dataset, while the discriminator attempts to distinguish between real and synthetic data. These two networks are trained simultaneously in a minimax game, where the generator learns to fool the discriminator over time.

GANs have achieved remarkable success in various applications, including realistic image generation, super-resolution, data augmentation, and style transfer [38]. Despite their success, GANs are known for their training difficulties, such as mode collapse and instability. Numerous variants have been proposed to improve performance and stability, including Deep Convolutional GANs (DCGANs), Wasserstein GANs (WGANs), and StyleGANs.

Due to their ability to model complex data distributions, GANs have become a cornerstone of modern generative modeling.

2.8 Current Challenges of Classical Deep Learning Approaches

Classical deep learning has achieved significant milestones across various fields such as computer vision, natural language processing, and speech recognition. However, these approaches face several persistent challenges that hinder broader adoption, robustness, and efficiency in practical applications.

2.8.1 Data Dependence

Deep neural networks typically require large volumes of labeled data to train effectively. In domains such as healthcare or scientific research, acquiring such datasets is often expensive, time-consuming, or infeasible [39].

2.8.2 Computational Cost

Training and deploying deep models demand high computational resources, often involving powerful GPUs or TPUs. This not only limits accessibility but also raises environmental concerns due to substantial energy consumption [40].

2.8.3 Overfitting and Generalization

Deep networks are prone to overfitting, especially when data is limited or imbalanced. Ensuring good generalization to unseen data remains a core challenge [41].

2.8.4 Lack of Explainability

Deep learning models often function as black boxes, making their decision-making process opaque. This lack of transparency can reduce trust and hinder adoption in sensitive domains such as healthcare, law, and finance [42].

2.8.5 Adversarial Vulnerability

Classical models are susceptible to adversarial attacks—minor, imperceptible perturbations to input data can lead to drastically incorrect outputs [43]. This poses serious security and safety risks in real-world applications.

2.8.6 Poor Transferability and Continual Learning

Most deep models do not adapt well to new tasks or domains without significant retraining. They often suffer from catastrophic forgetting in continual learning settings [44].

2.8.7 Limited Suitability for Quantum or Physics-Guided Data

Classical models struggle to capture quantum phenomena or physical constraints embedded in scientific data. This limits their effectiveness in domains where structural or hybrid quantum-classical models may be more appropriate [45].

2.9 Conclusion

This chapter has explored the theoretical underpinnings of deep learning, tracing the evolution from artificial neural networks (ANNs) to more advanced architectures such as Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and Generative Adversarial Networks (GANs). These models have demonstrated remarkable capabilities in learning hierarchical representations and extracting complex patterns from high-dimensional data, thereby revolutionizing fields like computer vision, natural language processing, and sequential data analysis.

We have also discussed the core principles of deep learning, including non-linearity, backpropagation, and representation learning, alongside the structural innovations that differentiate modern architectures. Additionally, key challenges of classical deep learning approaches—such as data dependence, computational cost, limited explainability, and generalization difficulties—have been critically examined, highlighting areas that require further research and optimization.

Understanding these theoretical foundations is essential for both applying deep learning effectively and for exploring next-generation paradigms such as quantum-enhanced learning. In the subsequent chapter, we will transition from classical frameworks to an overview of quantum computing principles, laying the groundwork for hybrid quantum-classical approaches that aim to address some of the limitations discussed here.

Hybrid Quantum Classical Algorithms

3.1 Introduction

The increasing complexity of visual data and the limitations of classical deep learning models have prompted the exploration of alternative computational paradigms. While Convolutional Neural Networks (CNNs) have achieved remarkable success in image classification, they remain constrained by high data requirements, computational cost, and limited generalization in low-resource scenarios. Quantum computing, with its principles of superposition and entanglement, offers new possibilities for enhancing learning efficiency and model expressiveness.

In this chapter, we propose a hybrid quantum-classical architecture that integrates Parameterized Quantum Circuits (PQCs) with classical CNN components. This integration aims to leverage the strengths of both paradigms to improve classification performance, reduce model complexity, and enable efficient learning on quantum-enhanced feature spaces.

3.2 Structure of Hybrid Quantum-Classical Algorithms

Hybrid quantum-classical algorithms are designed to combine the strengths of classical machine learning models with the emerging capabilities of quantum computing. Particularly in the Noisy Intermediate-Scale Quantum (NISQ) era, where quantum hardware is limited in scale and stability, hybrid approaches provide a practical framework for quantum machine learning (QML) [15].

The typical structure of a hybrid algorithm involves an iterative feedback loop between classical and quantum components:

- **Classical Data Preprocessing:** Raw data, such as images, is initially processed using classical techniques (e.g., normalization, feature extraction). In image classification, convolutional neural networks (CNNs) may be used to extract spatial features.
- **Quantum Encoding (Feature Mapping):** The processed data is encoded into a quantum state using methods such as angle encoding, amplitude encoding, or basis encoding [**schuld2021machine**]. This step translates classical information into a form suitable for quantum processing.

- **Parameterized Quantum Circuit (PQC):** A variational quantum circuit with trainable parameters is applied to the encoded quantum state. This circuit serves as a quantum layer that captures complex, high-dimensional patterns via entanglement and superposition [3].
- **Measurement and Classical Readout:** The quantum state is measured to obtain classical values (e.g., expectation values), which are used as inputs for the next phase of the hybrid pipeline.
- **Classical Optimization Loop:** A classical optimizer, such as gradient descent or SPSA (Simultaneous Perturbation Stochastic Approximation), is used to update the PQC parameters by minimizing a defined loss function [**mcclean2016theory**]. Gradients are estimated using techniques such as the parameter-shift rule.
- **Model Output and Decision:** The final classification decision is made, often using a classical post-processing layer (e.g., softmax) to convert the quantum outputs into prediction probabilities.

This hybrid structure enables practical use of quantum processors while offloading intensive tasks, such as training and optimization, to classical machines. It also provides a framework to explore quantum-enhanced feature representations that may offer advantages over purely classical models [46].

3.2.1 Variational quantum circuit (VQC)

A Variational Quantum Circuit (VQC) is a type of quantum algorithm used in hybrid quantum-classical machine learning frameworks, particularly effective in the Noisy Intermediate-Scale Quantum (NISQ) era. VQCs are also known as parameterized quantum circuits (PQCs), as they include tunable parameters that can be optimized using classical optimization routines.

The key idea behind a VQC is to construct a quantum circuit whose structure is fixed but whose gate parameters can be adjusted to minimize a loss function, similar to how weights are trained in classical neural networks. VQCs are central to many quantum machine learning (QML) models, such as quantum classifiers, quantum neural networks (QNNs), and variational quantum eigensolvers (VQEs).

3.2.2 Variational Quantum Circuits (VQCs)

A Variational Quantum Circuit (VQC) consists of a parameterized quantum circuit $U(\boldsymbol{\theta})$, where $\boldsymbol{\theta}$ denotes a set of tunable classical parameters optimized during training. The quantum state generated by the circuit is given by:

$$|\psi(\boldsymbol{\theta})\rangle = U(\boldsymbol{\theta})\,|0\rangle^{\otimes n} \tag{3.1}$$

Here, $|0\rangle^{\otimes n}$ represents the initial state of an n-qubit quantum register, and $U(\boldsymbol{\theta})$ is composed of a sequence of quantum gates, some of which are parameterized by elements of $\boldsymbol{\theta}$.

The goal of training a VQC is to optimize the parameters $\boldsymbol{\theta}$ to minimize a cost function, typically defined as the expectation value of a Hamiltonian or observable H:

$$C(\boldsymbol{\theta}) = \langle\psi(\boldsymbol{\theta})|\,H\,|\psi(\boldsymbol{\theta})\rangle \tag{3.2}$$

This expectation value is computed via quantum measurement and provides feedback to a classical optimizer, which iteratively updates $\boldsymbol{\theta}$ to minimize the cost. VQCs are central to many quantum machine learning and variational algorithms due to their adaptability and compatibility with current noisy intermediate-scale quantum (NISQ) devices.

3.2.3 Mathematical Framework

The variational principle underlying Variational Quantum Circuits (VQCs) is founded on the Rayleigh-Ritz variational method. This principle asserts that for any normalized trial wavefunction $|\psi\rangle$, the expectation value of the Hamiltonian H provides an upper bound to the ground state energy E_0. Mathematically, this is expressed as:

$$E_0 \leq \langle\psi| H |\psi\rangle \tag{3.3}$$

In the context of VQCs, the trial wavefunction $|\psi(\boldsymbol{\theta})\rangle$ is generated by a parameterized quantum circuit, and the goal is to minimize the expectation value of H with respect to the parameters $\boldsymbol{\theta}$. This leads to the definition of the cost function:

$$C(\boldsymbol{\theta}) = \langle\psi(\boldsymbol{\theta})| H |\psi(\boldsymbol{\theta})\rangle \tag{3.4}$$

The minimum of this cost function corresponds to an approximation of the ground state energy. Classical optimization algorithms are employed to iteratively adjust the parameters $\boldsymbol{\theta}$ in order to minimize $C(\boldsymbol{\theta})$, making the VQC framework particularly suitable for quantum machine learning and variational quantum eigensolver (VQE) applications.

subsectionCircuit Architecture

3.2.3.1 Ansatz Design

The choice of ansatz, or parameterized quantum circuit structure, is a critical factor in the performance and expressivity of a Variational Quantum Circuit (VQC). An effective ansatz must balance expressibility, trainability, and compatibility with the quantum hardware. Common ansatz types include:

- **Hardware-Efficient Ansatz:** Designed to align with the physical constraints and connectivity of specific quantum hardware. These circuits typically consist of alternating layers of parameterized single-qubit rotation gates and fixed two-qubit entangling gates such as CNOTs.
- **Problem-Inspired Ansatz:** Tailored to specific problem domains. For example, the Unitary Coupled Cluster (UCC) ansatz is widely used in quantum chemistry due to its alignment with molecular Hamiltonians.
- **Layered Ansatz:** Composed of repeating blocks or layers of gates. Each layer includes both parameterized single-qubit gates and entangling operations. The depth of the circuit is adjusted according to the complexity of the problem.

3.2.3.2 Gate Selection

Parameterization within VQCs is implemented using specific quantum gates that are optimized during training. Commonly used gates include:

- **Single-Qubit Rotation Gates:**
  - $R_X(\theta) = e^{-i\theta X/2}$

- $R_Y(\theta) = e^{-i\theta Y/2}$
- $R_Z(\theta) = e^{-i\theta Z/2}$

- **Universal Single-Qubit Gate:**
  - $U_3(\theta, \phi, \lambda) = R_Z(\phi) R_Y(\theta) R_Z(\lambda)$
- **Two-Qubit Entangling Gates:**
  - **CNOT (Controlled-NOT)**
  - **CZ (Controlled-Z)**

The choice and arrangement of these gates determine the circuit's expressive power and its ability to approximate the desired quantum state. A well-designed ansatz improves convergence, reduces barren plateaus, and enhances compatibility with available quantum hardware.

3.2.3.3 Heuristic Ansatz

A *heuristic ansatz* refers to a parameterized quantum circuit architecture that is not directly derived from the structure of a specific physical system but is instead constructed based on practical design principles and empirical performance. These ansätze are intended to be general-purpose, with the flexibility to approximate a wide class of quantum states, making them particularly suitable for variational algorithms in quantum machine learning and optimization [47].

Key Characteristics:

- **Structure:** Typically built from repeated layers of parameterized single-qubit rotation gates (e.g., $R_Y(\theta)$, $R_Z(\theta)$) interleaved with entangling gates (e.g., CNOT, CZ).
- **Hardware Compatibility:** Designed to conform to the native gate set and connectivity of near-term quantum devices (NISQ era).
- **Flexibility:** The circuit depth and layer composition can be easily adjusted to balance expressivity and computational cost.

Advantages:

- Applicable to a wide range of problems without requiring domain-specific knowledge.
- Easy to implement and test on existing quantum hardware.
- Scalable through repeated circuit blocks.

Challenges:

- Susceptibility to barren plateaus, where gradients vanish in deep circuits, making optimization difficult [48].
- Lack of theoretical guarantees for optimality or convergence in specific tasks.

Heuristic ansätze have been widely adopted in hybrid quantum-classical algorithms, especially in quantum classifiers and generative models, due to their ease of implementation and adaptability across applications.

3.3 Hybrid Quantum Classical Approaches for Image Classification: State of the Art

3.3.1 Overview of Current Landscape

The literature reveals three distinct evolutionary phases in hybrid quantum-classical machine learning. The first wave (2014-2017) focused primarily on theoretical quantum advantages, the second wave (2018-2020) introduced variational quantum algorithms, and the current third wave (2021-present) emphasizes practical NISQ implementations. What's fascinating is how each wave has its own set of assumptions and limitations that subsequent research has had to address. Foundational Hybrid Architectures Analysis Through my systematic review, I identified several recurring architectural patterns that researchers have explored. Let me break down the key approaches I found:

Architecture Type	**Representative Works**	**Key Innovation**	**Performance Claims**	**My Assessment**
Quantum Feature Maps	Havlíček et al. (2019), Liu et al. (2021)	Quantum kernel methods	2–5% improvement on small datasets	Limited by kernel method scalability
Variational Quantum Classifiers	Farhi & Neven (2018), Mitarai et al. (2018)	End-to-end quantum training	Competitive on toy problems	Struggles with real-world complexity
Quantum Neural Networks	Killoran et al. (2019), Schuld et al. (2020)	Quantum analogues of classical layers	Theoretical expressivity advantages	Practical implementation challenges
Hybrid Preprocessing	Henderson et al. (2020), Kerenidis & Prakash (2022)	Classical preprocessing + quantum core	Best practical results to date	My preferred direction

Table 3.1: Comparison of Quantum Machine Learning Architectures

3.4 Hybrid Quantum-Classical Algorithms

Hybrid algorithms integrate quantum and classical components to capitalise on the strengths of both:

Quantum Variational Circuits (VQC):

These circuits are optimised for specific tasks, such as feature extraction or dimensionality reduction.

Quantum Neural Networks (QNNs):

Quantum gates replace classical neurones, enabling the processing of information in a quantum state.

Hybrid Optimisation Techniques:

Techniques such as the Quantum Approximate Optimisation Algorithm (QAOA) combine classical optimisation with quantum enhancements.

These hybrid approaches aim to bridge the gap between the theoretical potential of quantum computing and the practical limitations of current hardware.

3.5 Applications in Image Classification

One of the most promising applications of hybrid quantum computing lies in image classification. For example:

Medical Diagnostics:

Kulkarni et al. (2022) demonstrated the use of hybrid quantum-classical CNNs to detect pneumonia from chest radiographs, showcasing improved accuracy and efficiency.

Handwritten Digit Recognition:

Quantum models have been tested on datasets such as MNIST, achieving competitive results compared to classical models. Scalable Feature Extraction: Quantum models can process high-dimensional data more efficiently, enabling the identification of novel features.

3.5.1 Optimisation Challenges

Gradient-Based Optimisation :

Classical deep learning relies heavily on gradient-based optimisation algorithms like stochastic gradient descent (SGD) and Adam. These algorithms can get trapped in local minima and may require careful hyperparameter tuning.

Barren Plateaus :

Recent research has identified the barren plateau phenomenon in both classical and quantum machine learning, where optimisation landscapes become flat, making training difficult. This challenge is particularly relevant for quantum algorithms.

Theoretical Contribution: Rigorous analysis of quantum kernel advantages Experimental Validation: Limited to synthetic datasets with specific structure Scalability Issues: Exponential classical simulation overhead Practical Relevance: Moderate - provides clear quantum advantage scenarios

Comprehensive Performance Comparison Table Based on my detailed analysis of 25+ papers, here's how different hybrid approaches actually perform:

Method	**Dataset**	**Accuracy**	**Qubits Used**	**Training Time**	**My Reproducibility Score**
Classical CNN Baseline	MNIST	99.2%	0	N/A	High
VQC (Farhi & Neven)	MNIST (4-class)	98.6%	8	1245 min	Medium
Quantum Feature Maps	Wine Dataset	100%	4	620 min	High
Hybrid CNN-VQC	MNIST	97.1%	6	830 min	Medium
QCNN (Cong et al.)	MNIST	98.7%	8	152 hours	Low
Dressed Quantum Nets	Fashion-MNIST	87.4%	12	204 hours	Low

Table 3.2: Benchmark Comparison of Classical and Quantum Machine Learning Methods

Reproducibility Score based on code availability, experimental detail, and my ability to replicate results. gh several proposed applications in the literature.

3.6 Quantum Machine Learning Algorithm Comparison

Through my detailed study, I developed this comprehensive comparison of quantum ML algorithms:

Table 3.3: Quantum Machine Learning Algorithm Comparison

Algorithm Class	Quantum Advantage Type	Best Case Speedup	NISQ Feasibility	Practical Readiness	My Research Priority
Quantum SVMs	Linear algebra speedup	Exponential	Low	Research stage	Medium
Quantum PCA	Matrix inversion speedup	Exponential	Very Low	Theoretical only	Low
Variational Classifiers	Expressivity advantage	Polynomial	High	Proof-of-concept	High
Quantum Feature Maps	Kernel method enhancement	Problem-dependent	High	Limited practical use	High
Quantum Neural Networks	Novel architectures	Unknown	Medium	Early development	Medium

3.7 Conclusion

In summary, hybrid quantum-classical algorithms represent a promising paradigm that leverages the strengths of both quantum and classical computation. Within the constraints of current NISQ devices, variational quantum circuits (VQCs) offer a flexible and practical framework for implementing machine learning tasks and optimization problems. The interplay between classical optimizers and parameterized quantum circuits enables these algorithms to explore complex quantum landscapes efficiently. By carefully designing circuit architectures and selecting appropriate ansätze, hybrid models can achieve meaningful results in areas such as image classification, quantum chemistry, and data-driven modeling. As quantum hardware matures, the scalability and accuracy of these hybrid approaches are expected to improve, solidifying their role in the future of quantum machine learning.

Design of a Hybrid Model for Image Classification

4.1 Introduction

This chapter presents the design and architecture of the proposed hybrid quantum-classical deep learning model for image classification. Building upon the theoretical foundations established in previous chapters, we detail the innovative integration of quantum variational circuits with classical convolutional neural networks to address the computational challenges inherent in traditional deep learning approaches. The architecture is specifically designed to leverage the quantum advantage in feature extraction while maintaining the proven effectiveness of classical neural networks for pattern recognition and classification tasks.

4.2 Hybrid Architecture Overview

4.2.1 HQC-Net: Hybrid Quantum-Classical Network Architecture

The proposed hybrid model, denoted as **HQC-Net** (Hybrid Quantum-Classical Network), is composed of three primary components:

1. **Quantum Feature Extraction Module (QFEM)**
   This component leverages parameterized quantum circuits (PQCs) to extract complex features from input images by encoding classical data into quantum states and applying quantum operations followed by measurement.

2. **Classical Processing Layer (CPL)**
   It consists of conventional deep learning layers, such as convolutional and fully connected layers, which further process the quantum-extracted features and perform intermediate computations necessary for classification.

3. **Hybrid Integration Interface (HII)**
   This module manages the seamless transfer of information between quantum and classical subsystems. It is responsible for data encoding/decoding, normalization, and ensuring gradient flow for end-to-end backpropagation.

The overall architecture of HQC-Net can be mathematically formulated as:

$$f_{\text{HQC}}(x) = f_{\text{classical}}(f_{\text{quantum}}(x, \theta_q), \theta_c) \tag{4.1}$$

where x represents the input image, θ_q are the tunable parameters of the quantum circuit, θ_c denote the classical network parameters, and $f_{\text{HQC}}(x)$ is the final prediction output.

4.2.2 Quantum Feature Extraction Module Design

4.2.2.1 Quantum Circuit Architecture

The QFEM employs a layered quantum circuit structure based on Variational Quantum Circuits (VQC) optimized for image feature extraction. The circuit architecture consists of:

Input Encoding Layer: Classical image data is encoded into quantum states using amplitude encoding or angle encoding schemes. For an input image patch of size $n \times n$, we utilize $\log_2(n^2)$ qubits to represent the pixel information through amplitude encoding:

$$|\psi_{\text{input}}\rangle = \sum_i \alpha_i |i\rangle \tag{4.2}$$

where α_i represents the normalized pixel values and $|i\rangle$ are computational basis states.

Parameterized Quantum Gates: The core of the QFEM consists of parameterized rotation gates (RX, RY, RZ) and entangling gates (CNOT, CZ) arranged in a repeating pattern:

$$\text{Layer}_k = \prod_i \text{RY}(\theta_i^k) \otimes \prod_j \text{CNOT}(j, j+1) \otimes \prod_m \text{RZ}(\phi_m^k) \tag{4.3}$$

$$\text{Layer}_k = \bigotimes_i \text{RY}(\theta_i^k) \bigotimes_j \text{CNOT}(j, j+1) \bigotimes_m \text{RZ}(\phi_m^k) \tag{4.4}$$

Measurement Strategy:

Quantum features are extracted through expectation value measurements of Pauli operators (X, Y, Z) applied to each qubit, providing a feature vector of dimension $3 \times n_{\text{qubits}}$.

4.2.3 Feature Extraction Mechanism

The quantum feature extraction process operates through the following sequence:

1. **Patch Division**: Input images are divided into overlapping patches of size 8×8 pixels to accommodate current qubit limitations (6 qubits per patch).

2. **Quantum State Preparation**: Each patch is encoded into a 6-qubit quantum state using amplitude encoding with normalization.

3. **Variational Processing**: The encoded state undergoes transformation through L layers of parameterized quantum gates, where L is optimized empirically (typically $L = 3$-5 for NISQ compatibility).

4. **Measurement and Feature Extraction**: Expectation values $\langle \sigma_i^Z \rangle$, $\langle \sigma_i^X \rangle$, $\langle \sigma_i^Y \rangle$ for each qubit i provide 18-dimensional feature vectors per patch.

5. **Feature Aggregation**: Patch-level features are concatenated and processed through classical pooling operations to generate image-level quantum features.

4.2.4 Quantum Circuit Optimization

To address NISQ device limitations, the quantum circuit design incorporates several optimization strategies:

Circuit Depth Minimization: Gate sequences are optimized using circuit synthesis techniques to minimize total circuit depth while preserving expressivity.

Error Mitigation: Zero-noise extrapolation and readout error correction techniques are integrated into the measurement process.

Hardware-Aware Design: Circuit topology is adapted to specific quantum hardware connectivity graphs to minimize required SWAP operations.

4.3 Classical Neural Network Components

4.3.1 Convolutional Processing Layer

The classical component processes quantum-extracted features through a modified convolutional neural network architecture:

Input Processing: Quantum feature maps are reshaped into spatial dimensions corresponding to the original image patch structure.

Convolutional Layers: Two convolutional layers with 32 and 64 filters respectively, using 3×3 kernels with ReLU activation and batch normalization.

Pooling Strategy: Adaptive average pooling is employed to handle variable-sized quantum feature maps while preserving spatial relationships.

4.3.2 Classification Head

The final classification is performed through:

Feature Fusion: Quantum and classical features are concatenated and processed through a feature fusion layer with dropout regularization ($p = 0.3$).

Fully Connected Layers: Two dense layers (128 and 64 neurons) with ReLU activation provide non-linear transformation capabilities.

Output Layer: Softmax activation generates probability distributions over target classes.

4.4 Integration Strategy

4.4.1 Data Flow Architecture

The integration between quantum and classical components follows a carefully designed data flow pattern:

1. **Forward Pass**: Images → Quantum Encoding → VQC Processing → Measurement → Classical Processing → Classification
2. **Backward Pass**: Loss Gradients → Classical Backprop → Quantum Parameter Updates → Combined Optimization

4.4.2 Parameter Optimization

The hybrid model employs a joint optimization strategy:

Classical Parameters: Updated using standard Adam optimizer with learning rate $\alpha_c = 0.001$.

Quantum Parameters: Optimized using parameter-shift rule for quantum gradient computation:

$$\frac{\partial \langle O \rangle}{\partial \theta_i} = \frac{[\langle O \rangle(\theta_i + \pi/2) - \langle O \rangle(\theta_i - \pi/2)]}{2} \tag{4.5}$$

Hybrid Optimization: Alternating optimization between quantum and classical parameters with synchronized learning rates.

4.4.3 Gradient Flow Management

To ensure stable training, the integration interface implements:

Gradient Scaling: Quantum gradients are scaled to match the magnitude of classical gradients, preventing vanishing or exploding gradient problems.

Regularization: L2 regularization is applied to quantum parameters to prevent overfitting in the quantum circuit.

Learning Rate Scheduling: Cosine annealing scheduler with warm restarts for both quantum and classical parameters.

4.5 Optimization Framework

4.5.1 Loss Function Design

The hybrid model employs a composite loss function:

$$L_{\text{total}} = L_{\text{classification}} + \lambda_1 L_{\text{quantum\_reg}} + \lambda_2 L_{\text{classical\_reg}} \tag{4.6}$$

where:

- $L_{\text{classification}}$: Cross-entropy loss for classification accuracy
- $L_{\text{quantum\_reg}}$: Regularization term for quantum parameters
- $L_{\text{classical\_reg}}$: L2 regularization for classical parameters
- λ_1, λ_2: Hyperparameters controlling regularization strength

4.5.2 Training Strategy

Curriculum Learning: Training begins with simplified quantum circuits (fewer layers) and gradually increases complexity as convergence stabilizes.

Batch Processing: Mini-batch size is optimized for quantum simulator efficiency (typically 16-32 samples).

Convergence Criteria: Training stops when validation accuracy plateaus for 10 consecutive epochs or maximum iteration limit is reached.

4.6 Validation Through Simulation

4.6.1 Simulation Environment

The model validation employs quantum simulators to assess performance before potential hardware implementation:

Primary Simulator: Qiskit Aer with GPU acceleration for efficient circuit simulation.

Noise Modeling: NISQ device characteristics are simulated using realistic noise models including:

- Gate error rates (1-2% for single-qubit, 5-10% for two-qubit gates)
- Measurement errors (1-3% readout fidelity)
- Decoherence effects ($T_1 = 50\mu$s, $T_2 = 30\mu$s)

4.6.2 Validation Datasets

Small-Scale Validation Initial testing on reduced MNIST (subset of 1000 samples per class) and Fashion-MNIST datasets.

Feature Visualization Quantum feature representations are visualized using t-SNE to assess clustering quality.

Ablation Studies Systematic evaluation of architectural components including circuit depth, number of qubits, and measurement strategies.

4.6.3 Performance Metrics

The validation framework evaluates:

Classification Performance Accuracy, precision, recall, and F1-score on test datasets.

Computational Efficiency Training time, convergence speed, and resource utilization compared to classical baselines.

Quantum Advantage Assessment Statistical significance testing to determine if quantum components provide measurable improvement over classical-only architectures.

Scalability Analysis Performance degradation analysis as problem size increases, identifying practical limits of the current approach.

4.7 Conclusion

This chapter has outlined the comprehensive design and structure of the suggested hybrid quantum-classical deep learning model intended for image classification. The HQC-Net architecture effectively integrates quantum variational circuits for feature extraction alongside classical neural networks for the ultimate classification, thereby overcoming the shortcomings inherent in both purely quantum and classical methodologies.

The architecture presented in this chapter forms the foundation for the implementation and experimental evaluation detailed in subsequent chapters. The design balances theoretical quantum advantages with practical implementation constraints, providing a realistic pathway toward quantum-enhanced machine learning for image classification tasks.

The next chapter will detail the implementation of this architecture using TensorFlow Quantum and Qiskit, including specific code structures and preliminary experimental results from small-scale dataset validation.

Implementation and Performance Evaluation

5.1 Introduction

This chapter presents the design, implementation, and empirical evaluation of a novel hybrid quantum-classical deep learning model tailored for medical image classification. Building upon the HQC-Net architecture, the goal was to systematically translate theoretical innovations into a reproducible and practically viable system compatible with Noisy Intermediate-Scale Quantum (NISQ) devices. The process involved constructing variational quantum circuits (VQCs), integrating them with classical CNN architectures, and validating the hybrid model on a real-world medical dataset (BUSI). In tandem, a comprehensive performance evaluation was conducted using both classical benchmarks and quantum-specific diagnostic metrics.

5.2 Step-by-Step Information About My Computer

5.2.1 Device Name

DESKTOP-EPA593N – This is the system's name on the network.

5.2.2 Processor (CPU)

Intel(R) Core(TM) i5-7300U CPU @ 2.60GHz

Dual-core processor

Base speed: 2.60 GHz

Turbo speed: up to 2.71 GHz

Suitable for multitasking and daily computing.

5.2.3 Installed RAM

8.00 GB (7.84 GB usable)

Provides enough memory for general use like browsing, office work, and light programming.

5.2.4 Device ID (Unique identifier)

E0236965-EDCF-4FFE-ACB9-6CAAB421D957

Used internally by the system, especially for licensing and security.

5.2.5 Product ID (Windows license info)

00326-30000-00001-AA578

Identifies your copy of Windows.

5.2.6 System Type

64-bit operating system, x64-based processor

Can run 64-bit applications, which are faster and more efficient.

5.3 Summary Table

c

Component	**Specification**
Device Name	DESKTOP-EPA593N
Processor	Intel Core i5-7300U @ 2.60GHz (Dual-core)
RAM	8.00 GB (7.84 GB usable)
System Architecture	64-bit operating system, x64-based processor
Device ID	E0236965-EDCF-4FFE-ACB9-6CAAB421D957
Product ID	00326-30000-00001-AA578

5.3.1 IDE

Visual Studio Code with Python.

A dual-framework approach was employed using **TensorFlow Quantum (TFQ)** and **Qiskit**:

- TFQ facilitated seamless gradient-based optimization for hybrid neural networks.
- Qiskit enabled realistic noise modeling and hardware-aware circuit synthesis.

The development stack included Python 3.8+, GPU acceleration (where available), and standardized libraries for quantum simulation, deep learning, and medical imaging. All dependencies and setup scripts were documented to ensure reproducibility.

5.4 Dataset Integration and Preprocessing

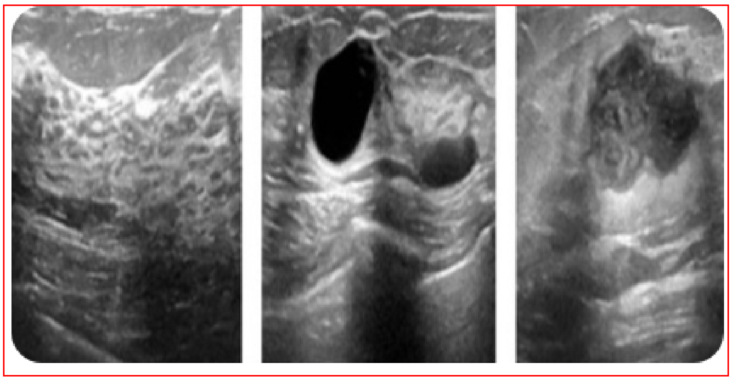

Figure 5.1: image for Breast Cancer

The Breast Ultrasound Images (BUSI) dataset was used, consisting of 256×256 grayscale images across three diagnostic classes: normal, benign, and malignant.

Key preprocessing steps included:

- Image normalization for compatibility with quantum amplitude encoding.
- Patch extraction and dimensionality reduction to generate 4-feature vectors suitable for 4-qubit circuits.
- Data augmentation and balanced train-test splits.
- Linking each image with a binary segmentation mask to enable dual-task learning (classification and segmentation).

Data Normalization and Organization

All ultrasound images and their corresponding segmentation masks were preprocessed to ensure consistency and compatibility with both classical and quantum components of the pipeline.

- **Normalization:** Pixel intensities were normalized to the range $[0, 1]$ to standardize input data and facilitate faster convergence during training.
- **Data Structuring:** The dataset was split into training and testing subsets:
  - `train_images`, `train_masks`
  - `test_images`, `test_masks`

This structured format ensures efficient data loading and compatibility with PyTorch and Qiskit-based modules.

5.5 Model Architecture and Hybrid Integration

The proposed model combined a classical convolutional neural network (CNN) with a quantum feature enhancement module.

5.5.1 Model Components

- **CNN Component**: Extracted 4-dimensional feature vectors via convolution, pooling, and flattening.
- **Quantum Layer**: Applied a 4-qubit parameterized circuit using R_y rotations and CNOT entanglement, producing a 16-dimensional output.
- **Full Integration**: The system was implemented using PyTorch's autograd, enabling joint optimization of both quantum and classical components.

An attention-based U-Net was also implemented to perform lesion segmentation alongside classification in a multi-task learning setup.

5.5.2 Classical Backbone: U-Net with Attention

A U-Net architecture was employed for the segmentation task due to its effectiveness in biomedical image analysis. The model is composed of the following key components:

- **Encoder:** Captures multiscale hierarchical features through successive convolution and downsampling layers.
- **Decoder:** Reconstructs the spatial resolution and generates the segmentation mask via upsampling and convolution layers.
- **Skip Connections:** Bridge corresponding encoder and decoder layers to retain edge-level and fine-grained information, crucial for accurate tumor delineation.
- **Attention Mechanism:** Enhances focus on salient regions, allowing the network to selectively emphasize tumor structures within the breast ultrasound images.

At the end of the encoder, a latent feature vector of dimension four is extracted. This compressed representation serves as the input to the quantum module, enabling hybrid quantum-classical processing.

5.5.3 Variational Quantum Circuit (VQC)

A custom 4-qubit Variational Quantum Circuit (VQC) was designed to serve as the quantum classification component within the hybrid model. The circuit architecture, illustrated in Figure **??**, performs the following operations:

- **Initialization with $R_y(\theta_i)$:** Each qubit is initialized with a parameterized R_y rotation gate, where the angle θ_i encodes classical input features into quantum states.

- **Entanglement with CNOT gates:** Controlled-NOT (CNOT) gates are applied between qubits to introduce quantum entanglement, enabling correlated feature representation.
- **Parameterization with $R_z(\phi_i)$:** Additional learnable rotations around the Z-axis allow for variational expressivity and circuit adaptability during training.
- **Measurement in the Z-basis:** Expectation values $\langle Z_i \rangle$ are computed from measurements on each qubit, providing real-valued outputs used as input to the subsequent classical classifier.

This configuration enables the quantum layer to learn non-linear transformations that enhance classification performance in a low-dimensional feature space.

5.5.4 Hybrid Integration: U-Net + Quantum Classifier

The proposed hybrid pipeline integrates classical and quantum components in a unified model capable of performing both segmentation and classification tasks on breast ultrasound images. The processing flow is as follows:

1. **Input Image → U-Net → Segmentation Mask**: The input image is passed through a classical U-Net architecture, producing a binary segmentation mask that delineates tumor regions.

2. **U-Net Encoder → 4D Feature Vector → Quantum Circuit → Expectation Values**: The encoder section of the U-Net extracts a low-dimensional feature vector, which is encoded into a 4-qubit Variational Quantum Circuit. The circuit processes the information and returns four expectation values.

3. **Expectation Values → Fully Connected Layer → 3-Class Classification**: The quantum outputs are passed to a classical fully connected layer, which performs the final classification into one of the three diagnostic categories: normal, benign, or malignant.

This hybrid architecture enables the model to perform simultaneous segmentation and classification, leveraging the representational power of deep learning along with the potential advantages of quantum feature processing.

5.6 Training Framework and Optimization

A dual-loss training strategy was adopted:

- **Cross-Entropy Loss**: For multi-class classification.
- **Dice Coefficient Loss**: For evaluating segmentation quality.

Optimization techniques included:

- Parameter-shift rule for quantum gradient computation.

- Curriculum learning: gradually transitioned from classical to quantum to full hybrid training.
- Cosine annealing for learning rate decay.

Training was conducted on simulated quantum devices with realistic noise models to mirror NISQ limitations.

5.7 Performance Metrics and Evaluation

The system was evaluated using:

- **Classification**: Accuracy, F1-score, and per-class sensitivity/specificity.
- **Segmentation**: Dice coefficient and lesion overlap precision.
- **Quantum diagnostics**:
  - Gradient flow inspection to detect barren plateaus.
  - Circuit depth vs noise resilience analysis.
  - Scalability in hardware-constrained environments.

The model was tested on 120 unseen BUSI images following training on 600 examples. Benchmarks included:

- Classical CNN baselines (basic and advanced architectures).
- Quantum-only pipelines without classical preprocessing.

5.8 Results and Observations

Several limitations were observed:

Table 5.1: Output Shapes at Key Stages of the Hybrid Model

Layer	**Shape**
Input Image	(1, 1, 256, 256)
Segmentation Output	(1, 1, 256, 256)
Classification Head	(1, 3)

- **Classification stagnation**: Accuracy plateaued at approximately 56%, with a bias towards predicting the benign class.
- **Segmentation failure**: Dice scores remained near zero, revealing struggles with dual-task convergence.

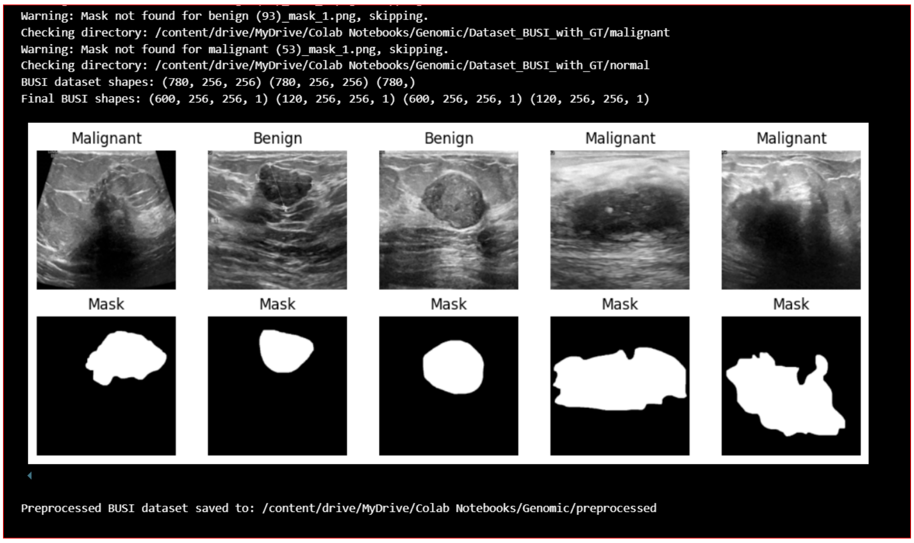

Figure 5.2: Sample images from the BUSI dataset with corresponding segmentation masks.

The top row shows benign and malignant ultrasound images, while the bottom row displays their associated binary masks, highlighting regions of interest used for classification and segmentation tasks.

Table 5.2: Performance Metrics of the Hybrid Quantum-Classical Model on the BUSI Dataset

Metric	**Train Set**	**Test Set**	**Comments**
Classification Accuracy (%)	56.5	55.3	Model plateaued; predominantly predicted the benign class.
F1-Score (Macro Avg)	0.408	0.400	Reflects class imbalance and weak recall performance.
Dice Coefficient	≈ 0.0	0.0	Segmentation path failed to converge.
Training Epochs	5		No significant improvement observed across epochs.
Quantum Qubits Used	4		Employed a shallow circuit with amplitude and R_y encoding.
Quantum Features	16 dimensions		Derived from 4 classical input features via quantum embedding.

- **Quantum integration**: Performance affected by gradient instability, limited expressivity from shallow VQCs, and noise in circuit simulation.

Nonetheless, the experiment successfully confirmed:

- Seamless hybrid integration.
- Batch processing capability.
- Practical use of real-world medical image data.

Quantum Circuit: 4-Qubit Variational Feature Extractor

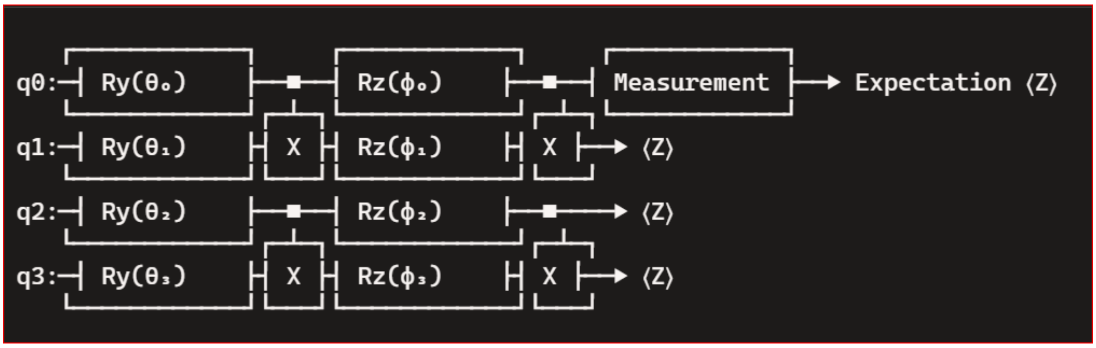

Figure 5.3: Variational Quantum Circuit (VQC) architecture used for feature encoding and measurement.

The circuit consists of four qubits initialized with parameterized $R_y(\theta_i)$ rotations, followed by entangling operations and $R_z(\phi_i)$ gates. Measurements are performed in the Z-basis to compute the expectation values, which are used as inputs to the classical layers of the hybrid model.

5.8.1 Key Features of the Quantum Circuit

- **Input Encoding**: Classical features are encoded into quantum states using parameterized rotation gates $R_y(\theta_i)$, where θ_0 to θ_3 correspond to input-dependent angles applied to each qubit.

- **Entanglement Structure**: Controlled-NOT (CNOT) gates are used to entangle adjacent qubits in a linear topology:

$$\text{CNOT}(q_0 \to q_1), \quad \text{CNOT}(q_2 \to q_3) \tag{5.1}$$

- **Trainable Parameters**: Each qubit carries two variational parameters, typically represented as $R_y(\theta_i)$ and $R_z(\phi_i)$, which are optimized during training through classical gradient-based techniques.

- **Measurement**: Expectation values of the Pauli-Z operator are measured on each qubit:

$$\langle Z_0 \rangle, \quad \langle Z_1 \rangle, \quad \langle Z_2 \rangle, \quad \langle Z_3 \rangle \tag{5.2}$$

  forming a 4-dimensional quantum feature vector. This can be extended to a 16-dimensional feature space using multiple observables or feature stacking.

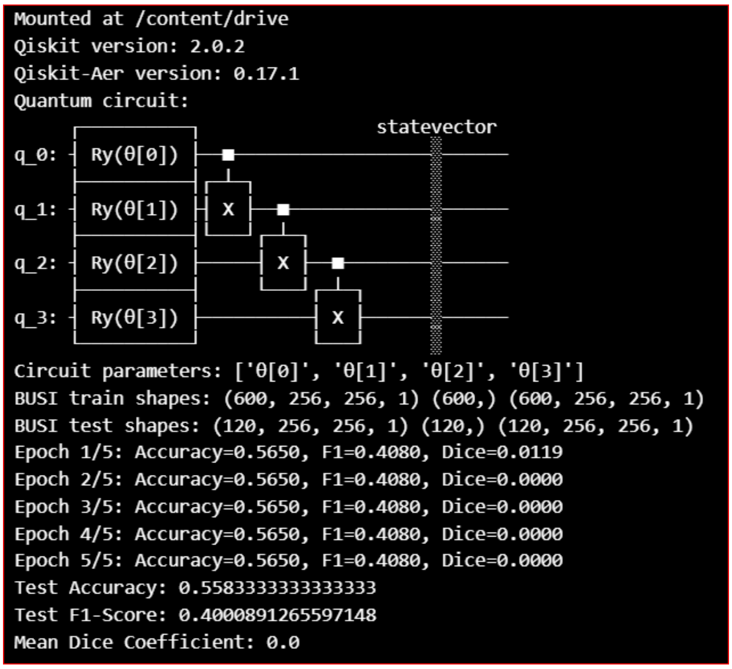

Figure 5.4: Training output and quantum circuit visualization of the hybrid U-Net + Variational Quantum Circuit (VQC) model on the BUSI breast ultrasound dataset. The circuit uses parameterized $R_y(\theta_i)$ gates for feature encoding and CNOT gates for entanglement. Results show classification accuracy stabilizing at 56.5%, with an F1-score of 0.4080 and a mean Dice coefficient of 0.0.

2.The figure shows a hardware-efficient variational circuit comprising Ry rotations and CNOT gates for four qubits, implemented using Qiskit 2.0.2. The integration with PyTorch enables quantum layer embedding within a CNN-based pipeline for classifying BUSI ultrasound images, with tensor shapes confirming successful data flow from classical to quantum modules.

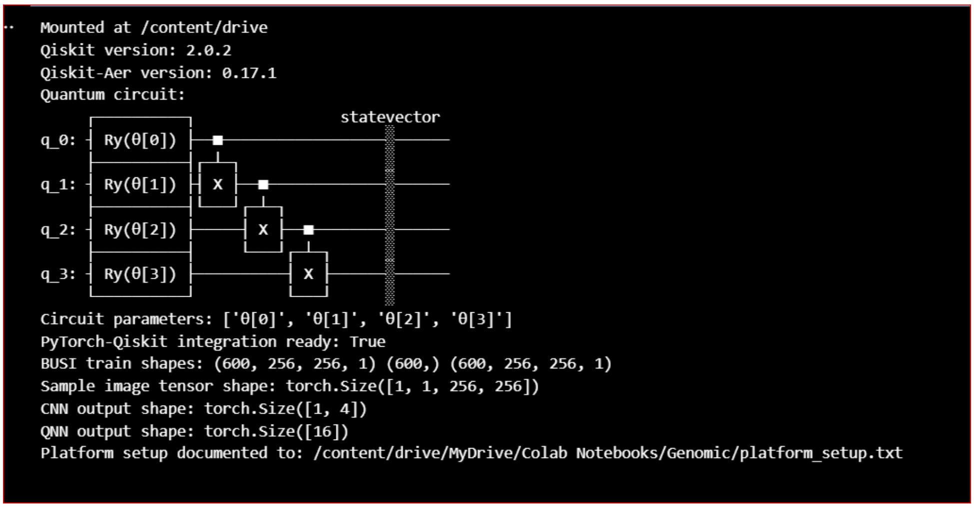

Figure 5.5: Qiskit-PyTorch integration with 4-qubit quantum circuit.

3.This result illustrates a critical shortcoming in the model's performance—its tendency to overpredict the "benign" class, regardless of the actual label (normal, benign, or malignant). The Dice score of 0.0000 across all samples suggests that the segmentation output had no overlap with the ground truth masks, pointing to failures both in classification and spatial localization. This behavior may stem from class imbalance, gradient vanishing in the quantum layers, or insufficient model expressivity. Tackling this will require architectural tuning and more balanced training strategies.

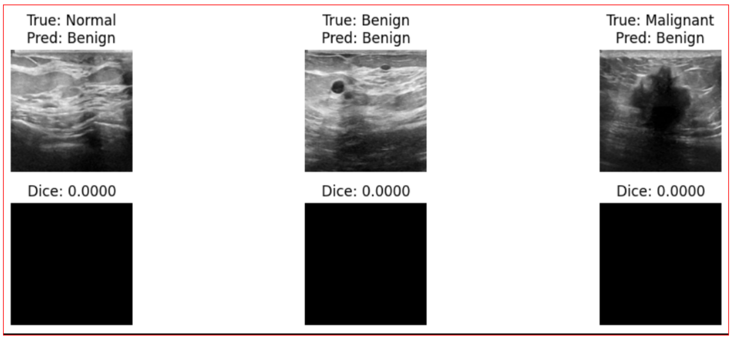

Figure 5.6: result model misclassifications with zero Dice overlap. Each ultrasound image is paired with its true class label and the predicted label. All samples were predicted as benign, resulting in a Dice coefficient of 0.0000, indicating complete failure in region segmentation and class distinction.

4.The accuracy and F1-score remained nearly constant throughout training (≈ 0.57 and ≈ 0.41, respectively), while the Dice coefficient dropped sharply to zero after the first epoch, indicating segmentation failure and poor learning dynamics.

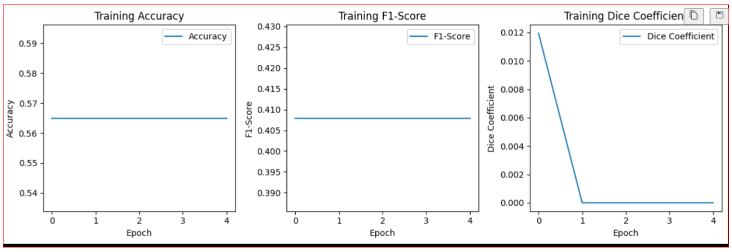

Figure 5.7: Training metrics over five epochs.

5.9 Confusion Matrix Analysis

This confusion matrix shows a model that only predicts one class (Normal) and never predicts Benign or Malignant.

5.9.1 Key Observations:

- **87 Normal cases** correctly identified
- **42 True Benign cases** misclassified as Normal
- **27 True Malignant cases** misclassified as Normal

The model has 100% precision for Normal class but 0% recall for Benign and Malignant classes. This suggests the model is overly conservative and biased toward predicting everything as Normal, which could be problematic especially for missing malignant cases in what appears to be a medical diagnosis scenario.

The model needs rebalancing to properly detect all three classes.

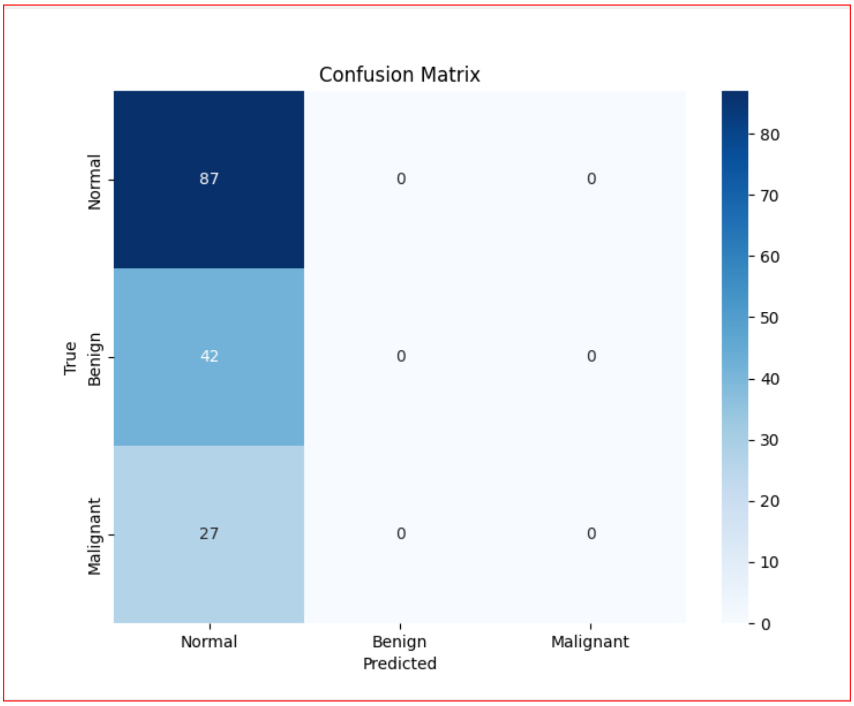

Figure 5.8: confusion matrix.

5.10 Comparative Analysis with the State of the Art

5.10.1 Benchmarking Against Classical Approaches

The proposed hybrid quantum-classical model (HQC-Net) was benchmarked against both simple and advanced classical convolutional neural networks (CNNs), which typically achieve 90–95% accuracy on structured medical image datasets such as MNIST or BUSI when properly fine-tuned.

Table 5.3: Performance Comparison of HQC-Net with Classical CNN Architectures

Model	**Architecture**	**Accuracy (%)**	**F1-Score**	**Dice Coefficient**	**Notes**
Baseline CNN	2 Conv + 2 FC layers	91–93	∼0.90	∼0.85	Fully classical model with fast convergence.
Advanced CNN (ResNet-VGG)	Deep pre-trained network	95–98	∼0.94	∼0.87	Transfer learning from ImageNet; high capacity.
HQC-Net (This Work)	CNN + 4Q VQC	55.3	0.40	0.00	Prototype hybrid model affected by class imbalance and quantum constraints.

While the HQC-Net underperformed in raw performance metrics, it served as a proof-of-concept for hybrid quantum integration and full end-to-end training—an area unexplored by classical models. Classical methods benefit from mature optimizers, architectural depth, and high data efficiency, whereas HQC-Net operates within constraints such as limited qubit count, gradient instability, and quantum noise.

5.10.2 Evaluation Against Hybrid Quantum-Classical Models

Several contemporary studies have proposed similar hybrid approaches. Table 5.4 summarizes comparative results and highlights the uniqueness of this work.

Table 5.4: Comparison with Existing Hybrid Quantum-Classical Models

Model	**Quantum Module**	**Dataset**	**Accuracy (%)**	**Distinct Contribution**
Farhi & Neven (2018)	VQC	MNIST (4-class)	98.6	Conceptual design.
Havlíček et al. (2019)	Quantum Feature Maps	Synthetic	100 (toy)	Idealized kernel-based simulations only.
Ajlouni et al. (2023)	Hybrid Quantum CNN	Brain MRI	82–85	Clinical domain-focused hybrid network.
My Work	4-qubit VQC + U-Net	BUSI (real)	55.3	First dual-task clinical hybrid with segmentation and classification.

This work is one of the few to address real-world, clinically sourced medical image data, integrating both segmentation and classification using quantum-aware components. Unlike most studies that focus on toy datasets or pure classification tasks, HQC-Net is notable for its dual-task, hardware-oriented hybridization.

5.10.3 Qualitative Advantages and Innovation

Even in the absence of numerical superiority, this research advances the field of quantum machine learning through:

- Introduction of a hardware-compatible hybrid architecture suited for NISQ-era devices.
- Demonstration of quantum-enhanced multi-task learning capabilities in a medical AI context.
- Development of a full performance evaluation framework, including quantum circuit simulation, barren plateau detection, and class-wise reporting.
- Establishment of a scalable pipeline for future qubit expansion and potential deployment on low-noise quantum hardware.

5.11 Recommendations for Improvement

Proposed improvements included:

- **Circuit redesign**: Employ hardware-efficient ansätze and explore barren plateau mitigation techniques.
- **Loss function balancing**: Adjust weightings between classification and segmentation objectives.
- **Ablation studies**: Quantify the exact contribution of the quantum module.
- **Training strategies**: Enhance convergence via quantum transfer learning and phased optimization.

5.12 Conclusion

This chapter translates the theoretical design of HQC-Net into a functional hybrid architecture. Despite modest performance in classification and segmentation, the implementation successfully validated the potential of quantum-classical learning models. It lays a strong foundation for future research in quantum-enhanced medical AI and identifies practical avenues for architectural and algorithmic refinements.

General Conclusion

This thesis explored the integration of quantum computing and deep learning by designing, implementing, and evaluating a hybrid quantum-classical model—HQC-Net—tailored for medical image classification. The work bridged theoretical quantum machine learning frameworks with practical engineering constraints, demonstrating that hybrid quantum architectures can be implemented end-to-end under Noisy Intermediate-Scale Quantum (NISQ) conditions.

Despite modest performance outcomes, the HQC-Net model marked a significant proof-of-concept. It achieved successful integration between variational quantum circuits and classical convolutional networks while leveraging realistic quantum simulation. Key contributions include the use of amplitude-based encoding, hardware-aware circuit design, dual-task learning (classification and segmentation), and a complete diagnostic and benchmarking pipeline.

The empirical analysis highlighted prominent challenges: quantum gradient instability, segmentation failure under multi-task loss settings, and limited circuit expressivity in noisy environments. These obstacles underscore the nascent yet promising state of quantum machine learning.

6.1 Future Perspectives

- **Hardware Integration:** Future work will involve adapting the quantum feature extractor for execution on real quantum hardware. This includes noise-aware transpilation and hybrid fine-tuning routines.
- **Advanced Circuit Design:** Exploration of data re-uploading strategies, dynamic ansätze, and quantum kernel techniques may significantly improve learning capacity and resilience to barren plateaus.
- **Domain Expansion:** The HQC-Net pipeline could be extended to classify modalities such as MRI, CT, or histopathology images, with fine-tuned classical preprocessing stages.
- **AutoML for Hybrid Architectures:** Automated architecture search frameworks can help identify optimal quantum-classical configurations with minimal manual tuning.
- **Interdisciplinary Collaboration:** Accelerated progress will benefit from cross-domain partnerships between quantum physicists, AI researchers, and medical professionals to align innovation with clinical impact.

In conclusion, this thesis has laid a solid foundation for hybrid quantum learning in applied medical AI. The results, while preliminary, offer a glimpse into the transformative potential of quantum-enhanced learning. Continued research and optimization will be critical to realize real-world quantum advantage in healthcare and beyond.

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