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STUDY OF QUANTUM ALGORITHMS FOR MACHINE LEARNING

Dr. Amit Bhusari [1], Dr. Prabhanjan Chaudhari [2], Dipali Bhusari [3], Amol Payghan [4]

[1] HOD, Dept. of MCA, Trinity Academy of Engineering, Yewalewadi, Pune, India
[2] HOD, Dept. of MCA, Saraswati College, Shegaon, India
[3] Assistant Professor, Trinity Academy of Engineering, Yewalewadi, Pune, India
[4] HOD, Dept. of BCA, College of Management and Computer Science, Yavatmal, India

Corresponding Author
Dr. Amit Bhusari, aabhusari@gmail.com

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ABSTRACT

Quantum algorithms for machine learning represent a paradigm shift in computational learning. While still in the early stages, QAML holds the promise to transform industries by enabling faster, more powerful models — especially for problems that are intractable for classical systems. As quantum hardware and algorithms improve, QAML will likely play a central role in the future of artificial intelligence.

Keywords: Quantum Algorithms, Machine Learning, Variational Circuits, Quantum Kernel, Hybrid Models

1. INTRODUCTION

Quantum Algorithms for Machine Learning (QAML) is an emerging interdisciplinary field that merges the power of quantum computing with the capabilities of machine learning (ML). The goal is to leverage quantum mechanics to speed up data processing, enhance pattern recognition, and solve complex problems that classical systems struggle with.

Why Quantum for Machine Learning?

Classical machine learning algorithms often face limitations in:

- Processing high-dimensional data
- Optimizing non-convex loss functions
- Handling large-scale datasets

Quantum computing introduces new possibilities:

- **Superposition:** Allows representing and processing multiple states simultaneously
- **Entanglement:** Links qubits for correlated data processing
- **Quantum Parallelism:** Enables faster computations across large data spaces

These features can potentially provide exponential speedups in certain ML tasks.

Key Quantum Machine Learning Concepts

Concept	Description
Quantum Data Encoding	Classical data is embedded into quantum states using amplitude or angle encoding
Quantum Kernel Methods	Enhances SVMs by calculating kernel functions in high-dimensional quantum space
Variational Quantum Circuits (VQC)	Hybrid models using parameterized quantum circuits optimized via classical methods

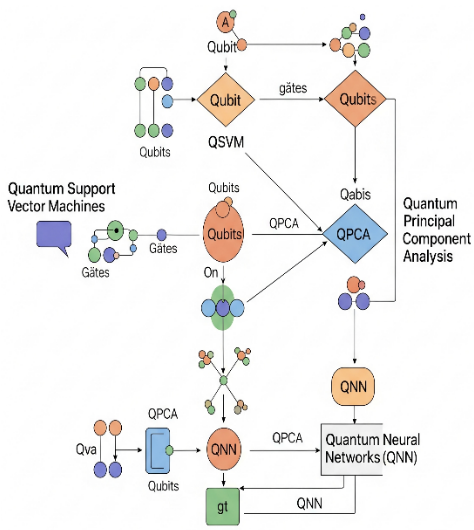


Figure 1 Quantum Computing

2. POPULAR QAML ALGORITHMS

- Quantum Support Vector Machine (QSVM)
- Quantum k-Means Clustering
- Quantum Boltzmann Machines
- Variational Quantum Classifier
- Quantum Reinforcement Learning

These algorithms are usually hybrid — they combine quantum subroutines with classical ML techniques to work efficiently on near-term quantum devices.

Here's the revised explanation of the Popular Quantum Algorithms for Machine Learning (QAML) with numbering and icons removed:

1) Quantum Support Vector Machine (QSVM)

What it is:

QSVM is a quantum version of the classical Support Vector Machine (SVM), used for classification.

How it works:

- Maps classical data into a high-dimensional quantum feature space using quantum circuits.

- Calculates quantum kernel functions (inner products of quantum states).
- A classical optimizer finds the optimal hyperplane for classification.

Advantage:

Can offer exponential speedup in computing kernel functions for complex datasets.

Use case: Classification tasks such as fraud detection, image classification.

2) Quantum k-Means Clustering

What it is:

A quantum-enhanced version of the classical k-means algorithm used for unsupervised clustering.

How it works:

- Encodes data into quantum states.
- Uses quantum distance estimation and search algorithms (like Grover's) to find nearest centroids efficiently.
- Iteratively updates cluster assignments.

Advantage:

Quadratic speedup in distance calculations and faster clustering on large datasets.

Use case: Market segmentation, customer clustering, image compression.

3) Quantum Boltzmann Machines (QBM)

What it is:

Quantum version of Boltzmann Machines—a type of generative model that learns complex data distributions.

How it works:

- Uses quantum systems to represent the energy landscape of data.
- Applies quantum annealing or Gibbs sampling for training.
- Learns probability distributions by adjusting weights to minimize energy.

Advantage:

More efficient in modeling and sampling from complex probability distributions.

Use case: Feature extraction, pattern recognition, generative tasks.

4) Variational Quantum Classifier (VQC)

What it is:

A hybrid quantum-classical model using parameterized quantum circuits for classification tasks.

How it works:

- Data is encoded into quantum states.
- A variational circuit processes the data with tunable quantum gates.
- Measurements provide outputs compared to expected labels.
- A classical optimizer updates circuit parameters.

Advantage:

Works on current NISQ devices; adaptable for both classification and regression.

Use case: Binary or multiclass classification for structured datasets.

5) Quantum Reinforcement Learning (QRL)

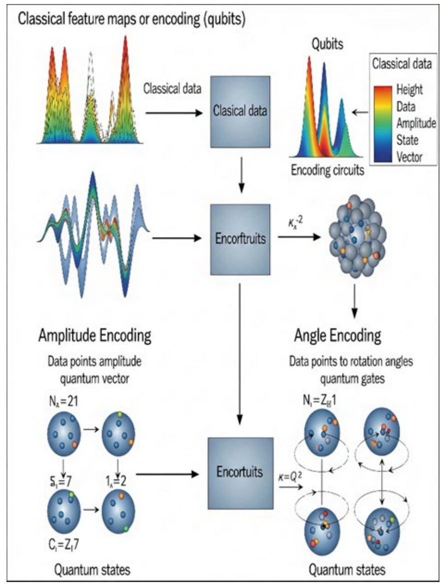
What it is:

An extension of reinforcement learning where quantum computing enhances policy learning and decision-making.

How it works:

- Quantum circuits represent policy or value functions.
- Quantum superposition and amplitude amplification improve exploration.

- Can encode and retrieve quantum-enhanced memories.



Advantage:

Faster learning and improved exploration in environments with complex dynamics.

Use case: Game playing, quantum robotics, adaptive decision systems.

Algorithm maturity: Many QAML algorithms are theoretical or work only on small-scale problem.

Noisy Intermediate-Scale Quantum (NISQ) era: Current devices are limited in qubit count and stability.

CONFLICT OF INTERESTS

None.

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None.

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