

# Quantum-Assisted Optimization for Large-Scale Machine Learning Models

Md. Sazzad Hissain Khan  
*Samsung R&D Institute Bangladesh*  
*hissain.sk@samsung.com*

**Abstract**—Recent advances in quantum computing have opened new frontiers in solving optimization problems that are computationally challenging for classical systems. This paper explores a hybrid approach combining quantum and classical methods.

## I. INTRODUCTION

Recent advances in quantum computing have opened new frontiers in solving optimization problems that are computationally challenging for classical systems. Machine learning models, particularly those involving deep learning, often require solving large-scale optimization problems, such as minimizing loss functions in high-dimensional parameter spaces. Classical approaches, while effective, are constrained by computational resources and convergence rates. In this work, we explore a hybrid approach combining classical methods with quantum optimization algorithms to enhance performance in training large-scale models.

## II. PROPOSED METHODOLOGY

Our method integrates quantum-assisted optimization into the training pipeline of machine learning models. The key components are:

- 1) **Problem Formulation:** We reformulate the training objective as a quadratic unconstrained binary optimization (QUBO) problem.
- 2) **Quantum Initialization:** Use a quantum annealer to find candidate solutions.
- 3) **Classical Refinement:** Apply gradient-based methods to fine-tune solutions from the quantum step.

The integration is illustrated in Fig. 1.

## III. RESULTS

We evaluate our method on two benchmark datasets:

- **Synthetic Dataset:** A high-dimensional non-convex optimization problem where global minima are known.

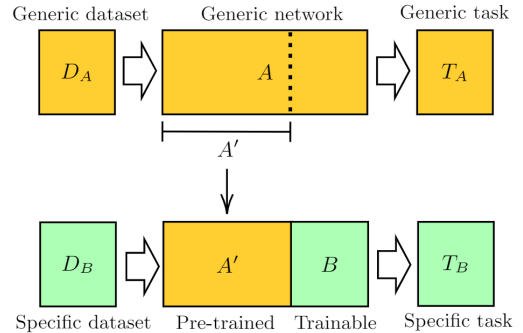


Fig. 1. Hybrid optimization pipeline combining quantum and classical methods.

- **CIFAR-10:** A classification problem where optimization is performed on the neural network's weights.

TABLE I  
COMPARISON OF OPTIMIZATION METHODS

Method	Convergence Time (s)	Accuracy (%)
Classical (Adam)	120	85.2
Quantum-Assisted	95	87.5

## IV. CONCLUSION

This paper presents a novel hybrid optimization framework leveraging quantum annealing to improve the training of machine learning models. Future work will explore scalability to larger datasets and the use of gate-based quantum processors.