Building Bridges Between AI and Quantum Computing: Architectures for Quantum Machine Learning for Superior Computational Power

G.Palanikumar
Department of Mathematics
Sri Venkateswara College of Engineering (SVCE)
Post Bag No.1,Pennalur Village
Chennai - Bangaluru High Road
Sriperumbudur Tk,
Tamil Nadu
gpalanimca@gmail.com

A Naga Lakshman Kumar
Department of MCA
Swarnandhra College of Engineering and Technology
scetmcahod@gmail.com

D.Nirmala
Department of ECE,
Rajalakshmi Engineering College,
Chennai,
nirmala.d@rajalakshmi.edu.in

Ala H. Jaber
Department of Mechanical Engineering, faculty of engineering,
Zarqa university, Zarqa, Jordan.
College of Engineering, University of Business and Technology, Jeddah,
21448, Saudi Arabia
ajaber@zu.edu.jo

Jayant Giri
Department of Mechanical Engineering, Yeshwantrao Chavan College of Engineering, Nagpur, India
Division of Research and Development,
Lovely Professional University,
Phagwara, India
jayantpgiri@gmail.com

Ragini Y P
Department of Biosciences,
Saveetha School of Engineering,
Saveetha Institute of Medical and Technical Sciences (SIMATS),
Saveetha University, Chennai
Mail id: raginiyp1526@gmail.com

Abstract— In recent years, the intersection of AI and quantum computing has been a rapidly evolving area in which quantum mechanics can be employed to improve machine learning constructs. Quantum Machine Learning (QML) is a field at the intersection of quantum computation and AI wherein the properties of quantum mechanics is integrated with the classical AI algorithms, allowing superior computational power due to classical AI model's inability to describe complex, high-dimensional data. some quantum architectures, notably variational quantum circuits, quantum neural networks, and hybrid quantum-classical models, have shown potential for achieving an exponential speedup in tasks such as optimization, pattern recognition, and data classification. These breakthroughs set the stage for the development of AI systems capable of processing enormous datasets with greater efficiency, as well as tackling computationally intractable problems that cannot be efficiently solved using classical computers. While substantial progress has been made, challenges persist in the areas of scalable quantum hardware, efficient quantum algorithms, and noise mitigation, all of which are critical to realizing any practical implementations. As of now, the latest research focuses on investigating quantum-enhanced approaches to reinforcement learning, quantum generative models, and quantum-inspired deep learning architectures, which has the potential to revolutionize various domains, including cryptography, drug discovery, financial modeling, and autonomous systems. Hybrid quantum-classical framework in which a portion of the quantum computations acts as the descriptor or complement for classical deep learning models could be one plausible route to reaching near-term quantum advantages in AI applications. With the rapid advancements in quantum computing technology, the merging of AI and quantum computing will likely hit new heights in artificial intelligence as quantum computations will be able to solve problems that cannot be achieved within classical limits. Potential future work would be in quantum error correction, quantum learning algorithms, and hardware-efficient quantum AI models. The combination of these two technologies has the capacity to transform approaches towards data-driven decisions, expedite scientific breakthroughs, and develop next-level intelligent systems with superior computational efficiency.

Index Terms —Quantum Neural Networks (QNNs), Variational Quantum Circuits (VQCs), Quantum-Classical Hybrid Models, Quantum Algorithms, Quantum Entanglement, Quantum Data Encoding, Fault-Tolerant Quantum Computing,

1. INTRODUCTION

Artificial Intelligence (AI) has been like a boon to various fields including healthcare, finance, autonomous systems, and NLP (natural language processing) among others. Nonetheless, the increasing complexity of AI-driven applications has outstripped the capabilities of classical computing, calling for an investigation of new computational paradigms. By taking advantage of quantum mechanics, quantum computing has therefore become a promising path for increasing AI capabilities, offering greater computational power for high-dimensional data and more complex optimizations [1]. The combination of AI with quantum computing, commonly known as Quantum Machine Learning (QML) hopes to leverage quantum parallelism and entanglement to enhance learning processes, streamline complex models, and address challenges that are still intractable by classical AI methods [2].

Unlike classical bits, which can hold the value 0 or 1, quantum computing uses these basic units called qubits, which can exist in superpositions of states. It allows quantum algorithms to operate on a huge parallel scale, which may reduce the time complexity of AI tasks such as optimization, clustering, and feature selection [3]. Noteworthy quantum algorithms including the Harrow-Hassidim-Lloyd (HHL) algorithm for linear systems solving [4] and Grover's search algorithm [5] have shown that quantum speedups are possible in some cases of AI

979-8-3503-1502-8/23/$31.00 ©2025 IEEE