Performance and Benchmarking of Quantum Convolutional Neural Networks in the Astrophysical Signal Detection: Focus on Transient Gamma-Ray Bursts

Abstract:

The intersection of Quantum Computing and Machine Learning, known as Quantum Machine Learning (QML), offers powerful tools to explore the frontiers of science, particularly in Astrophysics.

Astrophysics, heavily reliant on Big Data, requires fast, accurate, and reliable methodologies for data exploration and related discoveries. Scientists in this field are inundated with vast amounts of data from ground-based and satellite experiments. Consequently, the application of new methodologies such as Deep Learning (DL) in astrophysics is becoming essential. The use of DL methods to solve astrophysical problems is increasing exponentially, although the potential of Quantum DL remains largely unexplored.

In this work, we evaluate the performance of Quantum Convolutional Neural Networks (QCNNs) in astrophysical signal detection, focusing on Transient Gamma-Ray Bursts (GRBs).
GRBs are sudden explosions of gamma-rays, isotropically distributed and of cosmological origin. There are two types of GRBs: short-duration (less than two seconds), caused by the merger of two neutron stars or a neutron star and a black hole, and long-duration (lasting several seconds to minutes), triggered by the collapse of a massive star and the birth of a black hole.

Our previous work (Rizzo et al. 2024) demonstrated that QCNNs can accurately identify GRB signals in AGILE space mission data. Building on this, we applied various QCNN architectures to a new dataset from Cherenkov Telescope Array (CTA) simulations.

The CTA, the next generation of ground-based observatories for high and very-high energy science, will enhance gamma-ray astronomy with over a hundred highly sensitive, fast-reacting Cherenkov telescopes. The facility will be equipped with real-time analysis software that automatically generates science alerts and analyzes ongoing observational data in real-time. Prompt and precise detection of GRB signals in real-time is crucial for generating reliable science alerts.

In this study, we utilized hybrid quantum-classical machine learning, implementing our Quantum Neural Network using Parametrized Quantum Circuits. We explored the performance of our QCNN using both Pennylane and Qiskit libraries. Additionally, we investigated different architectures and encoding methods, such as Data Reuploading, Angle, and Amplitude encoding.

Initially, we compared the performance of QCNNs with classical CNNs to assess improvements in terms of time and model complexity. We found that QCNNs achieved comparable accuracy levels, often exceeding 90%, with fewer parameters than classical CNNs. This reduction in parameter count suggests a more efficient model that could potentially offer benefits in terms of computational resources and energy consumption. However, the training times for QCNNs were notably longer due to the current lack of highly optimized quantum deep learning implementations. This indicates that while

QCNNs show promise, further development and optimization of quantum algorithms and hardware are necessary to fully realize their potential.

Subsequently, we conducted a comprehensive benchmark to study the effect of various hyperparameters on model accuracy and stability. We specifically examined the impact of the number of qubits, encoding methods, and the number of parameters. Our results showed that increasing the number of qubits and employing more sophisticated encoding methods, such as Data Reuploading, generally improved the model's performance. However, these improvements came at the cost of increased complexity and longer training times. The balance between accuracy and computational efficiency remains a critical factor in the practical application of QCNNs.

GRB signals can be represented as time series or sky maps (images), and we analyzed both types of datasets. For time series data, QCNNs demonstrated robust performance, accurately detecting GRB signals with a high degree of precision. When applied to sky maps, QCNNs also performed well, maintaining high accuracy levels. Notably, in both cases, QCNNs required fewer parameters than their classical counterparts, highlighting their potential for efficiency. However, in terms of time performance, QCNNs still do not show superiority. The longer training times observed underscore the need for advancements in quantum hardware and software optimization to make QCNNs a viable alternative to classical neural networks in real-time applications.

This work, being the first to study the application of QCNNs in Astrophysics, can pave the way for future experiments, highlighting the potential, advantages, and limitations of QCNNs in this field. By demonstrating that QCNNs can achieve similar accuracy to classical CNNs with fewer parameters, this study opens up new avenues for research and development. The insights gained from our benchmarks can inform future efforts to optimize quantum neural networks for specific astrophysical tasks, potentially leading to significant advancements in the speed and efficiency of data analysis in this data-intensive field.