

Quantum Computing for Gamma-Ray Astrophysics: Detecting and Localizing Sources with Variational Circuits and Quantum Annealing

DT-Lab Kick Off Meeting

Bologna, 30/09/2026

**Alessandro Rizzo - INAF (OACT)
USC-C WG Quantum Computing**



INAF Quantum Computing Workgroup

- INAF contributed to Spoke 10 (Quantum Computing) of the ICSC, Italian Research Center on High Performance Computing, Big Data and Quantum Computing
- We have recently established a Quantum Computing Thematic Group within INAF USC-C.
- **Goal:** Developing and benchmarking Quantum Algorithms to tackle computational challenges in Astrophysics and Cosmology.
- We are developing algorithms using simulators to be ready for real hardware.

Bologna:

- Andrea Bulgarelli
- Carlo Burigana
- Massimo Meneghetti
- Nicolò Parmiggiani
- Tiziana Trombetti

Catania:

- Farida Farsian
- Alessandro Rizzo
- Francesco Schillirò
- Fabrizio Roberto Vitello

Roma:

- Vincenzo Fabrizio Cardone
- Giuseppe Sarracino
- Roberto Scaramella
- Vincenzo Testa

Trieste:

- Giuseppe Murante

Quantum computing for astrophysics and cosmology: Results from the INAF activities[☆]

Andrea Bulgarelli ^{a,*,}, Carlo Burigana ^{b,c,}, Luca Cappelli ^{e,}, Vincenzo Fabrizio Cardone ^{f,}, Stefano Cavuoti ^{d,}, Farida Farsian ^{g,}, Irene Graziotti ^{d,}, Antonio Macaluso ^{h,}, Massimo Meneghetti ^{a,}, Giuseppe Murante ^{e,}, Nicolò Parmiggiani ^{a,}, Giuseppe Riccio ^{d,}, Alessandro Rizzo ^{g,}, Roberto Scaramella ^{f,}, Francesco Schillirò ^{g,}, Giuseppe Sarracino ^{f,}, Vincenzo Testa ^{f,}, Tiziana Trombetti ^{b,c}

^a INAF – Astrophysics and Space Science Observatory, Bologna, Via Pietro Gobetti 93/3, Bologna, 40129, Italy

^b INAF – Institute of Radio Astronomy, Bologna, Via Pietro Gobetti 101, Bologna, 40129, Italy

^c INFN – Bologna Division, Via Irnerio 46, Bologna, 40127, BO, Italy

^d INAF – Astronomical Observatory of Capodimonte, Salita Moiarriello 16, Napoli, 80131, Italy

^e INAF – Astronomical Observatory of Trieste, Via Tiepolo 11, Trieste, 34131, Italy

^f INAF – Astronomical Observatory of Rome, Via Frascati 33, Monte Porzio Catone, 00078, Italy

^g INAF – Astronomical Observatory of Catania, Via S. Sofia 78, Catania, 95123, CT, Italy

^h Agents and Simulated Reality Department, German Research Center for Artificial Intelligence (DFKI), Saarbrücken, Saarland, Germany

Full length paper

Comparing Classical and Quantum Deep Learning Techniques for Anomaly Detection of Short-Duration Gamma-Ray Signals[☆]

Alessandro Rizzo ^{a,*,}, Nicolò Parmiggiani ^{b,}, Andrea Bulgarelli ^{b,}, Antonio Macaluso ^{c,}, Carlo Burigana ^{d,e,}, Eric Burns ^{f,}, Luca Cappelli ^{g,h,}, Vincenzo Fabrizio Cardone ^{i,j,}, Farida Farsian ^{a,}, Savitri Gallego ^{k,}, Giuseppe Murante ^{g,}, Giuseppe Sarracino ^{i,}, Roberto Scaramella ^{i,j,}, Francesco Schillirò ^{a,}, Vincenzo Testa ^{i,}, Tiziana Trombetti ^{d,e,}, Dieter H. Hartmann ^{m,}, Carolyn A. Kierans ^{l,}, Eliza Neights ^{l,n,}, John A. Tomsick ^{o,}, Andreas Zoglauer ^o

^a INAF-Osservatorio Astronomico di Catania, Via S. Sofia 78, Catania, 95123, CT, Italy

^b INAF-Osservatorio di astrofisica e scienza dello spazio, Via Pietro Gobetti 93/3, Bologna, 40129, BO, Italy

^c Agents and Simulated Reality Department, German Research Center for Artificial Intelligence (DFKI), Saarbrücken, Saarland, Germany

^d INAF-Istituto di Radioastronomia, Via Piero Gobetti 101, Bologna, 40129, BO, Italy

^e INFN Sezione di Bologna, Via Irnerio 46, Bologna, 40127, BO, Italy

^f Department of Physics and Astronomy, Louisiana State University, Baton Rouge, 70803, LA, USA

^g INAF-Osservatorio Astronomico di Trieste, Via Tiepolo 11, Trieste, 34131, TS, Italy

^h Università degli Studi di Trieste, Dipartimento di Fisica, Via A. Valerio 2, Trieste, 34127, TS, Italy

ⁱ INAF-Osservatorio Astronomico di Roma, Via Frascati 33, Monte Porzio Catone, 00078, RM, Italy

^j INFN Sezione di Roma 1, Piazzale Aldo Moro 2, Edificio G. Marconi, Roma, 00185, RM, Italy

^k Institut für Physik & Exzellenzcluster PRISMA+, Johannes Gutenberg-Universität Mainz, Mainz, 55099, Germany

^l NASA Goddard Space Flight Center, 8800 Greenbelt Road, Greenbelt, 20771, MD, USA

^m Clemson University, Department of Physics and Astronomy, Clemson, 29634-0987, SC, USA

ⁿ George Washington University, 2121 I St NW, Washington, 20052, DC, USA

^o Space Sciences Laboratory, University of California, 7 Gauss Way, Berkeley, 94720-7450, CA, USA

Benchmarking Quantum Convolutional Neural Networks for Signal Classification in Simulated Gamma-Ray Burst Detection

Farida Farsian OACT, INAF Via S. Sofia 78, Catania, Italy farida.farsian@inaf.it	Nicolò Parmiggiani OAS, INAF Via Pietro Gobetti 93/3, Bologna, Italy nicolo.parmiggiani@inaf.it	Alessandro Rizzo OACT, INAF Via S. Sofia 78, Catania, Italy alessandro.rizzo@inaf.it
Gabriele Panebianco OAS, INAF Via Pietro Gobetti 93/3, Bologna, Italy gabriele.panebianco@inaf.it	Andrea Bulgarelli OAS, INAF Via Pietro Gobetti 93/3, Bologna, Italy andrea.bulgarelli@inaf.it	Francesco Schillirò OACT, INAF Via S. Sofia 78, Catania, Italy francesco.schilliro@inaf.it
Carlo Burigana IRA, INAF Via Pietro Gobetti 101, Bologna, Italy carlo.burigana@inaf.it	Vincenzo Cardone OAR, INAF Via Frascati 33, Monteporzio Catone, Italy vincenzo.cardone@inaf.it	Luca Cappelli OATs, INAF Via Tiepolo 11, Trieste, Italy luca.cappelli@inaf.it
Massimo Meneghetti OAS, INAF Via Pietro Gobetti 93/3, Bologna, Italy massimo.meneghetti@inaf.it	Giuseppe Murante OATs, INAF Via Tiepolo 11, Trieste, Italy giuseppe.murante@inaf.it	Giuseppe Sarracino OACN, INAF Via Moiarriello 16, Napoli, Italy giuseppe.sarracino@inaf.it
Roberto Scaramella OAR, INAF Via Frascati 33, Monteporzio Catone, Italy roberto.scaramella@inaf.it		Vincenzo Testa OAR, INAF Via Frascati 33, Monteporzio Catone, Italy vincenzo.testa@inaf.it
Tiziana Trombetti IRA, INAF Via Pietro Gobetti 101, Bologna, Italy tiziana.trombetti@inaf.it		



Quantum Annealing for Gamma-ray Source Detection and Localization with AGILE Data

Alessandro Rizzo^{1,*}, Nicolò Parmiggiani², Andrea Bulgarelli², Gabriele Panebianco², Carlo Burigana³, Vincenzo Fabrizio Cardone⁴, Farida Farsian¹, Massimo Meneghetti², Giuseppe Murante⁵, Giuseppe Sarracino⁴, Roberto Scaramella⁴, Francesco Schillirò¹, Vincenzo Testa⁴, Tiziana Trombetti³ and Fabio Roberto Vitello¹

¹ INAF – Osservatorio Astrofisico di Catania, Via Santa Sofia 78, 95123, Catania, Italy

² INAF – Osservatorio di Astrofisica e Scienza dello Spazio, Via Piero Gobetti 93/3, Bologna, 40129, Italy

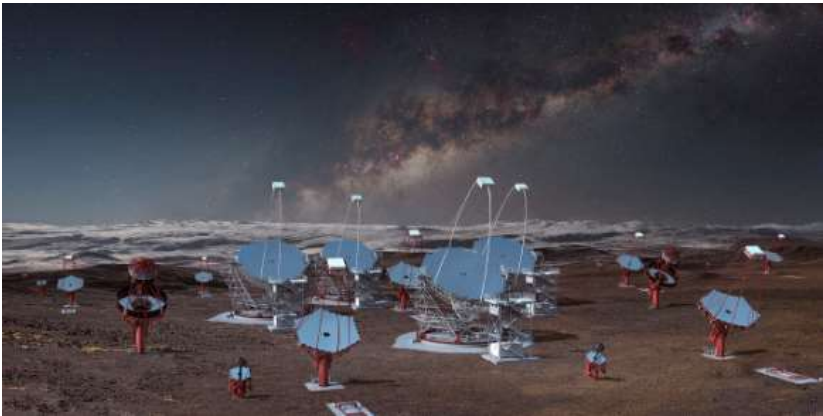
³ INAF – Istituto di Radioastronomia, Via Piero Gobetti 93/3, Bologna, 40129, Italy

⁴ INAF – Osservatorio Astronomico di Roma, Via Frascati 33, Monteporzio Catone, 00078, Italy

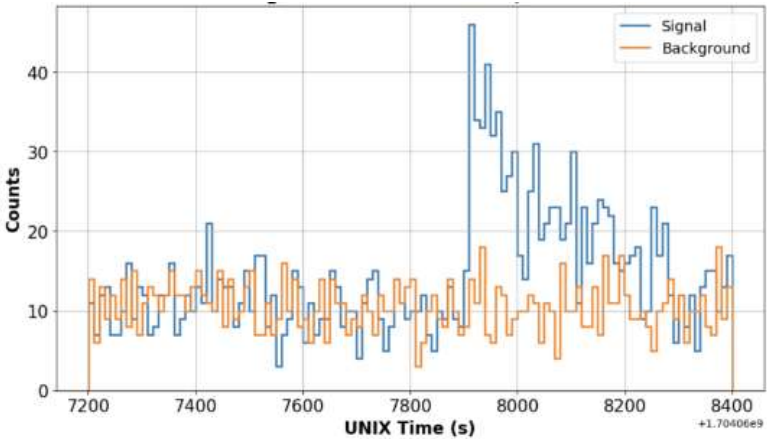
⁵ INAF – Osservatorio Astronomico di Trieste, Via Tiepolo 11, 34131, Trieste, Italy

Benchmarking Quantum Convolutional Neural Networks for Signal Classification in Simulated Gamma-Ray Burst Detection

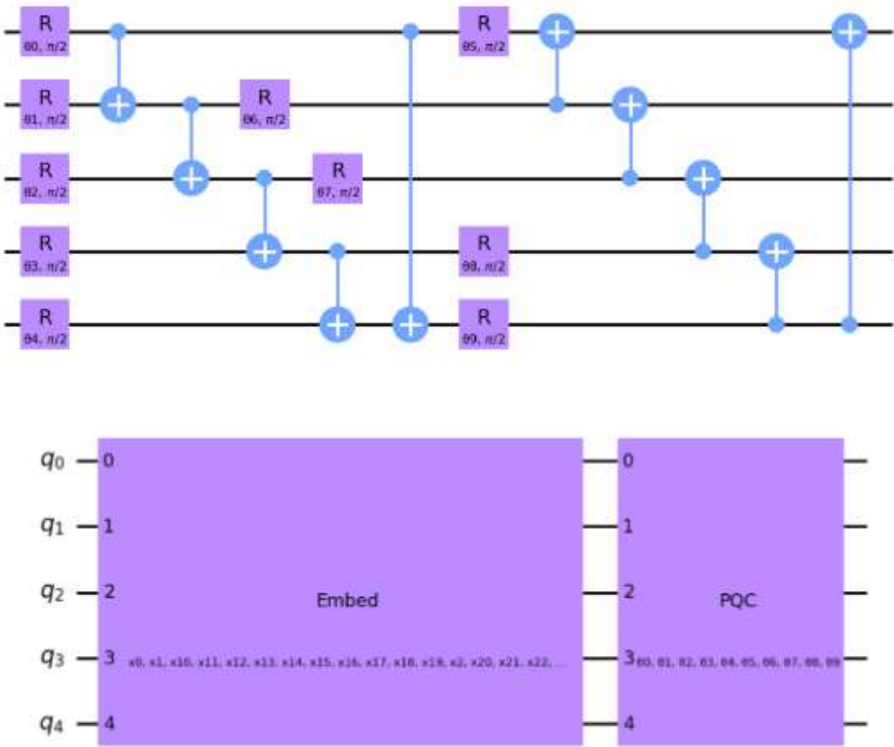
Cherenkov Telescope Array Observatory



Simulated Dataset: GRB Signal and Background noise



Parametrised Quantum Circuit in Qiskit



F.Farsian et al, 2025

- **Test on Quantum Neural Network performance and number of Qubits**

NN model	Num of Qubits	Num of parameters	Accuracy on Train set	Accuracy on Test set	Time
Classical CNN	-	56	99.7%	97.35%	21s
Quantum NN	4	8	Doesn't learn	-	-
Quantum NN	6	12	90.3%	87.7%	89s
Quantum NN	12	24	99.38%	97.5%	713s

- **Test on Sample complexity and Quantum Generalization Advantage (on 20 input samples)**

NN model	Num of Qubits	Num of parameters	Accuracy on Train set	Accuracy on Test set	Time
Classical CNN	-	56	55%	52.22%	91s
Quantum NN	6	24	95%	98.33%	23s

F.Farsian et al, 2025

- Quantum Neural Network performance on two types of Data Encoding

Data Encoding	Num of Qubits	Num of parameters	Accuracy on Train set	Accuracy on Test set
Amplitude Encoding	7	14	76.56%	66.67%
Data Reuploading	7	63	91.13%	88.12%

- QNN performance on Real Data from AGILE satellite

NN model	Num of Qubits	Num of parameters	Accuracy on Train set	Accuracy on Test set
Classical CNN	-	56	96.55%	93.91%
Quantum NN	7	14	91.17%	90.72%

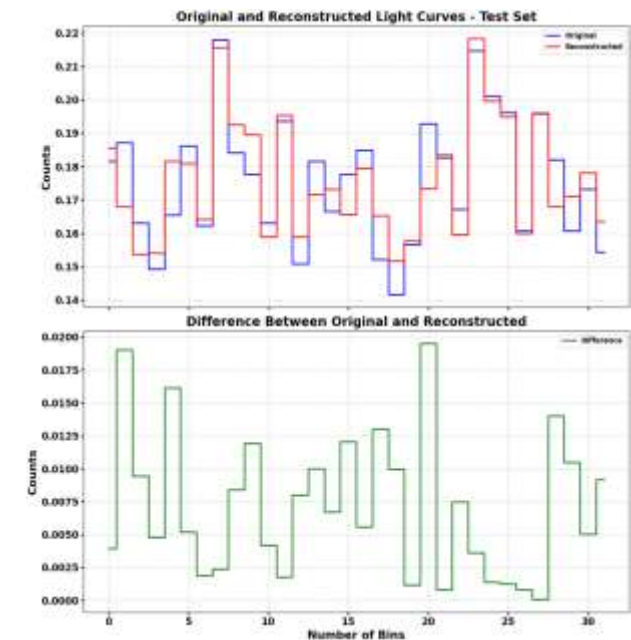
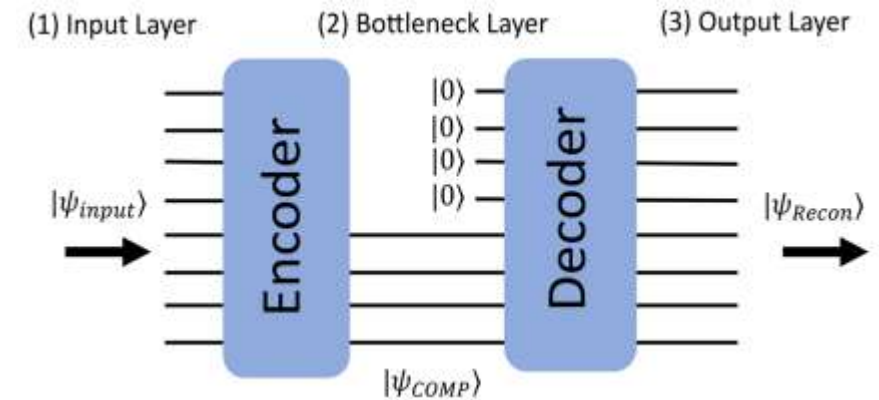
- The performance of QCNN in terms of **accuracy** is equal or better than the classical CNN in a specific case.
- Generalization power** of QML in case of very few training dataset and its advantage respect to classical ML.
In this case we have **only 20 light curves** as the training set
- In this study we reach **Quantum Advantage** in terms of **sample complexity**.

F.Farsian et al, 2025

Comparing Classical and Quantum Deep Learning Techniques for Anomaly Detection of Short-Duration Gamma-Ray Signals

- **Goal** → Compare the detection capabilities of short GRBs in the **COSI BGO light curves** using machine learning and quantum machine learning anomaly detection techniques.
- **Anomaly detection task** → Detect anomalies (short GRBs) from COSI BGO background light curves → An anomaly might indicate a GRB.
- Reproduce neural networks developed by **AGILE** team to compare quantum and classical machine learning algorithms. (*Parmiggiani et al., 2023*)
- A key focus is comparing performance under resource-constrained scenarios such as limited training data and fewer trainable parameters

Rizzo et al., 2026



Results – Comparison between Classical and Quantum Approaches

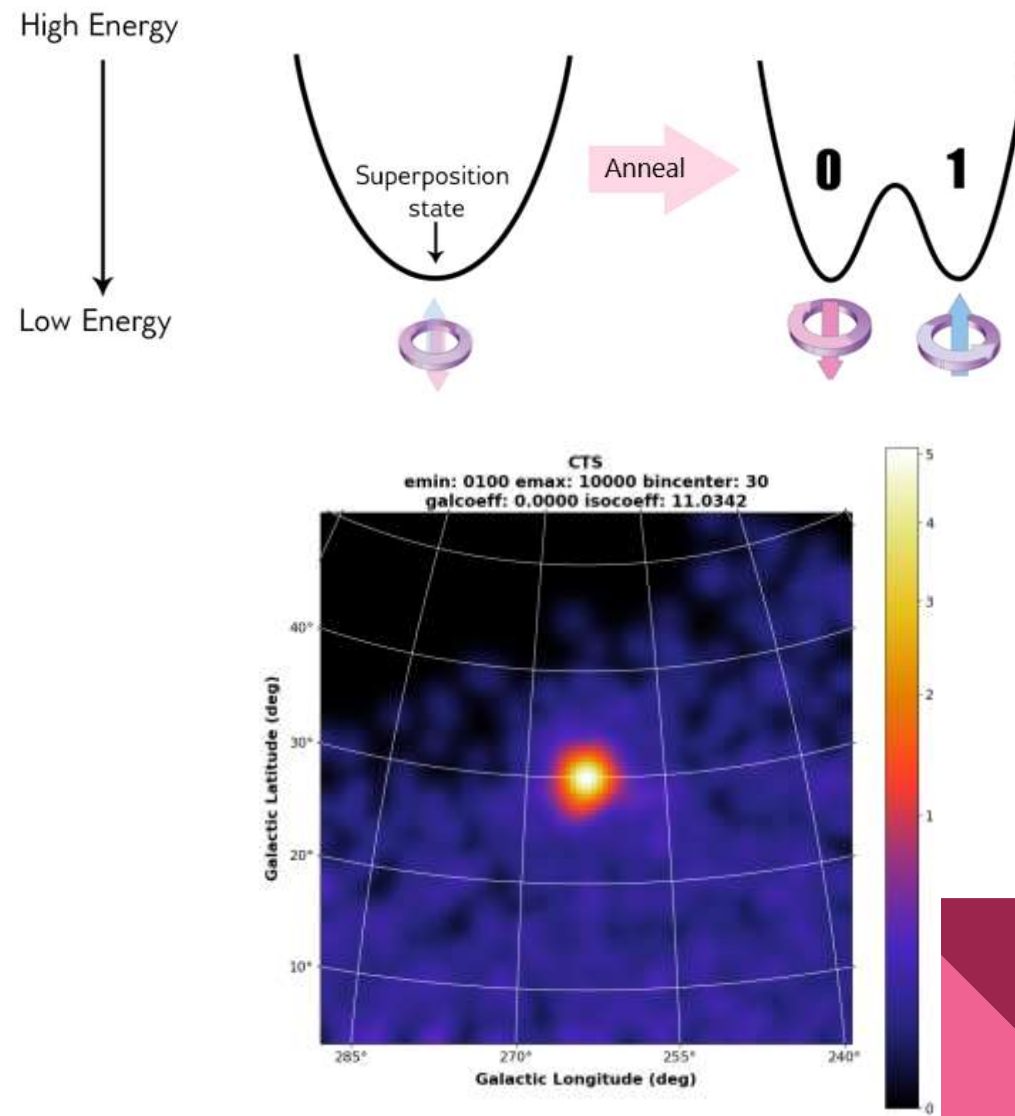
Dataset Configuration	Approach	Model Details	Mean Absolute Percentage Error
100 Samples - 32 Bins	Classical	6.5×10^5 Parameters	6.87 %
	Classical	705 Parameters	34.77 %
	Quantum	Real Amplitudes (10 parameters)	6.75%
1000 Samples - 32 Bins	Classical	6.5×10^5 Parameters	2.29 %
	Classical	705 Parameters	19.72 %
	Quantum	EfficientSU2 (20 parameters)	6.84 %
5000 Samples - 32 Bins	Classical	6.5×10^5 Parameters	0.82 %
	Classical	705 Parameters	9.90 %
	Quantum	EfficientSU2 (20 parameters)	6.73 %

- **Classical:** Excellent with large data and many parameters, but it drops significantly when data or parameters are limited.
- **Quantum:** Strong results with 10 parameters and robust on small datasets, outperforming the classical approach there.
- QML is well suited to resource-constrained settings, either with data scarcity or when simple models are needed.

Rizzo et al., 2026

Quantum Annealing for Gamma-ray Source Detection and Localization with AGILE Data

- **Goal** → Reformulate the maximum-likelihood analysis for gamma-ray source detection and localization as a **Quadratic Unconstrained Binary Optimization (QUBO)** problem
- Estimated parameters: source flux, background, source position, and detection significance
- 200 simulated sky maps at extragalactic latitude (**AGILE Science Tools**)
- Solved with **Simulated Quantum Annealing (SQA)**
- Benchmarked against the classical **AGILEpy** maximum-likelihood pipeline



Conclusions - Classical Maximum Likelihood Estimation and Quantum Annealing

- Both classical and quantum approaches recover the source flux accurately: systematic error of -0.3% (QUBO) and $+2.8\%$ (classical AGILEpy)
- The isotropic background is estimated with a mean residual of -0.87 (QUBO) and -0.58 (classical), in units of the background coefficient
- The QUBO identifies the correct source position among 81 candidates on a 0.5° -spaced grid in 90% of the maps
- The QUBO reproduces the classical estimates, showing that quantum annealing can be applied to gamma-ray source analysis without loss of accuracy
- **Future work:** deploy the QUBO on real annealer hardware (D-Wave), tackling embedding and noise.

