OSSERVATORIO DI ASTROFISICA E SCIENZA DELLO SPAZIO DI BOLOGNA

Deep learning techniques to detect and localize Gamma-ray Bursts in sky maps and time series acquired by the AGILE and COSI space missions.

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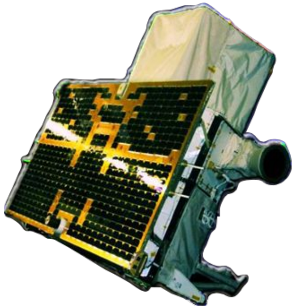


RICAP 24

25/09/24 Rome

Context and Research Goals

- This research aims to develop **Deep Learning** (DL) and **Quantum Deep Learning** models to analyze the data acquired by the **AGILE** instruments to detect and localize **Gamma-Ray Bursts**.

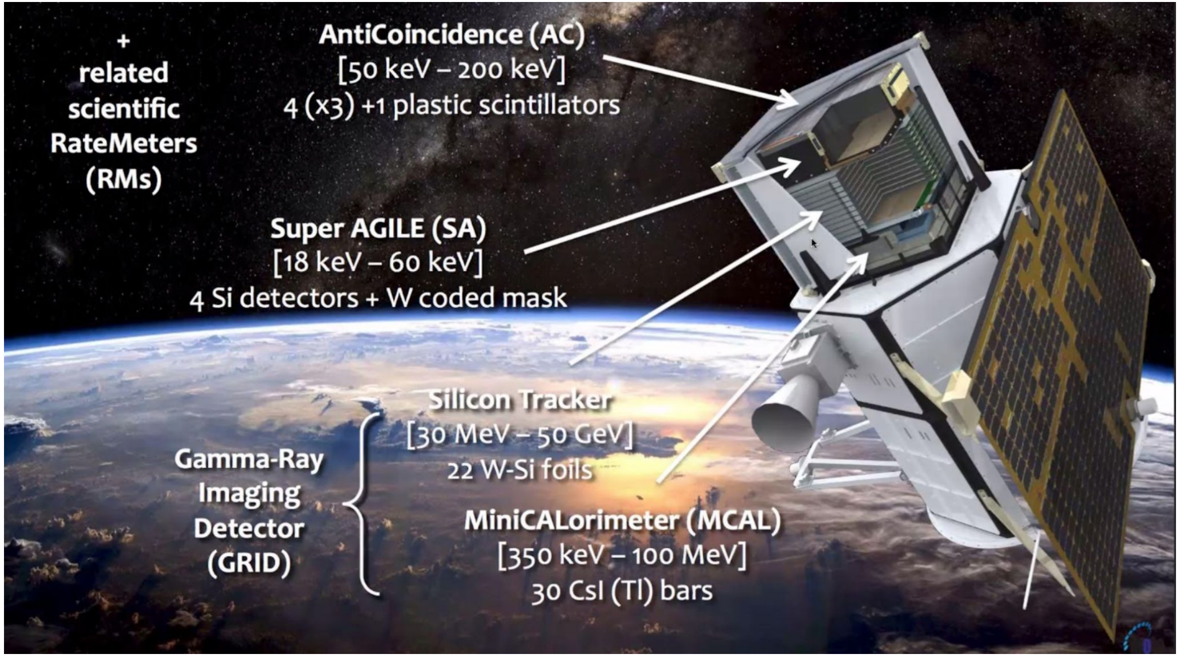
- We developed DL models to analyze **sky maps** as 2D images and **time series** acquired by the AGILE detectors.

- In addition, we are developing a **DL model for COSI to localize the GRBs** using simulated data acquired by its detectors.

- We approached different **classes of problems**:
    - Binary Classification
    - Anomaly Detection
    - Regression

AGILE satellite

- **AGILE** is an ASI space mission launched in 2007, designed to study X-ray and gamma-ray astronomy. AGILE terminated the in-orbit operations on February 2024, after almost 17 years of successful scientific observations.



COSI satellite

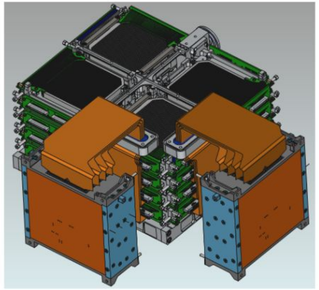
- The **Compton Spectrometer and Imager (COSI)** is a NASA Astrophysics Small Explorer satellite mission.

- COSI is a soft gamma-ray survey telescope (0.2-5 MeV) planned for launch in 2027.

- It is designed to probe the origins of Galactic positrons, uncover the sites of nucleosynthesis in the Galaxy, perform pioneering studies of gamma-ray polarization, and find counterparts to multi-messenger sources.

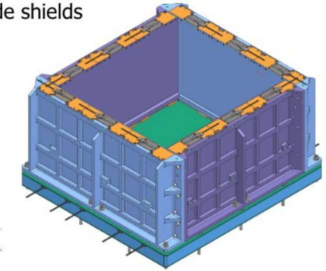
- COSI's compact Compton telescope combines improvement in sensitivity, spectral resolution, angular resolution, and sky coverage to facilitate groundbreaking science.

GeDs

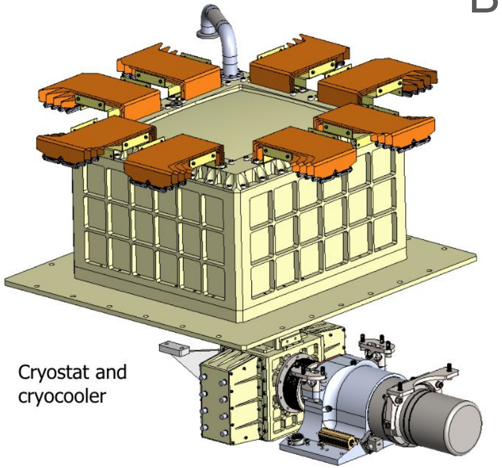


Detectors, flex circuits, and read out electronics

Side shields



BGO



[COSI Instrument]

Deep Learning Models for AGILE

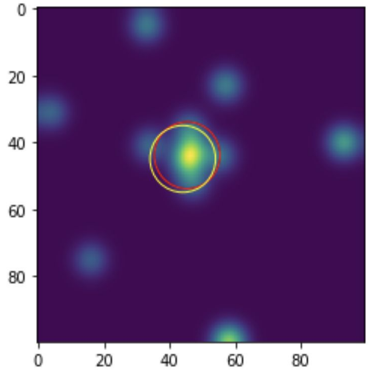
Detection and localization of GRBs in Sky Maps

- We developed two **Convolutional Neural Networks** (CNN) to **detect and localize** GRBs from the AGILE/GRID **counts maps**.

- We simulated three **datasets with 40 000 maps** for the training, testing, and validation phases. The CNN is trained with a **supervised learning technique**, so the datasets are labeled.

- We evaluated the CNN using the catalogs of other space missions detecting **21 GRBs with a sigma > 3** while the standard **Aperture Photometry** analysis detects **only two GRBs.**

- The localization is executed with a CNN to perform a **regression** on the coordinates of the GRBs with a **mean error of 0.7 degrees**.



Parmiggiani N. et al. A Deep Learning Method for AGILE/GRID Gamma-ray Bursts detection, Astrophysical Journal, Volume 914, Issue 1, id.67, 12 pp (2021)

Parmiggiani N. et al. Preliminary Results of a New Deep Learning Method to Detect and Localize GRBs in the AGILE/GRID Sky Maps. proceedings of the ADASS XXXII (2022) conference arXiv

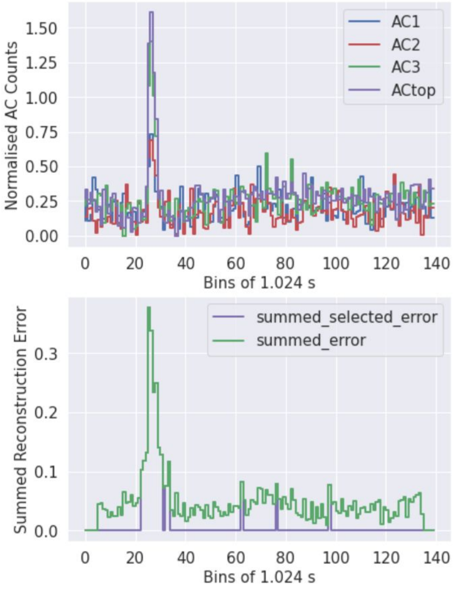
Anomaly Detection in time series

- We implemented a **Convolutional Neural Network autoencoder** to **detect GRBs** in the ratemeters of the AGILE Anticoincidence System (ACS).

- The autoencoder aims to reconstruct the input data, **minimizing the reconstruction error,** and can be used for **anomaly detection.**

- We trained the model using an **unsupervised technique** using 5000 background-only time.

- We evaluated the trained model using GRBs detected by other space missions, and the model **detected 72 GRBs**, **15 of which** were detected for the first time in the AGILE data.



Parmiggiani N., Bulgarelli A., Ursi A. et al. “A Deep-learning Anomaly-detection Method to Identify Gamma-Ray Bursts in the Ratemeters of the AGILE Anticoincidence System”, Astrophysical Journal, Volume 945, (2023)

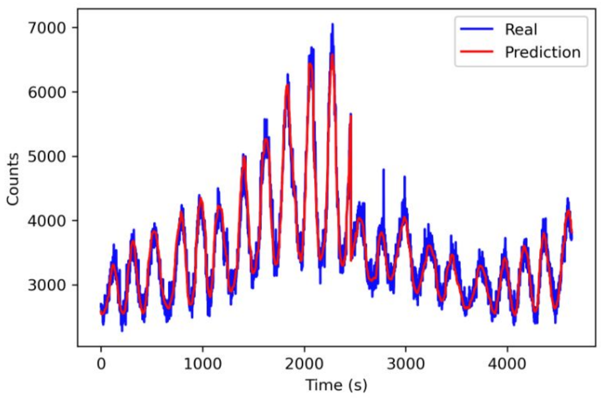
Deep Learning to predict the ACS background

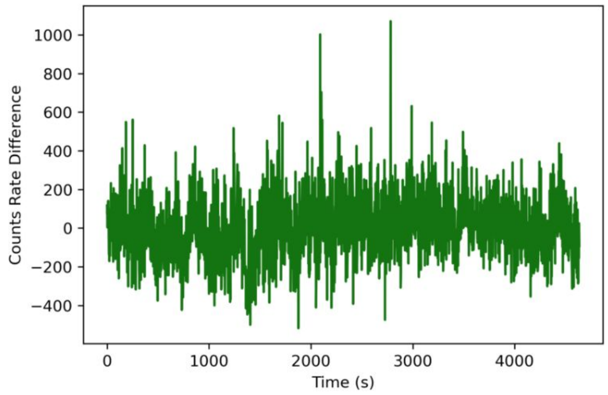
- **Goal**: predict the background count rates of the AGILE ACS system using the satellite **orbital and attitude parameters.**

- We calculated the **difference** between the **real** and **predicted** counts of the test dataset to check the accuracy of the model. The model has a mean prediction error of 3.8%.

- We can use the predicted counts of the background **to detect GRBs** where the differences with the acquired counts are higher than a predefined threshold.

- We can apply this detection method to raw data **without applying the detrending algorithm** that can introduce artificial anomalies.

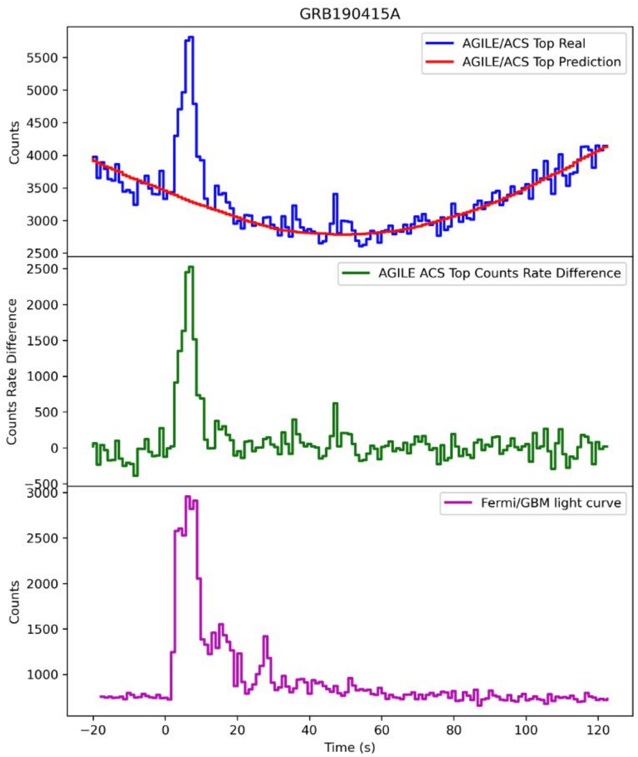




Similar approach used by R. Crupi et al. *Searching for long faint astronomical high energy transients: a data driven approach.* EA 2023

Detect GRBs using the predicted values

- We tested this detection method using the **GRB web catalog** and extracting light curves from the ACS archive (2019-2022).
- The method **detects 39 GRBs** with sigma > 3. **Four GRBs are new detections** that were not detected in previous analyses.
- We also compared the results obtained with the **light curve of the Fermi/GBM** detector because they have a similar energy range. ACS (50-200 keV) and Fermi/GBM (50-300 keV)
- We are investigating other possible applications of this kind of Deep Learning model to predict the background level of the AGILE detectors.



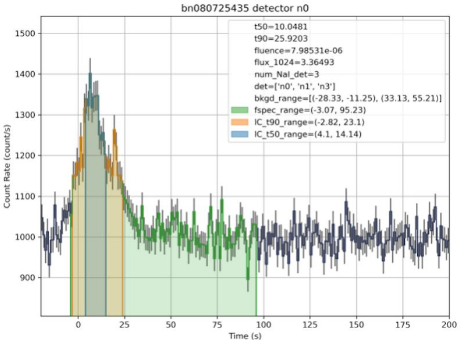
Parmiggiani N., et al. “A New Deep Learning Model to Detect Gamma-Ray Bursts in the AGILE Anticoincidence System”, Astrophysical Journal, Volume 973, (2024)

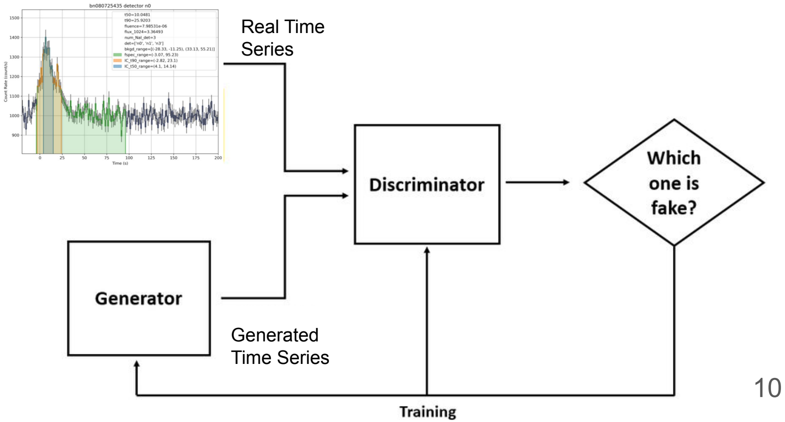
Deep Learning to simulate GRB light curves

- **Goal**: **simulate the light curves of GRBs** using Deep Learning generative architectures such as **Generative Adversial Network** (GAN) and **Variational Autoencoder** (VAE).

- The training of the DL model is done using the light curves of the **fourth Fermi-GBM GRB** catalog after applying filters to remove light curves not suitable for this study.

- There is a work in progress to use **conditional/controlled GAN** to use other parameters such as the fluence and the t90 as input of the model to generate a specific class of GRBs.





Credits: R. Falco

Quantum Computing and Deep Learning

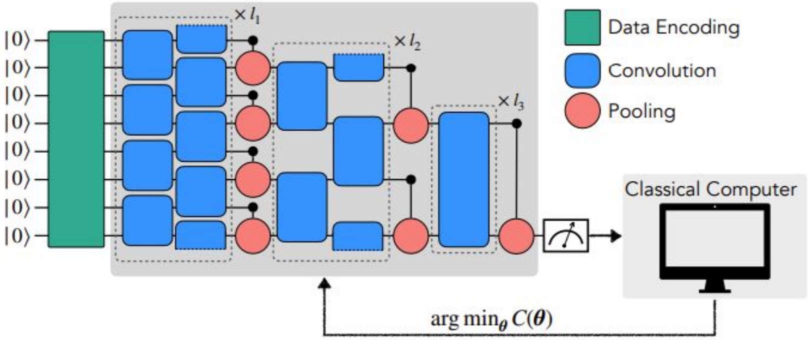
INAF ISTITUTO NAZIONALE DI ASTROFISICA
OAS BOLOGNA

- **Goal**: develop **Quantum Neural Networks** to exploit Quantum Computer features to improve the Deep Learning models.

- **We implemented Quantum CNN models** and compared the results obtained between quantum and classical models. For now, we simulated the Quantum Computers using frameworks such as Qiskit.

- In the future, we have to test these models with **real Quantum Computers** to verify these results.

- The results obtained with simulated Quantum Neural Networks achieve an **accuracy comparable** to that of classical Deep Learning models.



Credits: A. Rizzo

INAF Spoke 10 (quantum computing) members: A. Bulgarelli, C. Burigana, V. Cardone, F. Farsian, M. Meneghetti, G. Murante, A. Rizzo, R. Scaramella, F. Schillirò, V. Testa, T. Trombetti.

Deep Learning for COSI GRB localization

Localization of GRBs using BGO and GeDs data

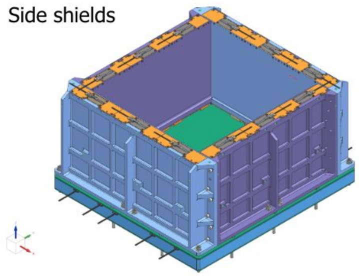
- **The model aims to localize the GRBs using the count rates of the BGO shield composed of five panels.**

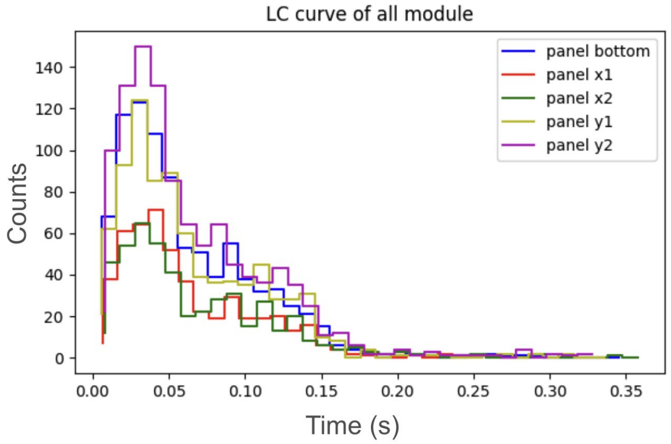
- In addition, to improve the results, we used the counts detected by the **Germanium detectors (GeDs)**.

- We simulated 50 000 GRBs (without background) at different sky coordinates to create our labeled dataset.

- **We calculated the ratios between the integral of counts** detected by different panels to have **a measure independent from the flux of the GRB**.

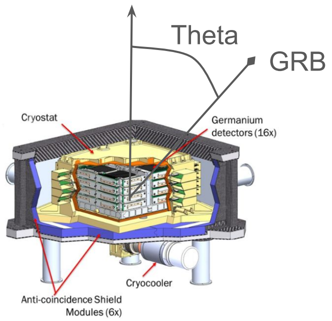
- These ratios are the input of the DL model and the GRB positions are the labels.



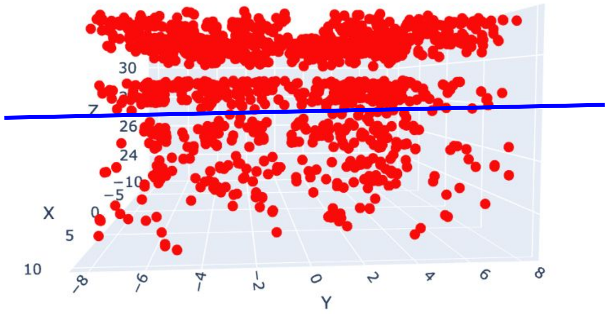


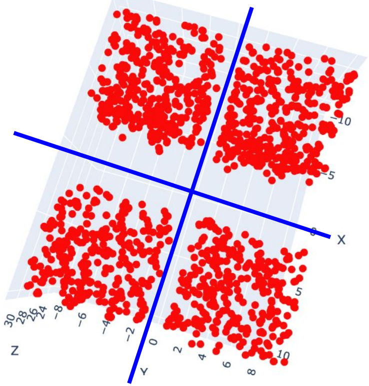
Additional data: GeDs counts

- We can add the counts collected by the GeDs to **improve the localization when the angle Theta < 60° (see figure)**.



- We use the four columns of GeDs divided into two layers -> 8 count rates and **we calculate the ratios between these count rates**



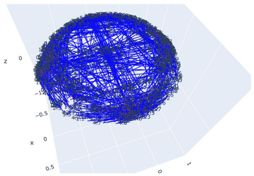


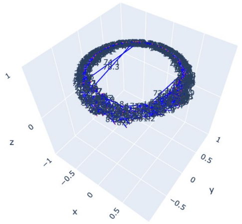
Model Training and evaluation

- The model is implemented using a **feedforward neural network** with four hidden layers. We use **dropout layers** for the regularization and to prevent overfitting.

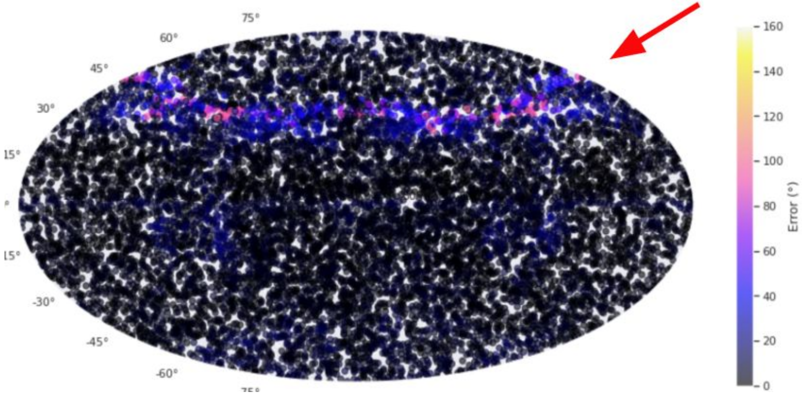
- After the training, we evaluated the model using the test dataset.

- **The results with BGO data only have an issue at Theta near 45 ° but by adding the GeDs data this issue is solved.**

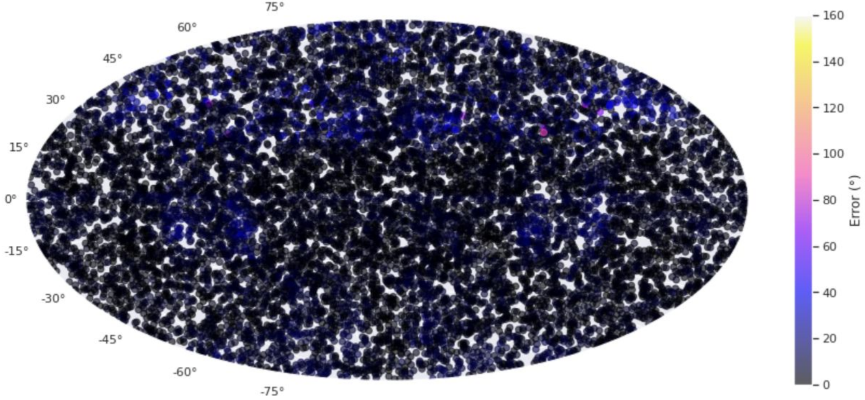




Only BGO: mean error is **6.8°**
Loc. error at 40-50° is **30°**



With GeDs: mean error is **4.8°**
Loc. error at 40-50° is **8.4°**



Summary and Results

- With the current simulations (without background) the model can localize a GRB with a **mean localization error of 4.8°** using the data of BGO and GeDs.
    - These position determinations will complement **COSI's Compton localizations**.
- When Theta ≈ 45° the BGO data cannot localize the source with a low error. **We introduced the GeDs counts to help the model reduce the localization error from 30 to 8.4°.**
- In future work, we have to **evaluate the impact of the background** on the localization error. Currently, the COSI team is simulating a background dataset that we will use for the evaluation.

Conclusions

Conclusions and Future Works

- We developed **Deep Learning and Quantum Deep Learning models to detect GRBs in the sky maps and time series** generated with the data acquired by the detectors onboard the AGILE space mission.

- The results obtained prove the **capability of neural networks to analyze high-energy astrophysical data,** and in the analyzed context, they outperform classical analysis methods.

- We developed a Deep Learning model **to localize the GRBs using the COSI BGO and GeDs** simulated data. We still have to evaluate the impact of the background noise.

- Our goal is to use the knowledge acquired during the development of Deep Learning models for AGILE for the next generation of high-energy projects such as COSI.

Thank You!