



GEFÖRDERT VOM

Bundesministerium für Bildung und Forschung





# Machine Learning for Real-Time Processing of ATLAS Liquid Argon Calorimeter Signals with FPGAs

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# The ATLAS Detector at the LHC



## Large Hadron Collider (LHC):

- Proton bunches collide with **25 ns** spacing (40 MHz)
- 2029: Start of High Luminosity LHC (HL-LHC) with up to ~7 x nominal luminosity

## **ATLAS Detector**

- From ~20 collisions to up to ~200 collisions per bunch crossing (BC) → pileup increases
- 2026-2028: Phase-II upgrade
- Readout electronics of Liquid-Argon (LAr)
   calorimeter need to be improved







[1,2]

# LAr Calorimeter Readout



proportional to deposited energy



# LAr Calorimeter Readout

#### FPGA – Field Programmable Gate Array



[7]

- Real-time signal processing
- Installation of 556 highperformance FPGAs
- 250 Tbps total data rate
- 150 ns maximum latency

## **Optimal Filtering Algorithm (OF)**

• calculates deposited energy per cell





- Development of Neural Networks to improve energy reconstruction
- > Keep parameters low ( $\approx$  100) due to FPGA resource limits

# **Convolutional Neural Networks for LAr Readout**

## Plain 2-layered CNN (2-Conv CNN)

- Dilation enables larger Field of View (FoV)
- ReLU activation functions
- Output: reconstructed energy

## 4-layered CNN with Tagging (4-Conv CNN)

- Sigmoid and ReLU activation functions
- Intermediate output tags signal overlaps
- Output: reconstructed energy





Energy Reconstruction

# **Performance Evaluation: Energy Resolution**



## **Optimal Filter:**

- Larger deviation spread in low energy region
- Negative bias in high energy region

## **CNNs:**

- Improvement in energy resolution, more symmetric and centered distribution
- Performance stable within large energy range



# **Performance Evaluation: Sequence Comparison**

## **Example Sequence**

## **Optimal Filter**

- Close signals cannot be resolved
- Signals within undershoot underestimated



## CNN

 Optimized to reconstruct overlapping signals





# **Performance Evaluation : Energy Reconstruction as Function of Gap**





# **Performance Evaluation - Combining all: Star Plot**



# **Firmware Implementation**





Integrated circuits, configurable by user after manufacturing

- **DSP:** digital signal processor
- **ALM:** adaptive logic module with lookup table

Firmware development on **Intel Stratix-10** FPGA

Final design uses Intel Agilex







# **CNN Firmware Implementation**

- Fully configurable CNN network implementation in VHDL
  - Layer building blocks with configurable
    - Inputs
    - Outputs
    - Activation functions
  - Chaining of components , with configurable
  - Kernel sizes
  - Filters per layer
  - Dilation
- Parameter automatically extracted from Keras output files
- Calculation in 18 bit fixed point numbers
- Supports pipelining and time division **multiplexing**:
  - Design runs at 12x ADC frequency with cyclic processing of 12 detector cells





# **FPGA Resource Estimation**

- Trigger latency requirement ≈ 150 ns
- Need to process 384 detector cells on 1 FPGA
   > E.g. 12-fold multiplexing with 33 parallel instances
- Resource estimates (based on Intel Quartus reports):



FPGA	Network	Multiplexing	Detector cells	$f_{ m max}$	ALMs	DSPs
Stratix-10	2-Conv CNN	12	396	415 MHz	8 %	28 %
	4-Conv CNN	12	396	481 MHz	18 %	27 %
Agilex	2-Conv CNN	12	396	539 MHz	4 %	13 %
	4-Conv CNN	12	396	549 MHz	9 %	12 %



# **Summary and Outlook**

## Summary

- CNNs are able to replace Optimal Filtering algorithm
- CNNs show good performance results in energy resolution and especially on signal overlaps
- Firmware implementation of CNNs with VHDL
- Resource requirements regarding latency and bandwidth are satisfied

## Outlook

- Further improvements by applying quantization aware training and more CNN parameters (100  $\rightarrow$  400)
- Study for influence of energy reconstruction by CNNs for full event reconstruction
- Further tests on FPGA hardware ongoing



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Thank you for your

attention!

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# Sources I

Slide 2:

- [1] URL: <u>https://static1.bmbfcluster.de/3/4/3/8\_ef6a5eef8f44963/3438meg\_22ce2885dae52af.jpg</u>.
- Joao Pequenao. Computer generated image of the whole ATLAS detector. CERN. Mar. 27, 2008.
   URL: <u>https://cds.cern.ch/record/1095924</u> (visited on 05/10/2023).
- [3] Peter Vankov, ATLAS Upgrade for the HL\_LHC: meeting the chalenges of a five-fold increase in collision rate.
   CERN. Jan. 25, 2012. URL: <u>https://cds.cern.ch/record/1419213/</u> (visited on 05/10/2023).

Slide 3:

- [4] Joao Pequenao. Computer generated image of the ATLAS Liquid Argon. CERN. Mar. 27, 2008.
   URL: <u>https://cds.cern.ch/record/1095928</u> (visited on 05/17/2023).
- [5] Karl Jakobs. Lecture Material. CERN. 2015.
   URL: <u>https://www.particles.uni-freiburg.de/dateien/vorlesungsdateien/particledetectors/kap8</u>
- [6] ATLAS Collaboration. *Monitoring and data quality assessment of the ATLAS liquid argon calorimeter.* CERN. May 13, 2014. URL: <u>https://cds.cern.ch/record/1701107</u> (visited on 05/24/2023).

Slides 4, 10:

[7] Intel. *Stratix 10 FPGA*.

URL: https://newsroom.intel.com/editorials/intels-stratix-10-fpga-supporting-smart-connected

<u>-revolution</u> (visited on 04/18/2021).



# **Sources II**

Slides 10, 11:

- [8] *Keras Logo*. URL: <u>https://keras.io/</u> (visited on 05/25/2023)
- [9] *Tensorflow Logo*. URL: <u>https://www.vectorlogo1.zone/logos/tensorflow/index.html</u> (visited on 05/25/2023)

Papers related to these slides:

 Georges Aad et al. Artificial Neural Networks on FPGAs for Real-Time Energy Reconstruction of the ATLAS Lar Calorimeters. In: Computing and Software for Big Science 5.1 (Oct. 2021) DOI: 10.1007/s41781-021-00066-y. URL: <u>https://doi.org/10.1007/s41781-021-00066-y</u>.



# **Convolutional Neural Networks (CNNs)**

- Convolutional operation with certain kernel size
- Activation function gives opportunity to classify, weight, cut





 $A \dots$  activation function







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- **Training** minimizes difference between output and target







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- Feature maps focus on different properties
- **Training** minimizes difference between output and target
- **Dilation** varies field of view (FoV) without increasing parameters
- Keep parameters low ( $\approx 100 / \approx 400$ ) and FoV realistic ( $\leq 24$ ) due to FPGA implementation







## **Performance Evaluation: Different Detector Regions**



> Same architecture trained for different detector regions  $\rightarrow$  shows similar results



# Studying Influence of Size of Training Dataset with the Star Plot



- Training dataset consists of several subdatasets that hold different scenarios
- Study influence of dataset size by enhancing all sub-datasets D equally:
  - [200, 400, 600, 800, 1000]\*D for each scenario
- Some scores not affected
- For others: at least 600\*D for each

# Performance Evaluation: Signal Efficiency vs Background Rejection



## **Receiver Operating Characteristic (ROC) Curves**

- Indicate detection performance
- Signal efficiency = true positives true positives+false negatives

   Background rejection true negatives
  - $=\frac{1}{true \ negatives+false \ positives}$
- Dependent on threshold

# CNNs reach **higher signal efficiencies** at same background rejection level compared to OFMax



# **Performance Studies: Fakes**

Spectrum of predicted transverse energy in BCs without energy deposition





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- Time division **multiplexing**:
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