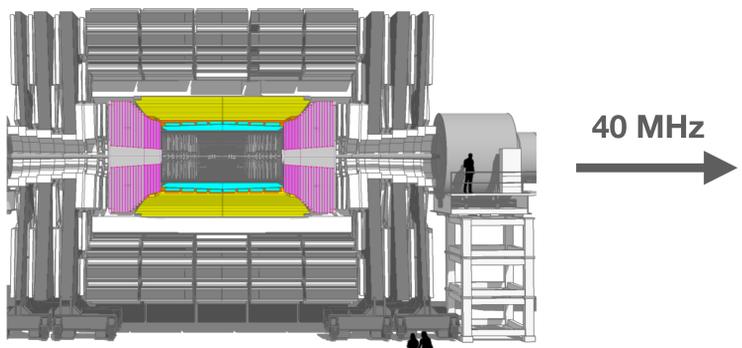


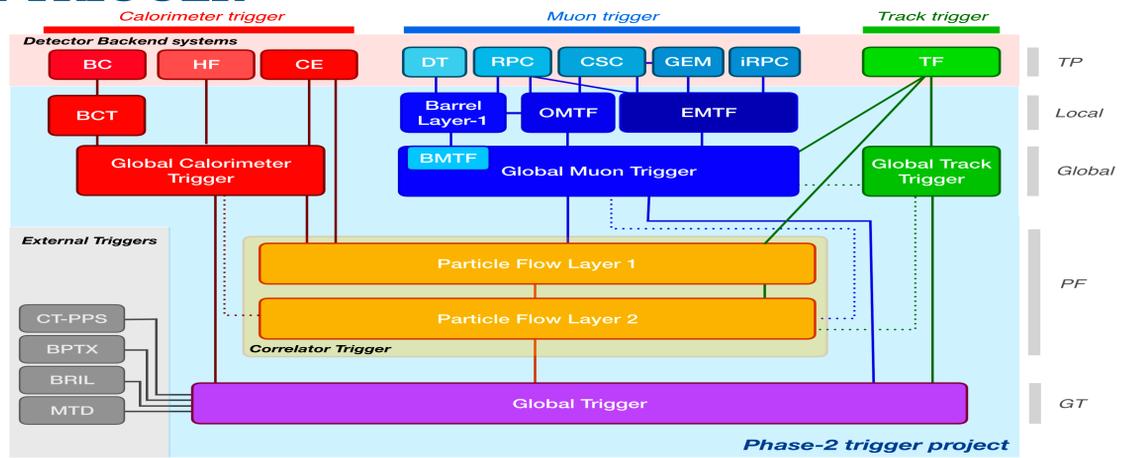
# Development and firmware implementation of a machine learning based hadronic tau lepton Level-1 Trigger algorithm in CMS for the HL-LHC

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## HL-LHC AND THE CMS PHASE 2 LEVEL-1 TRIGGER



40 MHz



HL-LHC =  $\begin{cases} \times 10 \text{ LHC(Run 1-2-3) integrated luminosity} \\ \times 2.5 \text{ LHC(Run 3) instantaneous luminosity} \\ \text{unprecedented radiation and pile-up (PU)} \end{cases}$

CMS detector will undergo large upgrade campaign

→ relevant for this work are:

- \*the upgraded barrel backend electronics
- \*the new HGAL endcap calorimeter

- \* state-of-the-art FPGA broad use
- \* high-speed optical links broad use
- \* highly modular architecture
- \* new Correlator and Track Trigger
- \* increased latency
- \* HGAL 3D-clusters (CL3D) inclusion

### The Phase-2 Level-1 Trigger upgraded system

## THE TAUMINATOR ALGORITHM

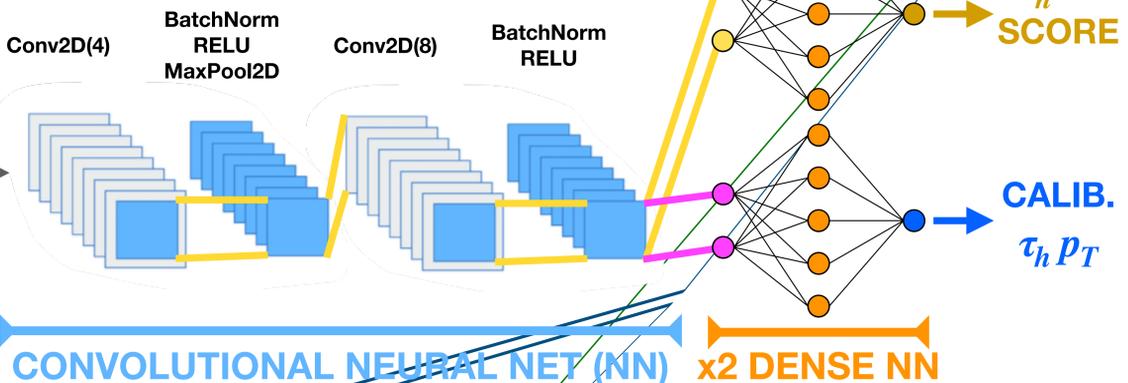
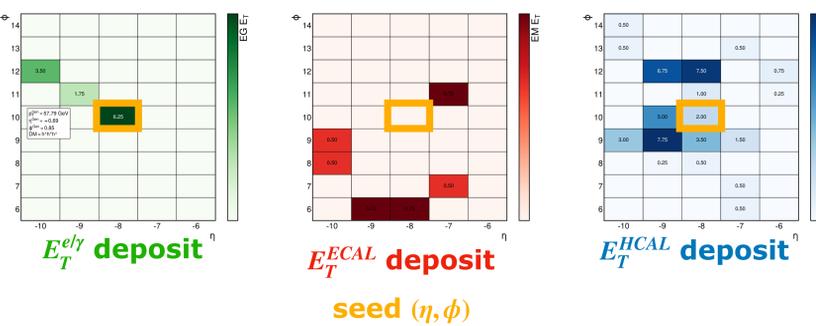
### Algorithm development

Hadronically decaying taus ( $\tau_h$ ) are challenging objects and need clever treatment of decay multiplicity  
Run 2/3 reconstruction: dynamical Calorimeter Trigger Towers (TTs) clustering followed by  $\tau_h$  isolation

TauMinator algorithm presented here: is the Run 2/3 approach evolution, optimised to exploit Phase 2 Level-1 Trigger features optimally to cope with the large PU environment of HL-LHC



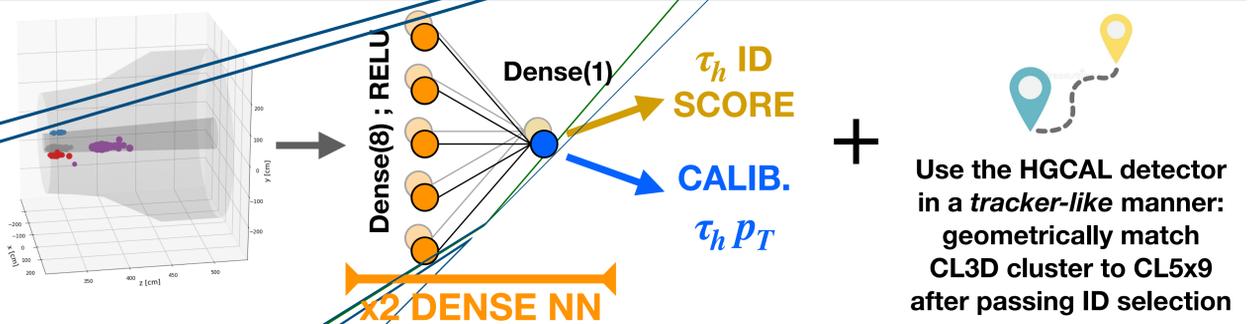
Over the full calorimetric  $|\eta| < 3.0$  coverage  
 $\tau_h$  reconstructed as  $(\eta, \phi) = 5 \times 9$  TTs clusters (CL5X9)  
build from a seed TT with energy deposit  $E_T > 2.5\text{GeV}$



In the HGAL detector  $1.5 < |\eta| < 3.0$   
 $\tau_h$  also reconstructed as single CL3D with  $E_T > 4\text{GeV}$

Several shape features computed for each CL3D in HGAL backend and sent to Level-1 Trigger

Optimal set of variables for DNN is selected via random backward skimming strategy



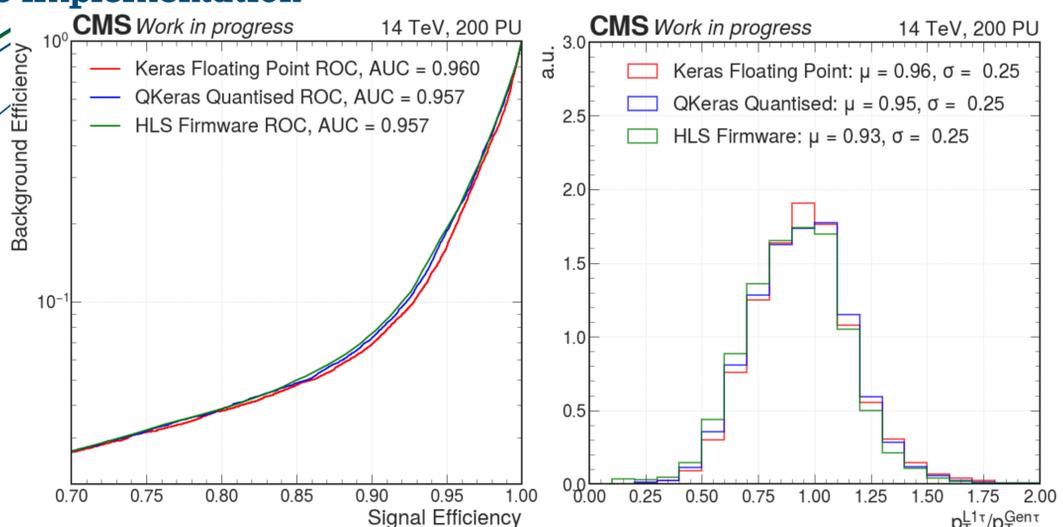
### Firmware implementation

Foreseeing FPGA firmware (FW) implementation all models are developed with quantisation-aware training and pruned

CNN FW implementation aims for lowest inference latency  
DNN FW implementation aims for lowest FPGA resources usage

Resources usage evaluated on Xilinx VU13P FPGA board (board foreseen for Phase 2 Global Calorimeter Trigger)

	LUT [%]	CLB [%]	DSP [%]	Latency [ns]	Interval [ns]
CNN	1.08	0.40	0.00	100	55
CL5x9 ID DNN	0.43	0.05	0.17	60	15
CL5x9 CALIBRATION DNN	0.45	0.06	0.61	40	15
CL3D ID DNN	0.20	0.03	0.22	40	13
CL3D CALIBRATION DNN	0.26	0.04	0.76	30	20



No significant performance loss from Keras floating point model, through QKeras quantised model, to HLS FW model for both  $\tau_h$  ID and calib.

## CONCLUSIONS AND OUTLOOK

- \*  $\tau_h$  challenging object: this innovative approach exploits combination of NNs for optimal  $\tau_h$  reconstruction, identification and calibration
- \* The Phase 2 Level-1 Trigger permits complex NNs FPGA FW implementation while ensuring modest resources usage and inference latency
- \* The algorithm showcases satisfactory performance (such as promising rate reduction) w.r.t to the current calorimeter-based algorithm
- \* The ongoing and next steps include: deeper physics and rate performance studies, full firmware implementation, and Vivado simulation