π^o rejection using the Preshower/CMS detector

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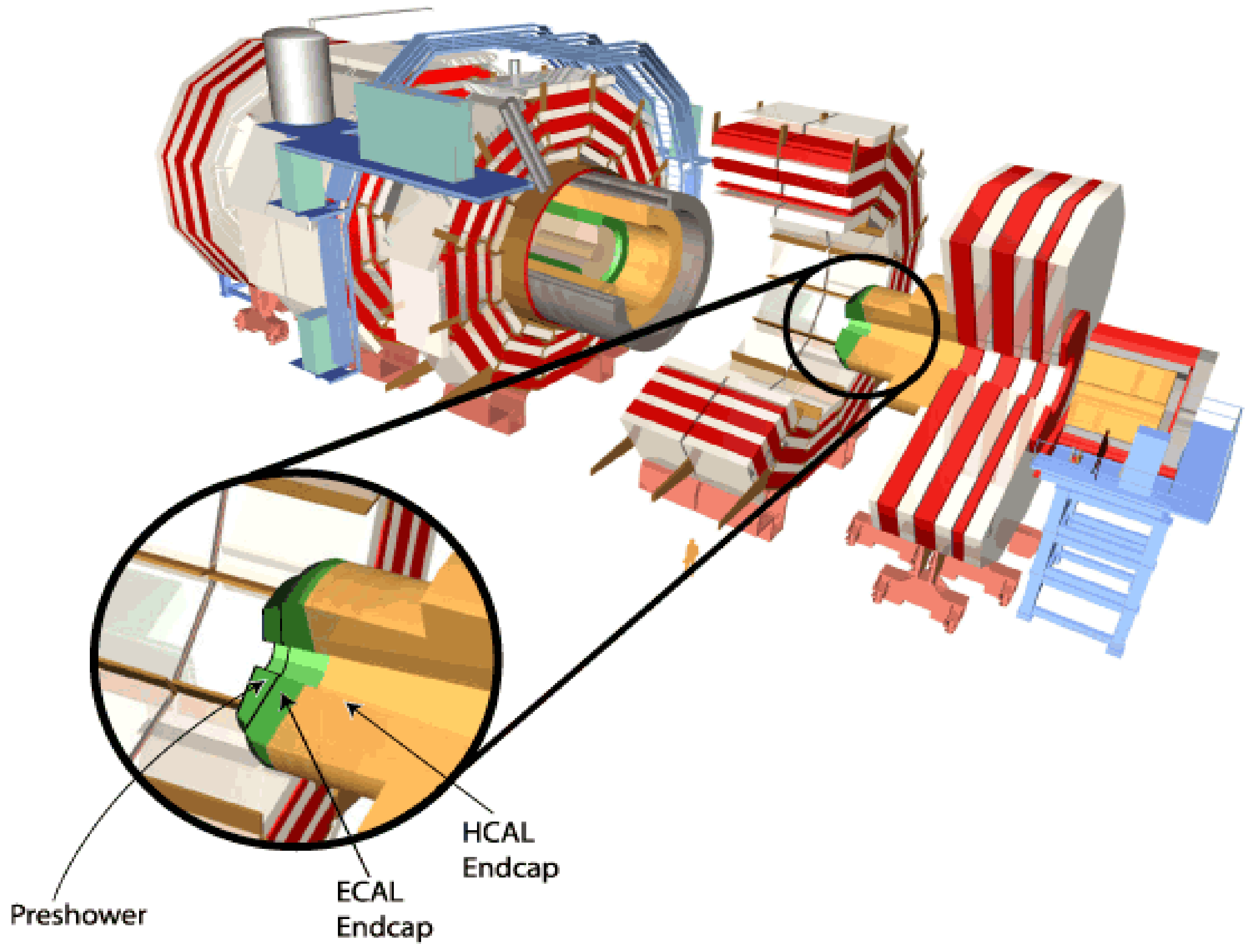
OUTLINE

- The need for π^0 rejection
- The CMS Preshower detector
- Energy deposition on Preshower Strips
- The Algorithm
- Efficiency of the Outside – inwards Tracking
- Neural Net variables
- Test with Higgs Events
- NN training in “real life”
- Conclusions

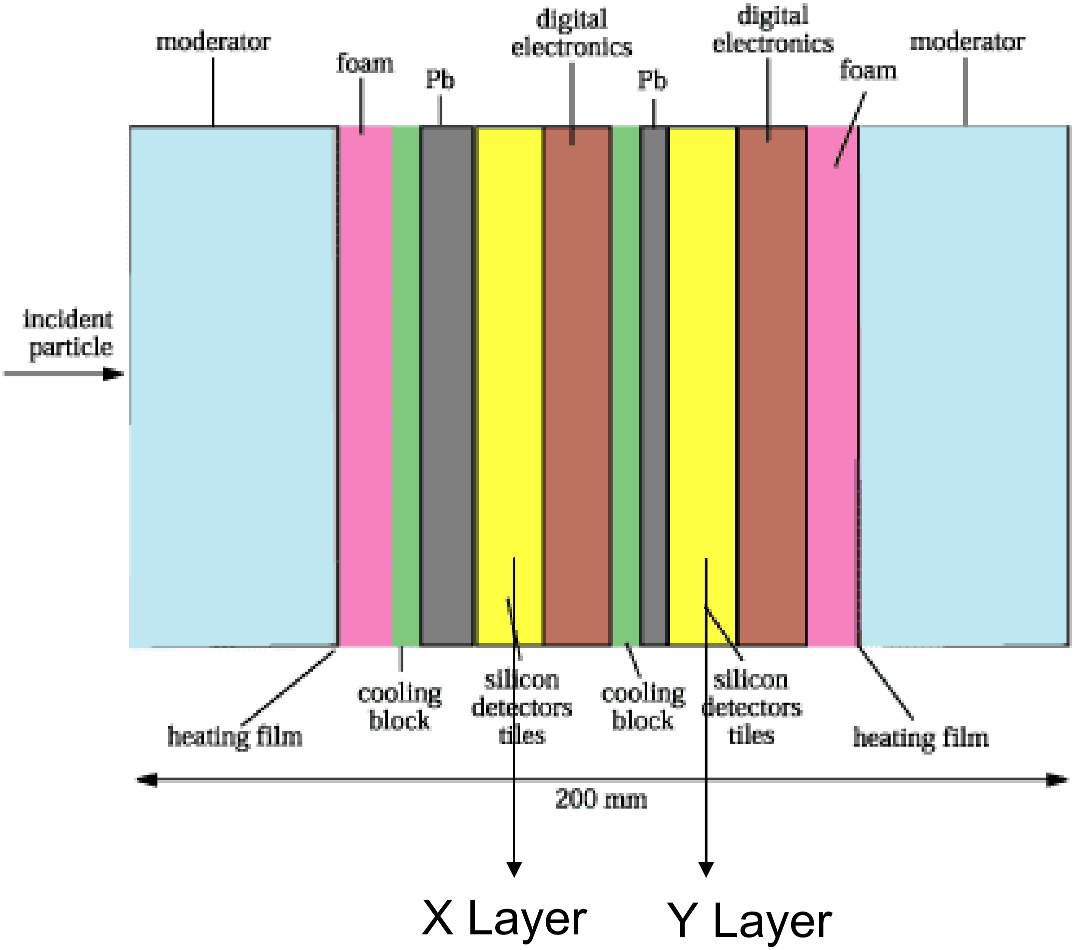
The need for π^0 rejection

- For low mass Higgs the clearest signature comes from the decay $H\rightarrow\gamma\gamma$
  - Background:
    - Irreducible: 2 photon events
    - Reducible: jets+γ events with high p_t π^0 in the jet, with $\pi^0\rightarrow\gamma\gamma$
      - » The angle between the two photons can be very small (especially in the endcaps region) that the ECAL can not distinguish them from a **single** photon
      - » For this reason a high granularity silicon detector (Preshower) is placed in front of the Endcap ECAL

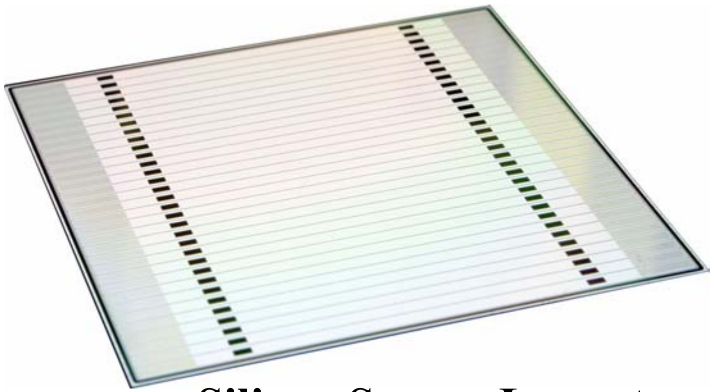
CMS Preshower



Preshower Layout

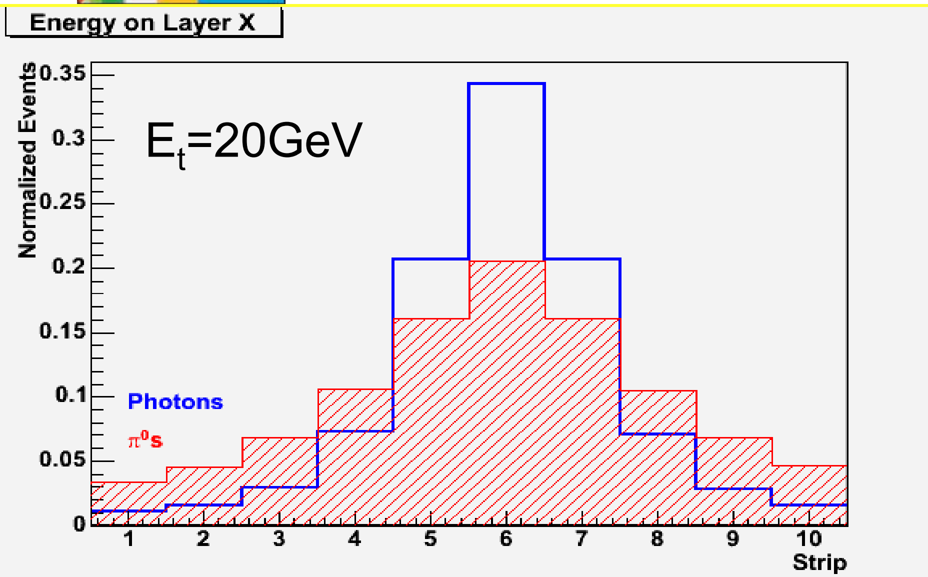


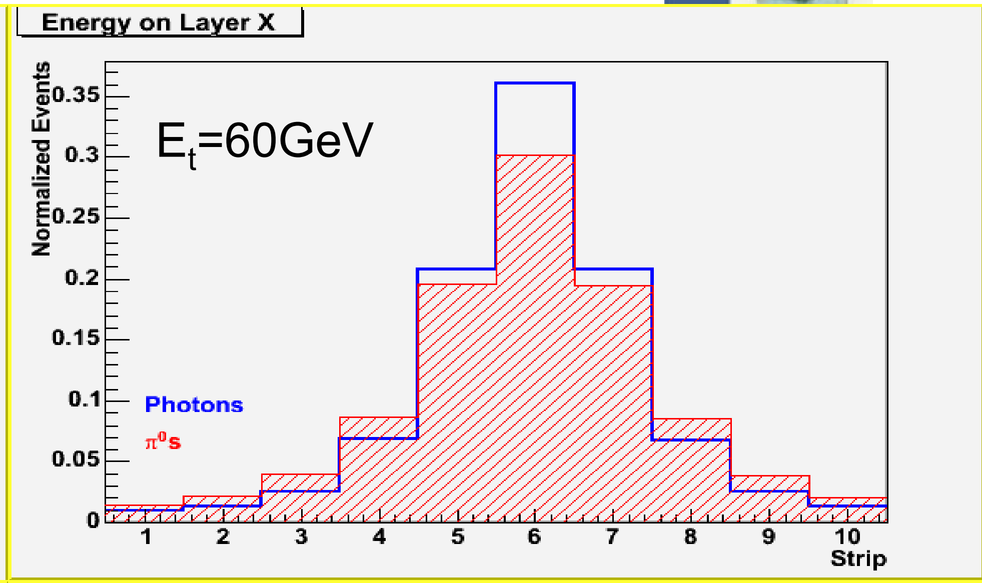
➲ ***Preshower Layout***

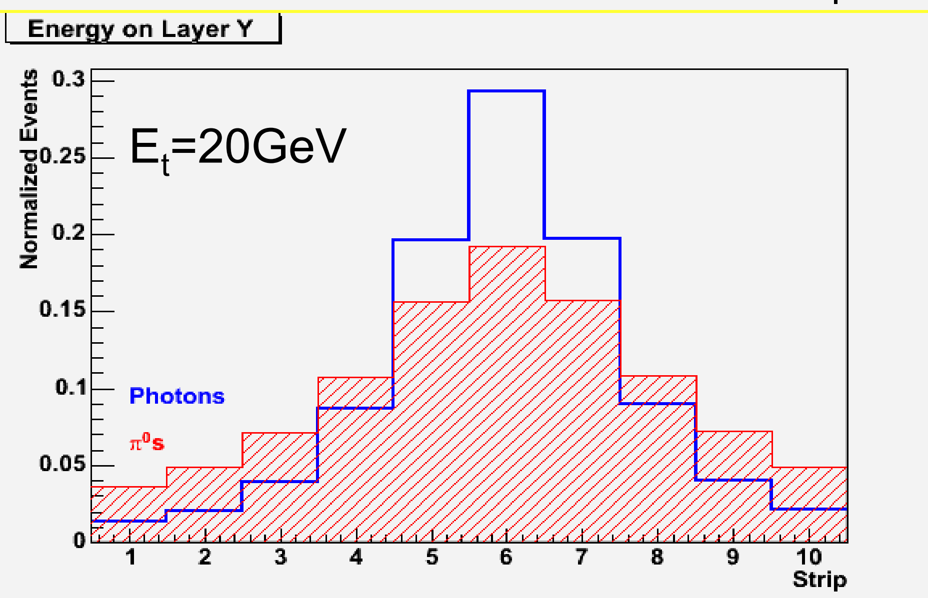


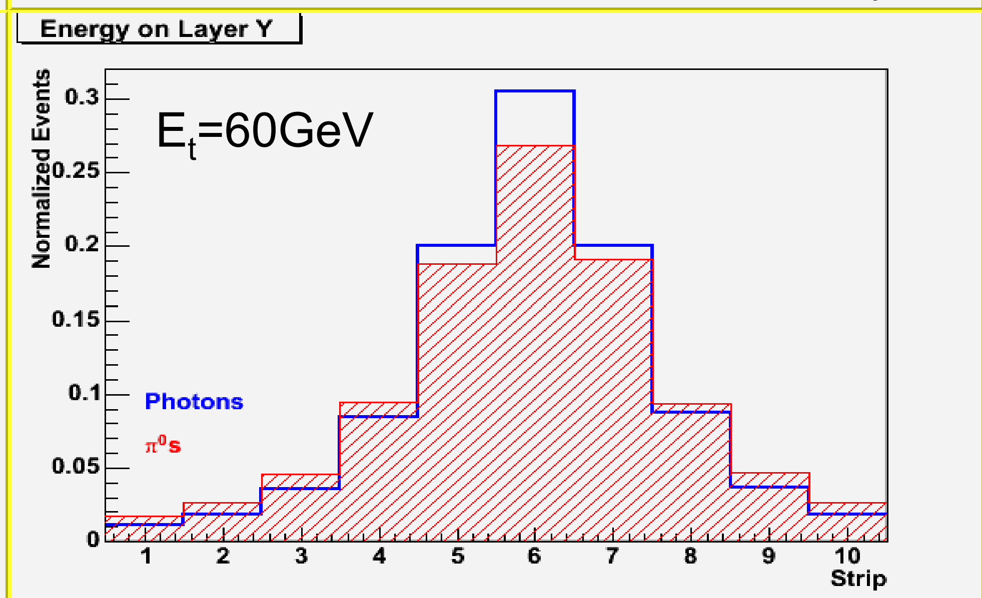
Silicon Sensor Layout

Energy deposition

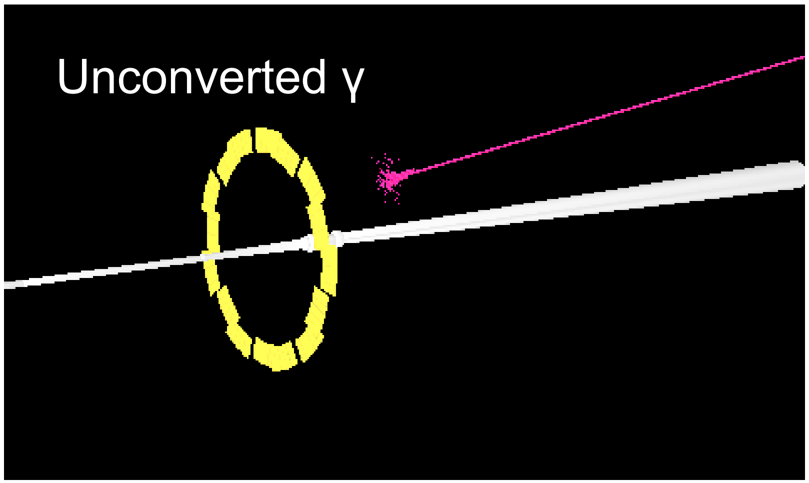


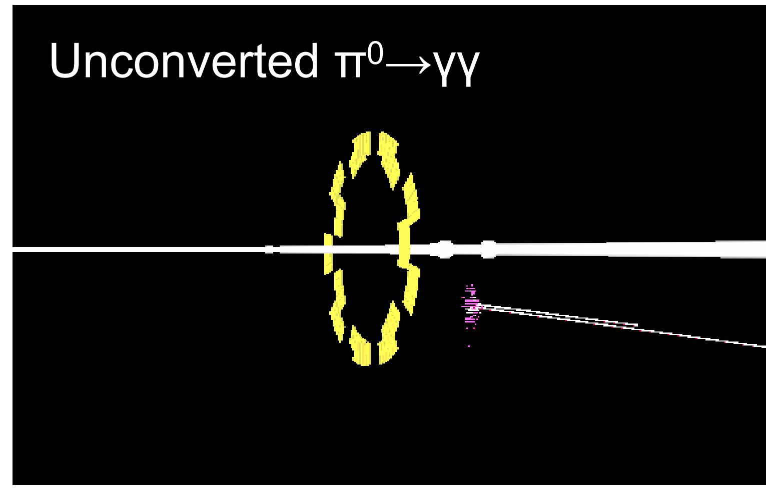


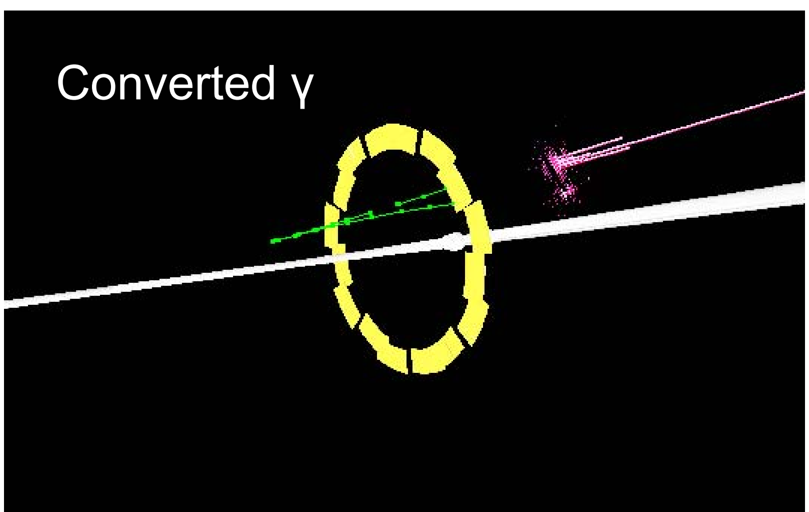


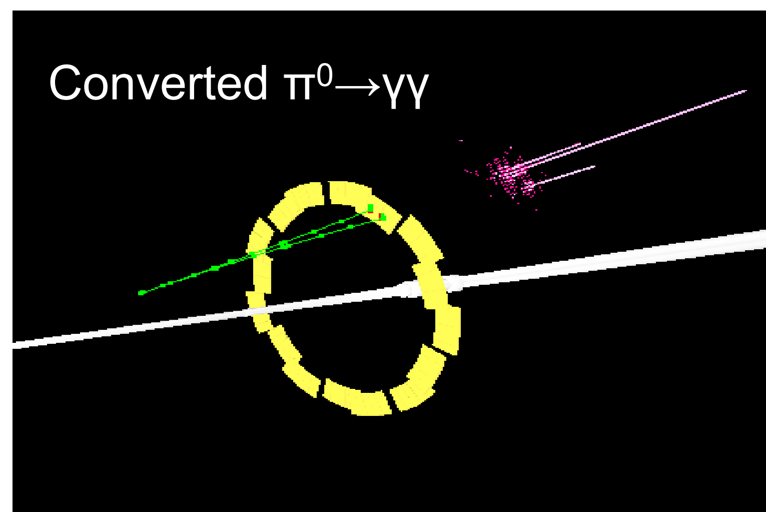


Event Visualization





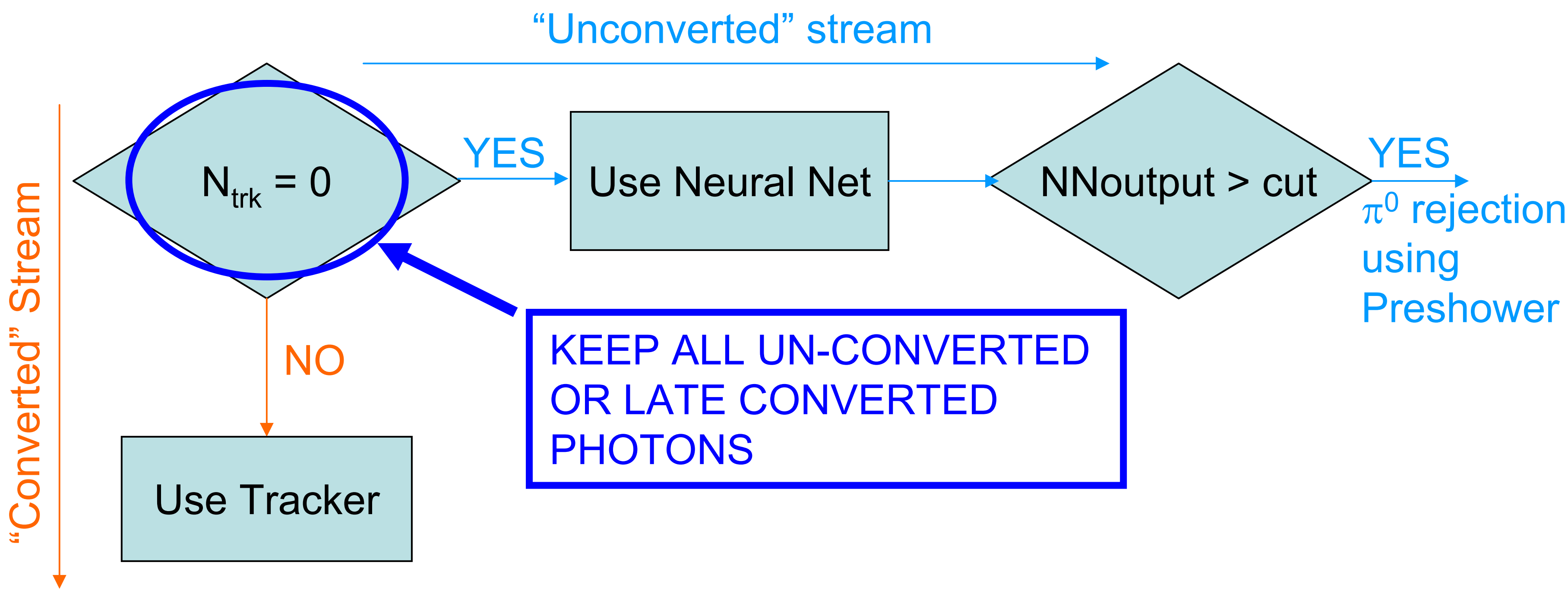




E_t=20GeV photon events

E_t=20GeV π^o events

Adapted Approach in π^0 Rejection



- N_{trk} : Number of tracks related to an ECAL Endcap SuperCluster
- NNoutput : the output of the Neural Network that combines Preshower + ECAL information

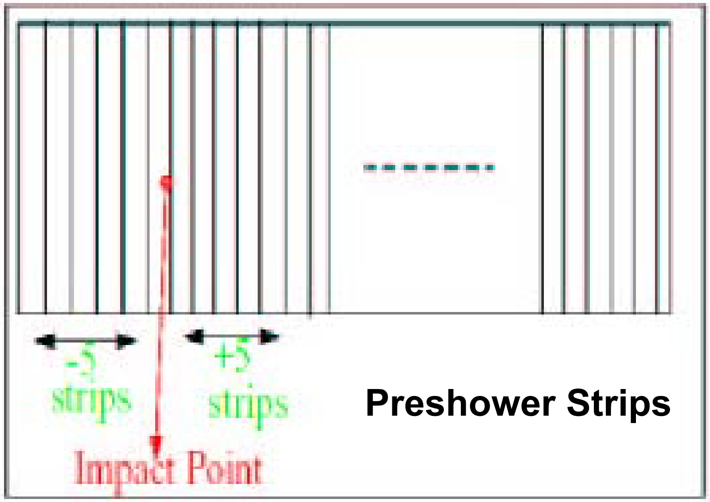
The Algorithm

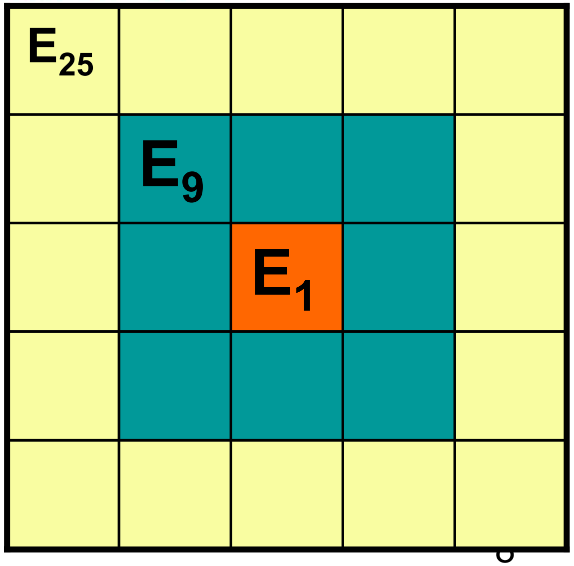
- After finding a neutral ECAL cluster, define a line connecting the (Center of Gravity) COG of this cluster with point (0,0,0).

- Then find the intersection of this line with the two Preshower planes and retrieve the energy information of +/-5 strips around the strip that is closest to the intersection point.

- 11 quantities (Energy deposition per strip) are defined from the 1st Preshower Plane(X-Plane) and 11 from the 2nd Preshower Plane(Y-Plane)

- 3 more quantities from Endcap ECAL are used
  - E_1 = energy of the most energetic crystal
  - E_9 = energy of 3x3 crystals surrounding E_1
  - E_{25} = energy of 5x5 crystals surrounding E_1





5x5 Endcap ECAL crystals

Outside – inwards Tracking in Endcaps

- Start from a given Endcap ECAL cluster
- Define a helix from:
  - **the centroid of the BasicCluster**
  - **the vertex point taken to be the point (0.,0.,0.) OR**

    the barycenter of the second Preshower Plane Cluster if any
  - **the curvature calculated from the energy of the Cluster and the Magnetic Field.**
- Extrapolate the helix into the OUTERMOST Endcap Tracker disk and search for compatible Hits

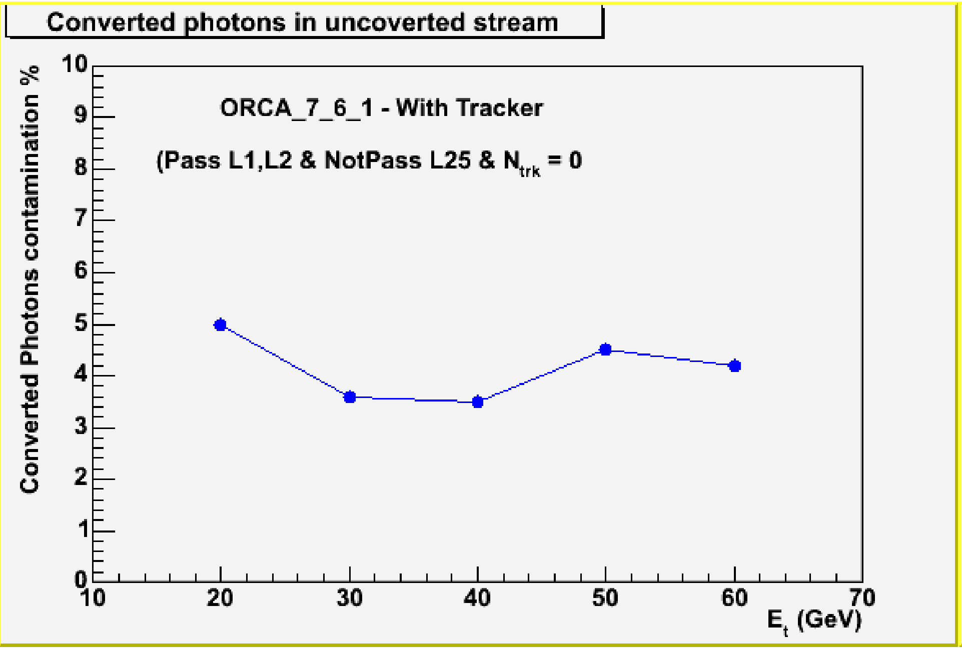
Event Samples

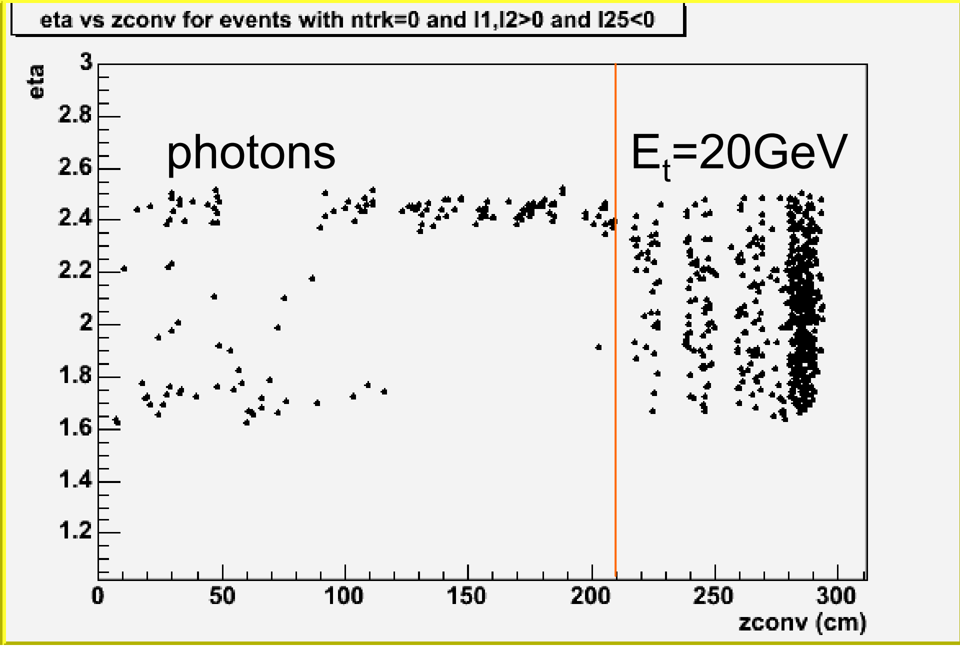
•The study has been done with full detector simulaton & digitazation using the extra code for the outside – Inward tracking for conversion reconstruction

•The events samples are Single photons & π^0s events (produced in Demokritos) at various E_t (= 20, 30, 40, 50, 60 GeV/c, 45K γ /60K π^0 events per E_t) and $1.65 < \eta < 2.5$ and with tracker information

•**The Neural net has been trained using the above samples**

Efficiency of the conversion reconstruction algorithm





- A maximum of 5% of converted photons enters the unconverted photon steam.
- As unconverted photons we consider the late converted ones (z_{conv} > 210 cm) as well
- The contamination comes mainly from events with η≈2.5, that are problematic anyway in the track reconstruction because tracker layers do not cover well this region

Some Numbers

	photons		π^0	
E_T(GeV)	Events with N_{Trk} = 0 (%)	Events with N_{Trk} > 0 (%)	Events with N_{Trk} = 0 (%)	Events with N_{Trk} > 0 (%)
20	68	32	54	46
30	69	31	54	46
40	69	31	55	45
50	69	31	54	46
60	68	32	53	47

New Neural Net

Neural Net description:

-25 input -26 hidden – 1output

-Inputs:

$$Var_{1-11} = \frac{E_i^X}{C_i} (i = 1,...,11)$$

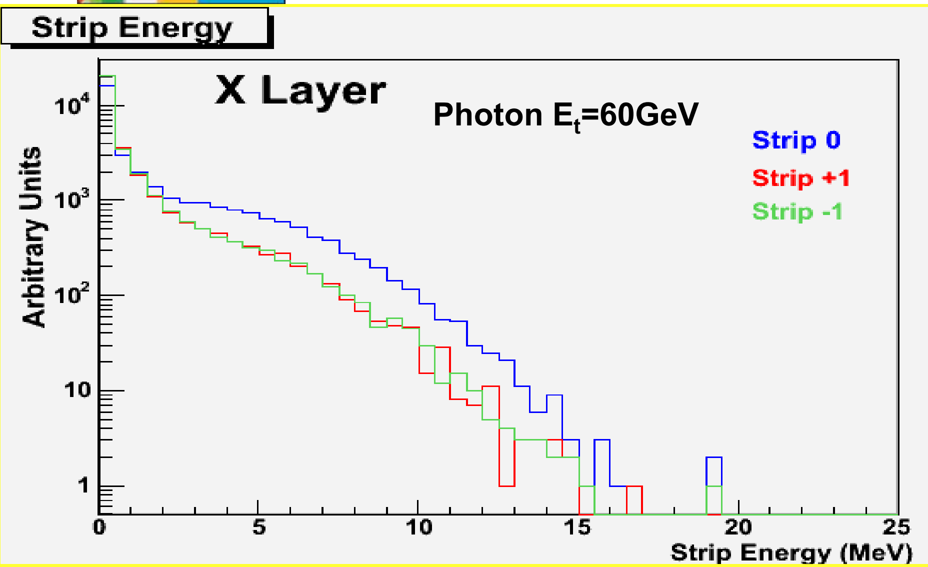
$$Var_{12-22} = \frac{E_i^Y}{C_i} (i = 1,...,11)$$

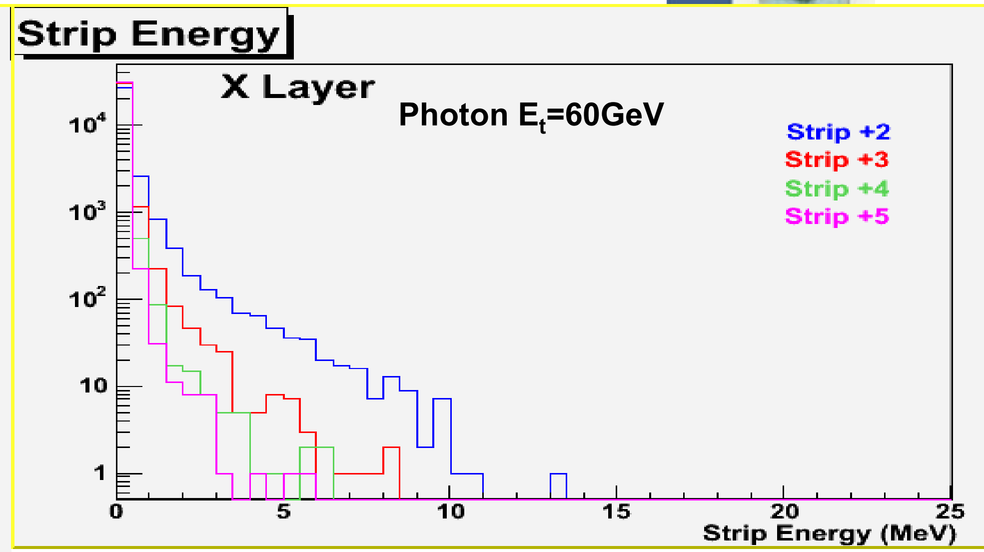
$$Var_{23} = \frac{E_1^{ECAL}}{C_{ECAL}}$$

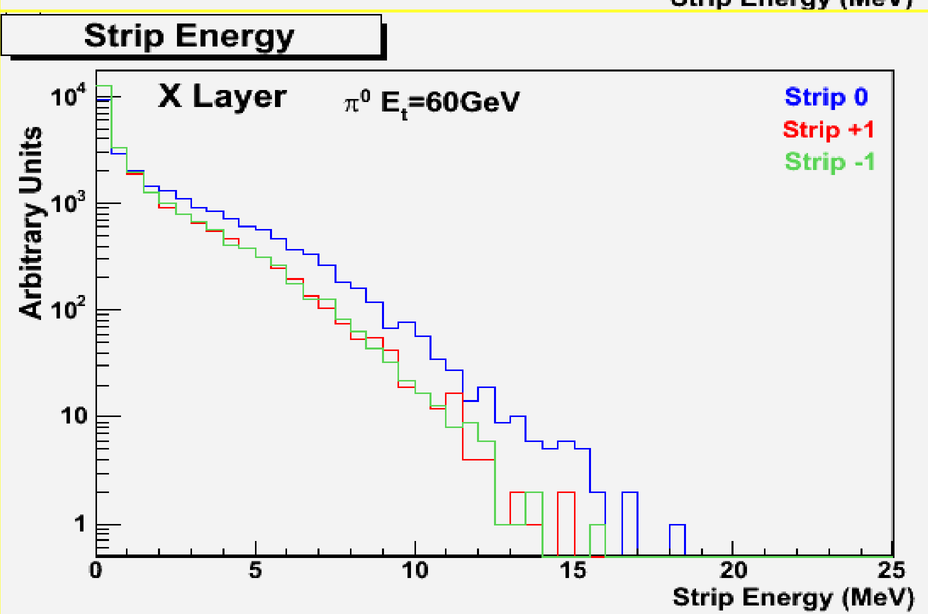
$$Var_{24} = \frac{E_9^{ECAL}}{C_{ECAL}}$$

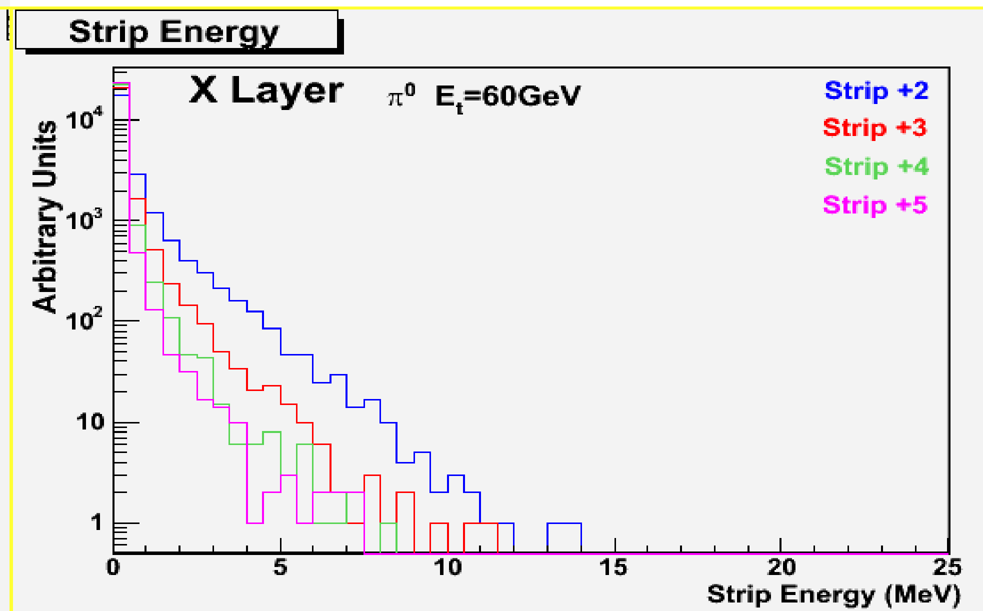
$$Var_{25} = \frac{E_{25}^{ECAL}}{C_{ECAL}}$$

NN Variables

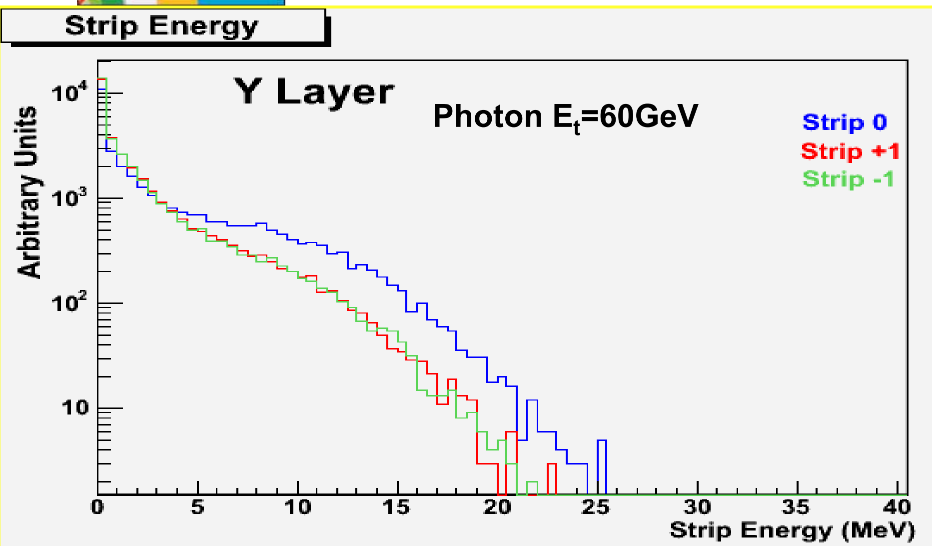


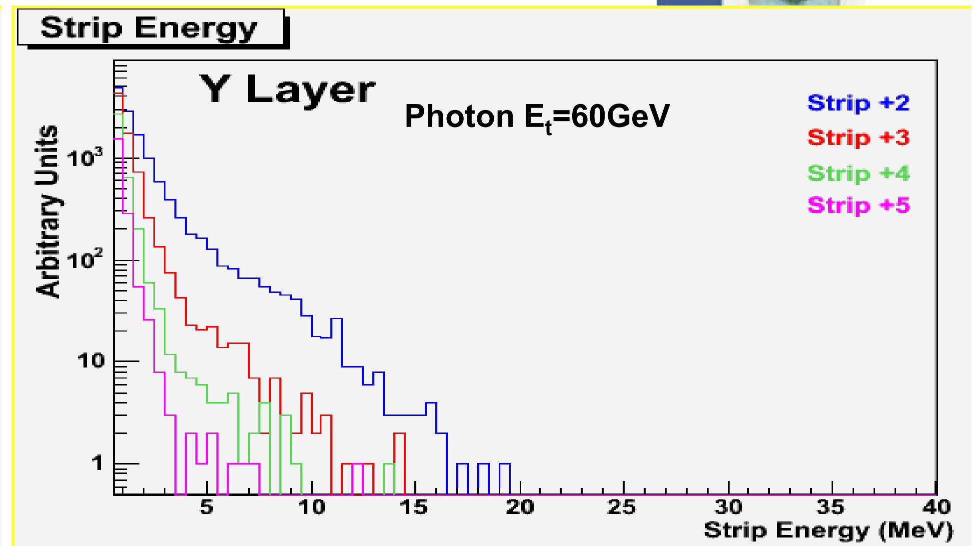


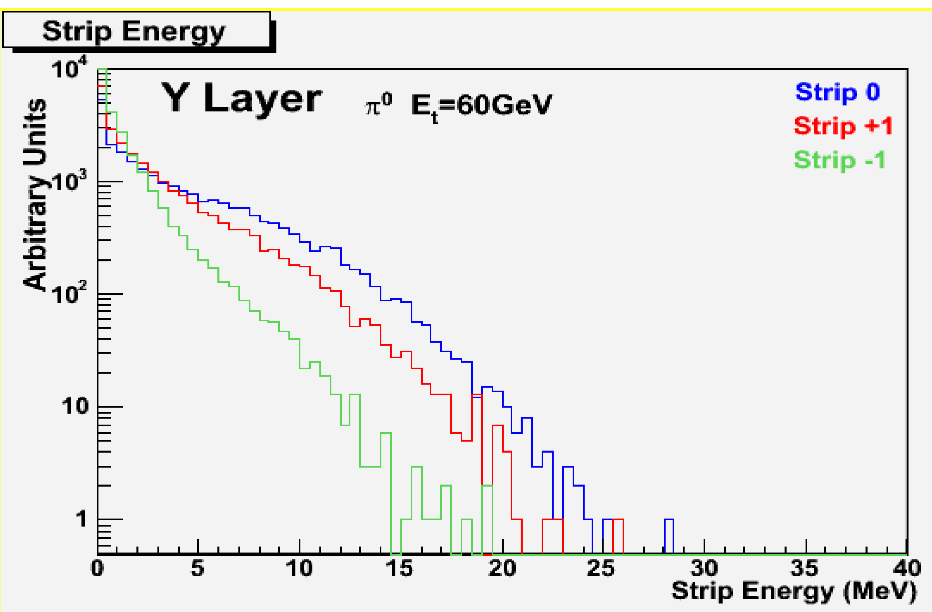


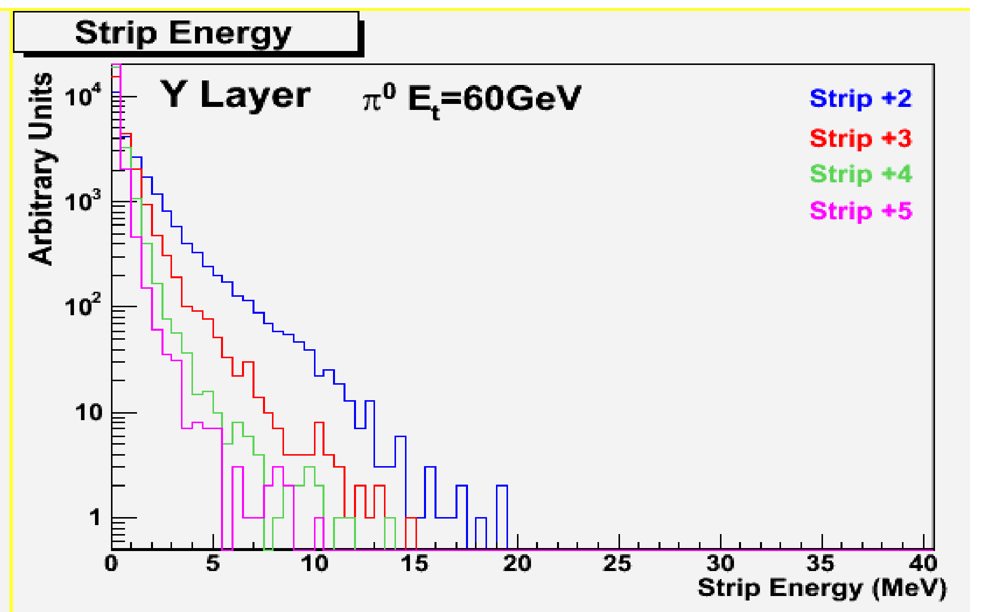


NN Variables

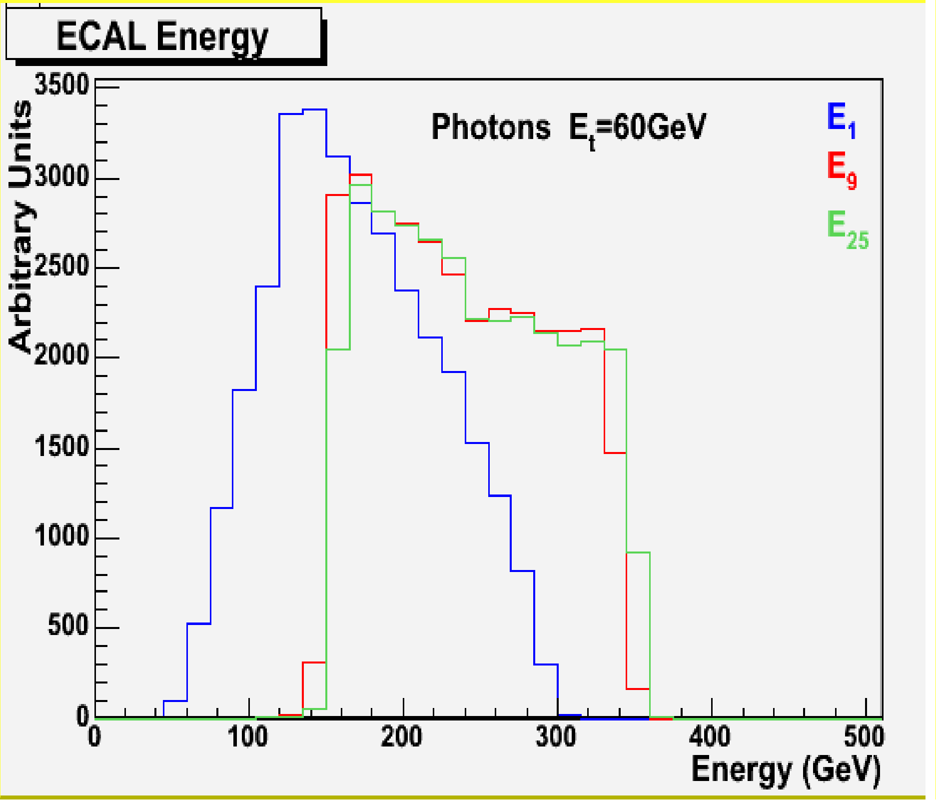


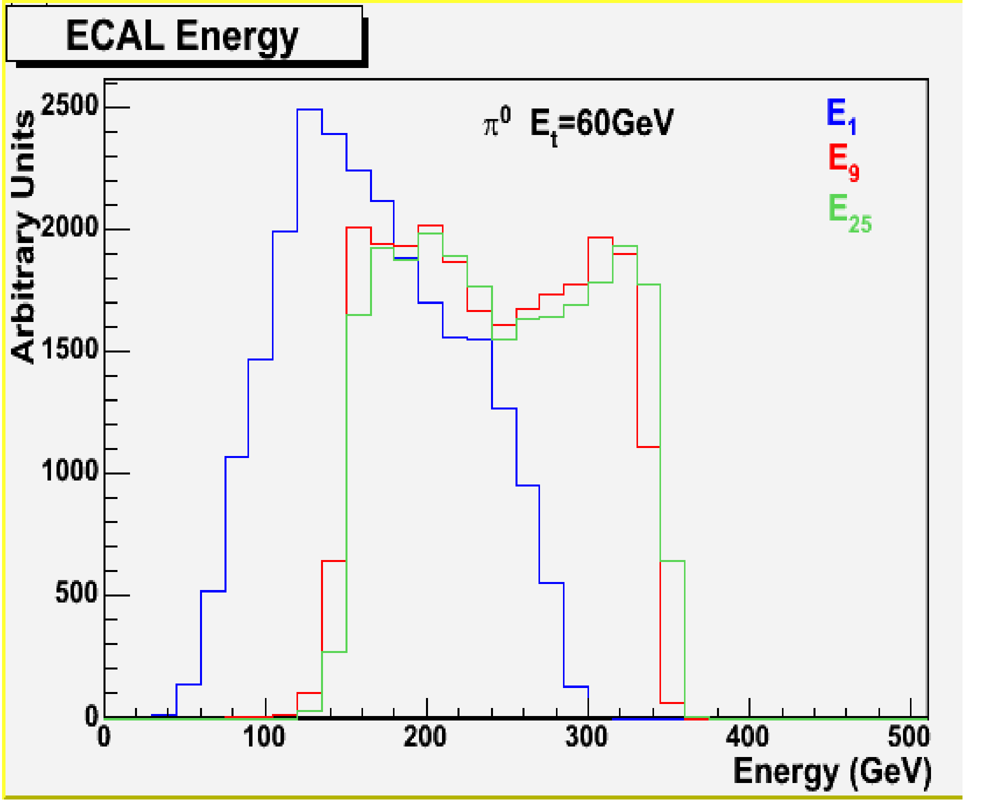






NN variables

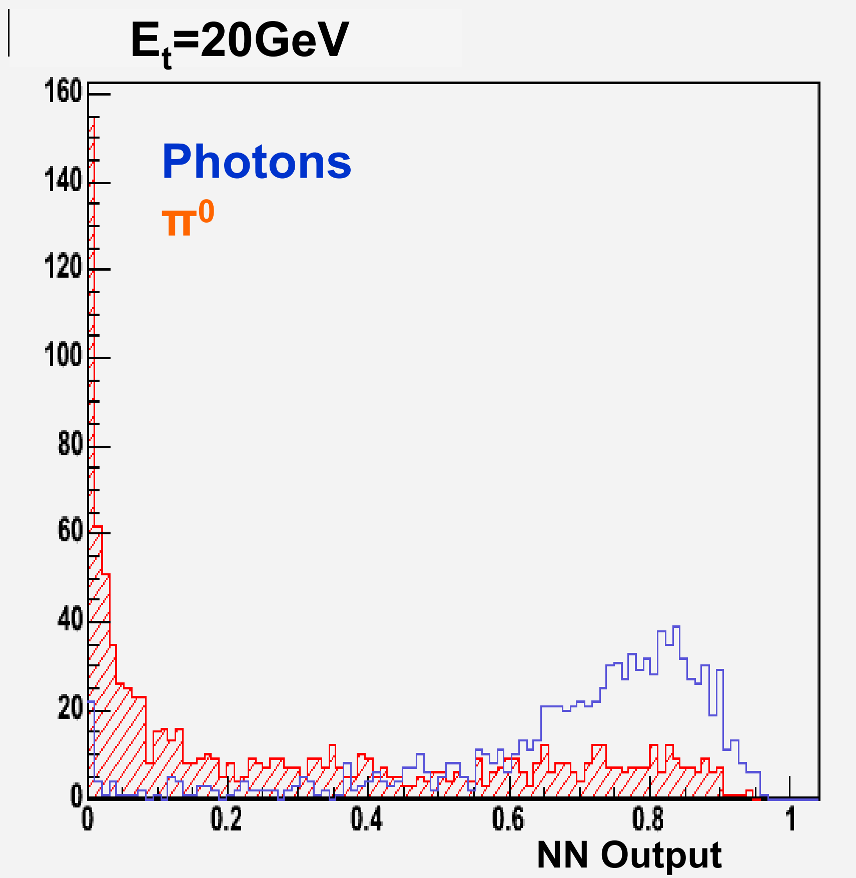


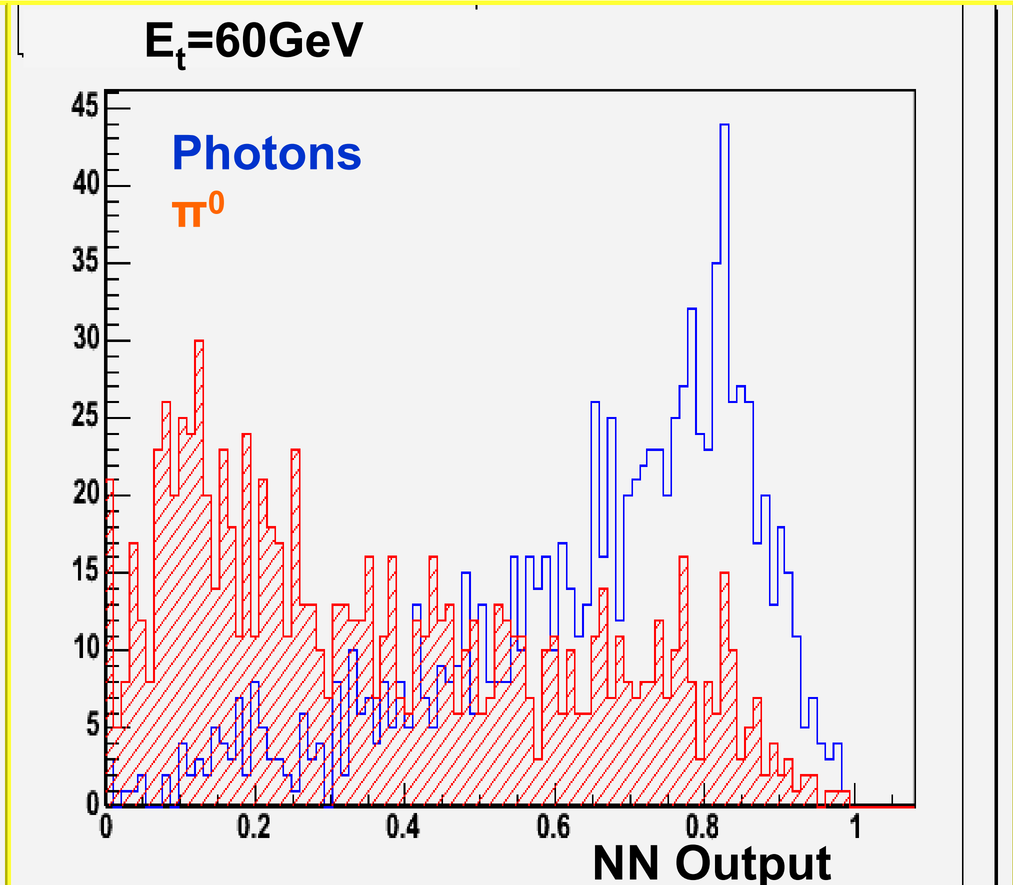


Normalization Constants

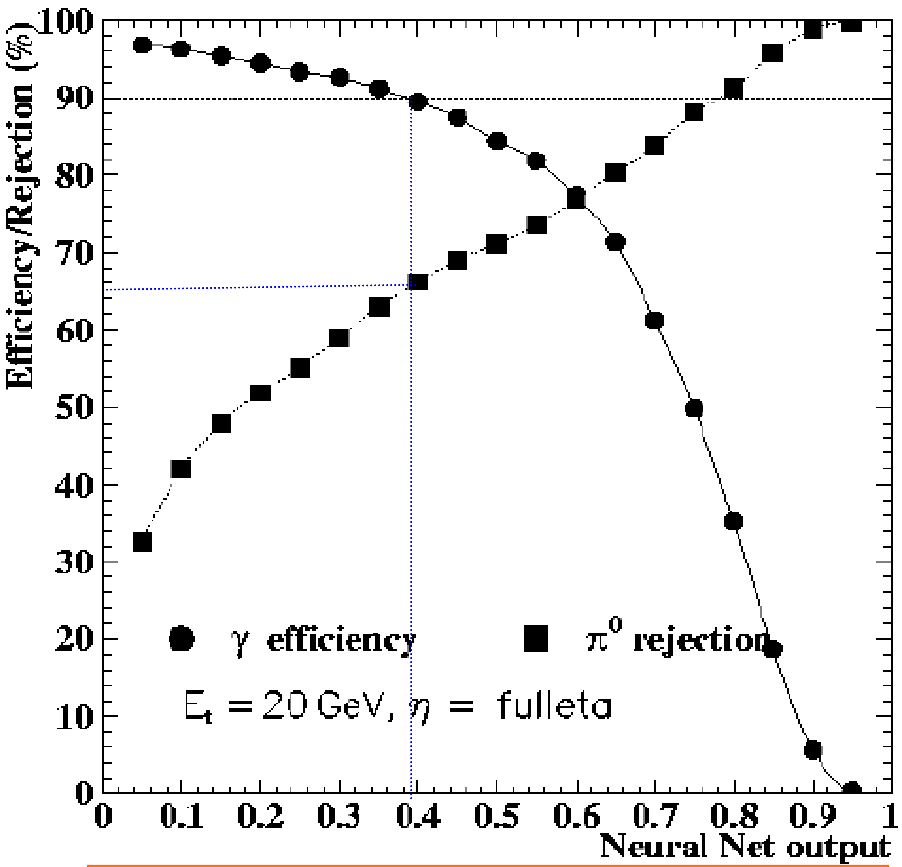
- X Layer
  - Strips: 0, ±1 normalized to 20MeV
  - Strips: other normalized to 10MeV
- Y Layer
  - Strips: 0, ±1 normalized to 40MeV
  - Strips: other normalized to 20MeV
- ECAL energies:
  - E_1, E_9, E_{25} normalized to 500 GeV

NN Output for events with N_{trk}=0

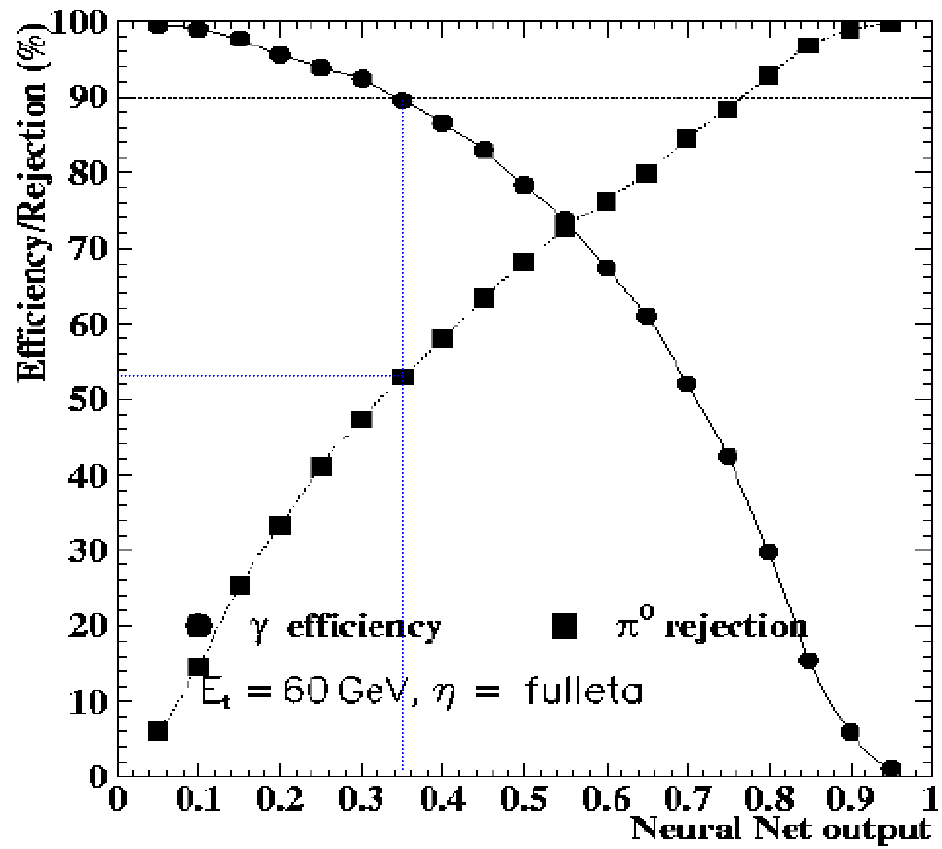




Efficiency-Rejection vs NNoutput

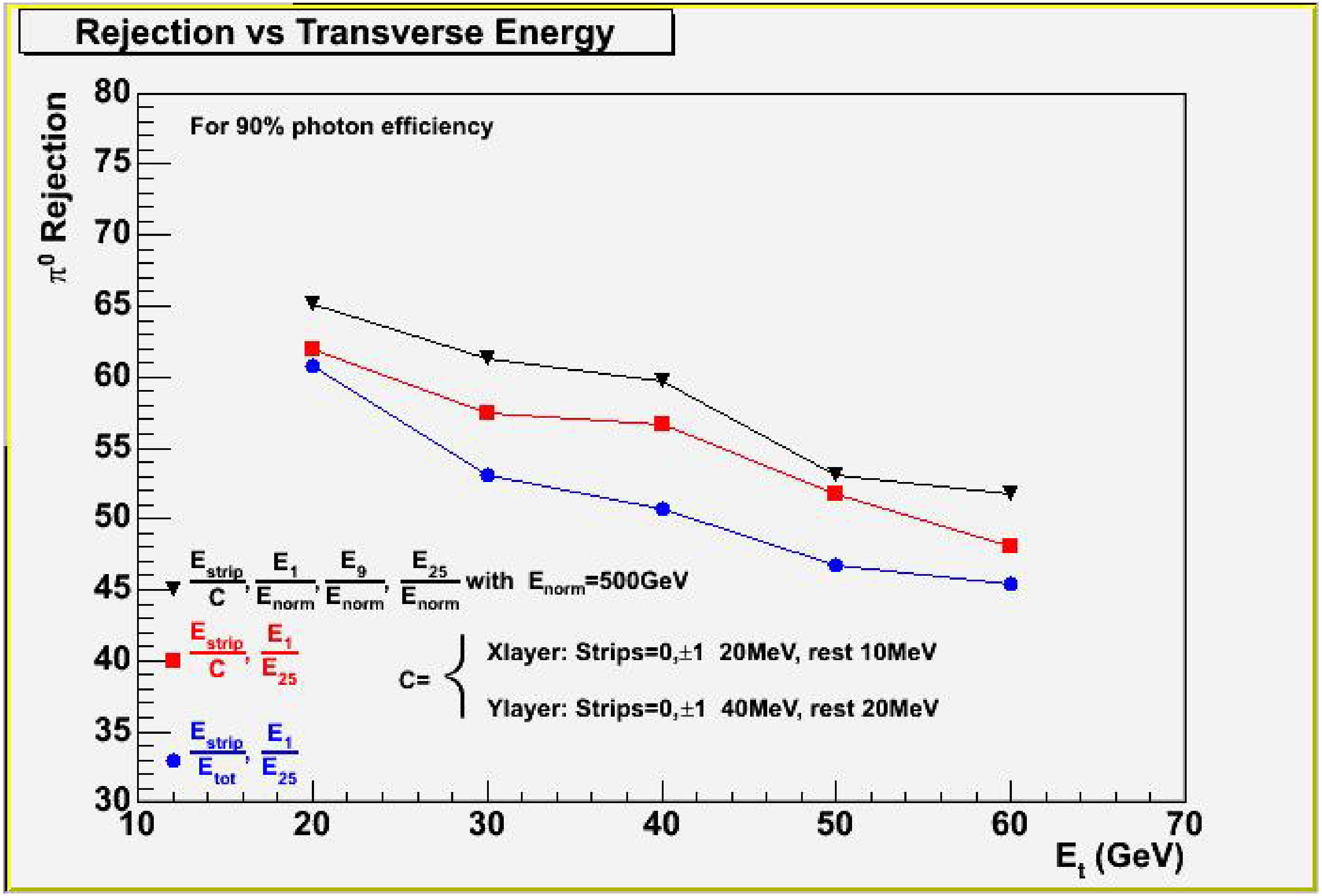


65.1% π^0 Rejection keeping 90% of the Photons at E_t=20GeV

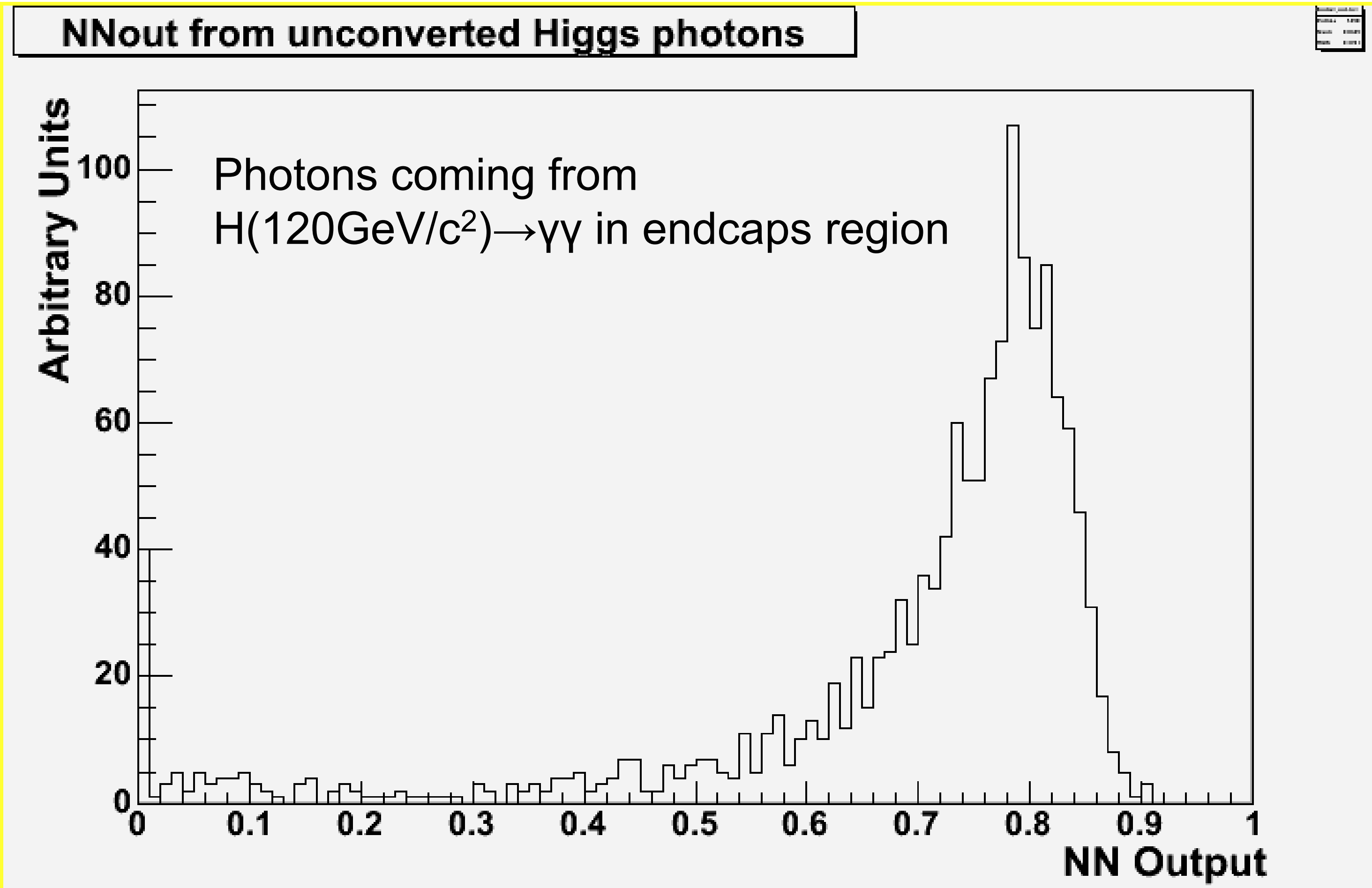


51.7% π^0 Rejection keeping 90% of the Photons at E_t=60GeV

Algorithm Improvements



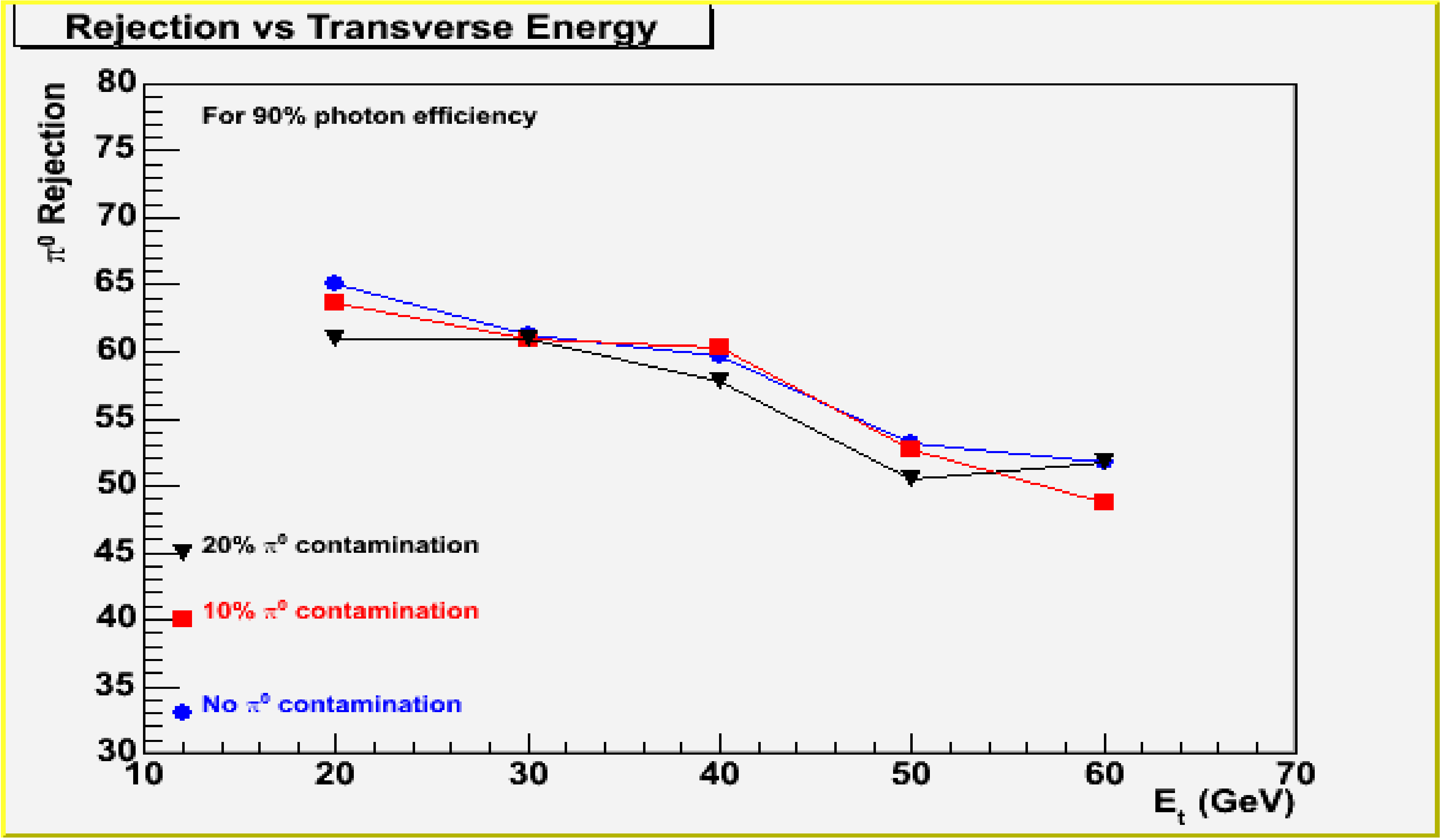
NNout from Higgs' photons



NN training in real life

- How to train the NN with real data?
  – Use an *"Iterative"* procedure, where the first training will be done with MC data. Studies with contaminated event samples look promising
  – Use brem photons of well known processes such as $W \rightarrow e\nu$ with bad E/p end estimate brem photon energy

Contaminated Samples



Conclusions

• The Neural Net has been designed using 25 input variables and trained using a sample of unconverted photons and π^0 events

• π^0 rejection varies from **65%** at E_t=20GeV to **51%** at E_t=60GeV for <u>90% photon efficiency</u>

• An initial test of the NN in Higgs events with PileUps has been done

• The NN *"survives"* a 20% π^0 contamination in the training phase, which indicated that an "iterative" training procedure with real data could be feasible.