Particle identification with an electromagnetic calorimeter using a Convolutional Neural Network

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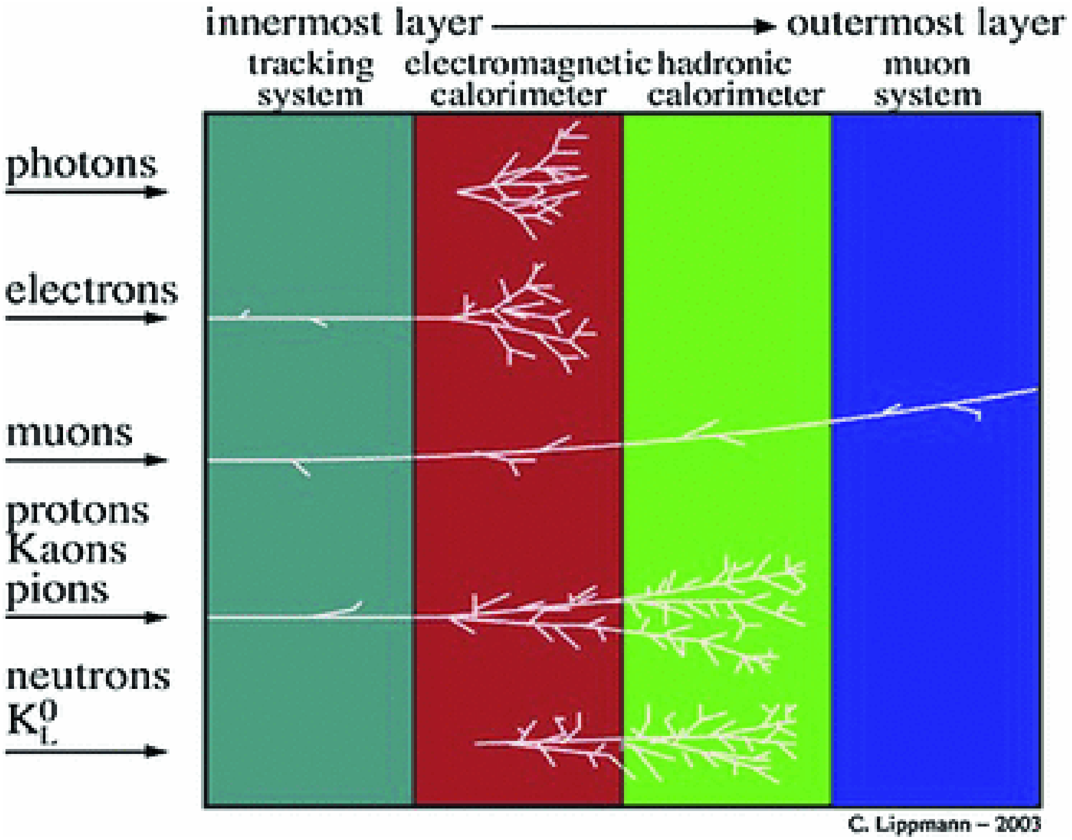
Particle identification scheme in particle detectors



Ref: C.Lippmann Particle Identification, Nucl.Instr.Meth. A666 (2012) pp 148-172

CAN PARTICLE IDENTIFICATION BE ACHIEVED USING ONLY CALORIMETER INFORMATION ?

IDEA: USING THE SHAPE OF THE ENERGY DEPOSIT

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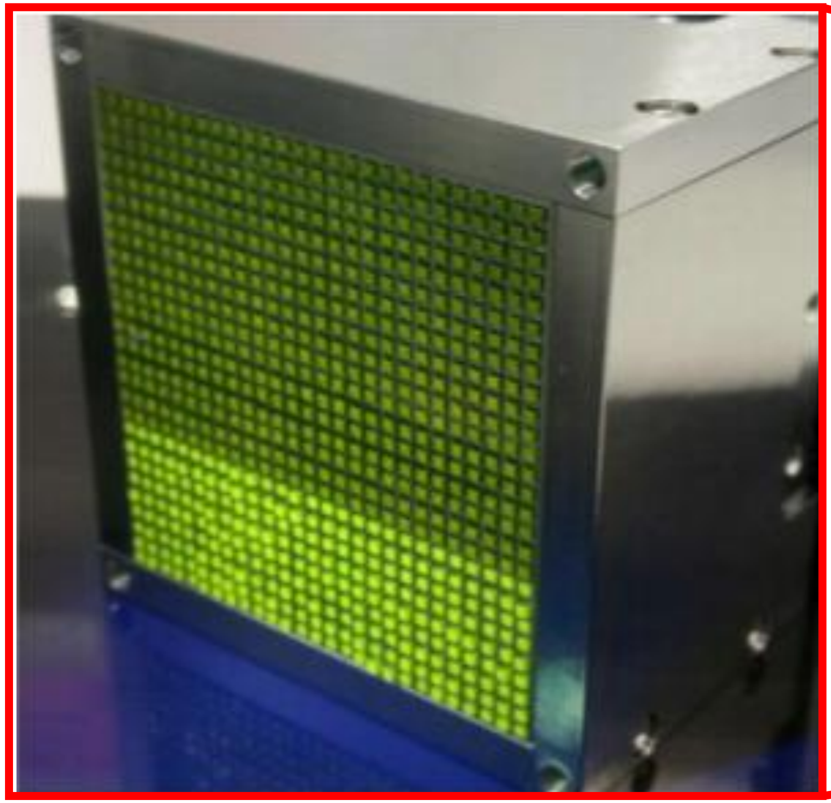
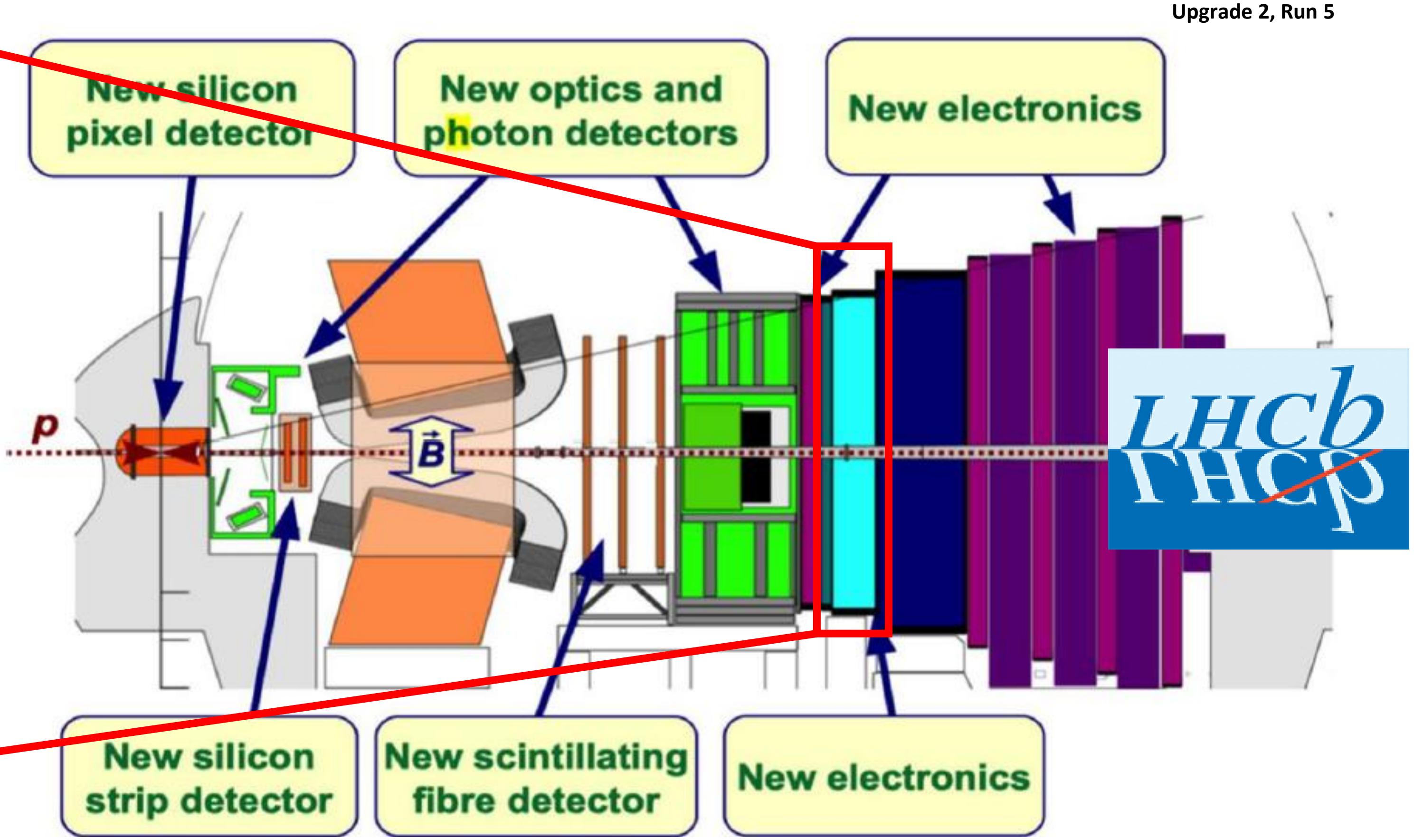
CALORIMETERS ARE USUALLY DESIGNED TO FIT MOST OF THE ENERGY DEPOSIT IN A SINGLE CELL

WE WOULD NEED A HIGH GRANULARITY CALORIMETER

INSPIRATION : LHCb Upgrade II - SPACAL

LHCb

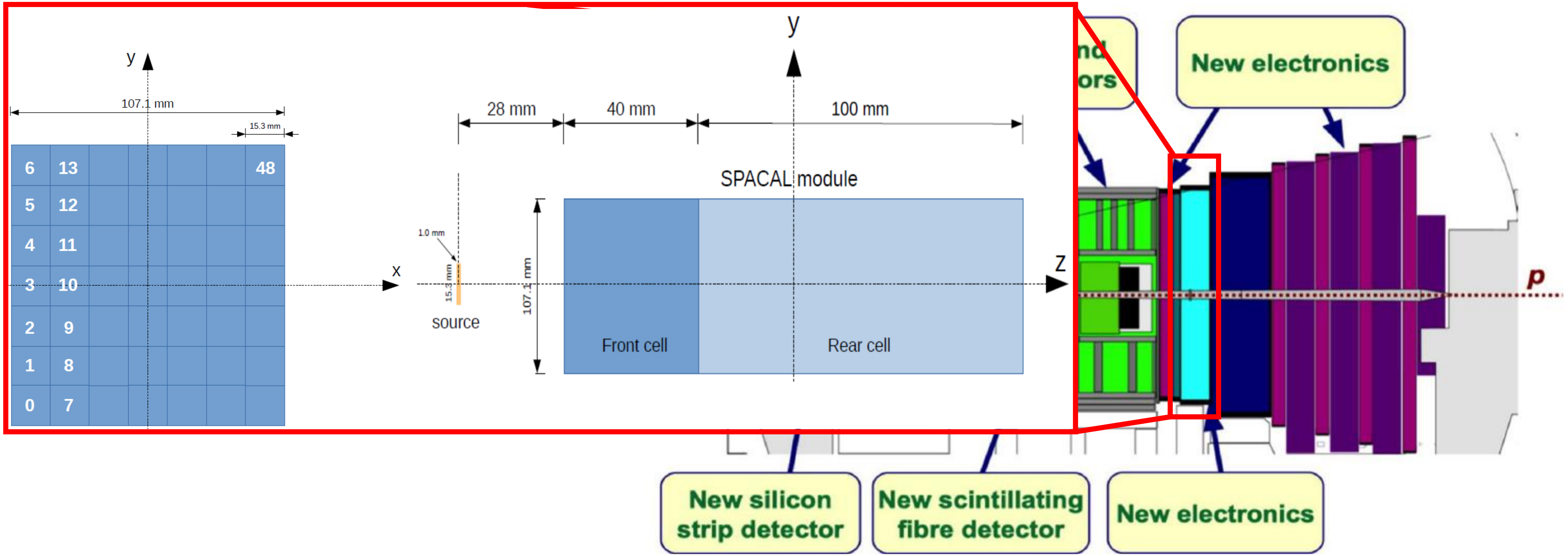




Ref: Loris Martinazzoli. Crystal Fibers for the LHCb Calorimeter Upgrade. IEEE Trans. Nucl. Sci. 67 (2020) 1003.

SIMULATING DATA FROM A SPACAL-LIKE CALORIMETER

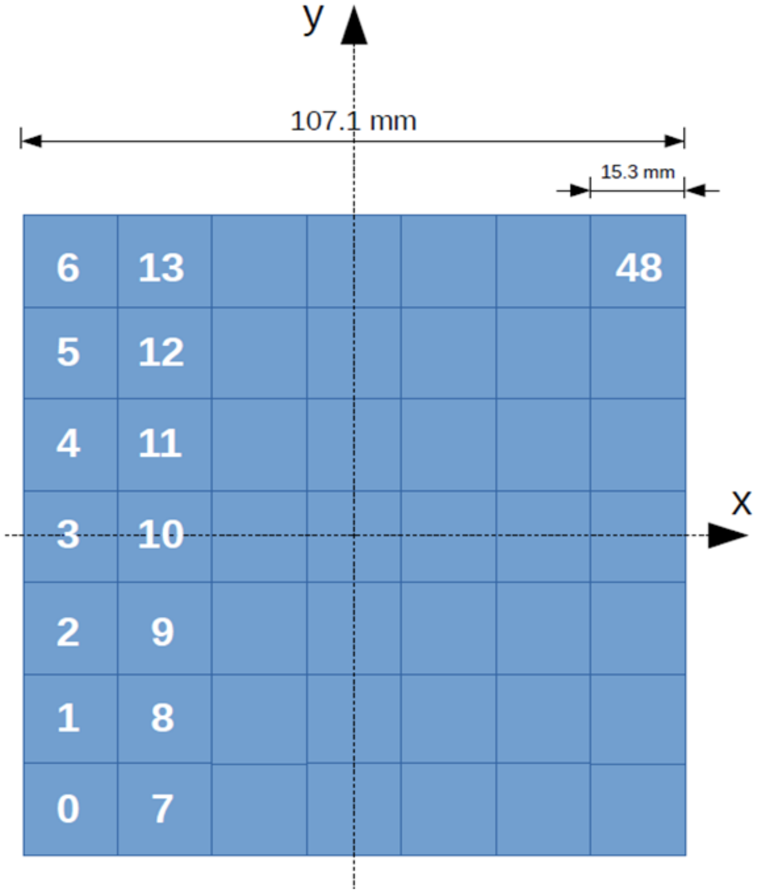
SPACAL



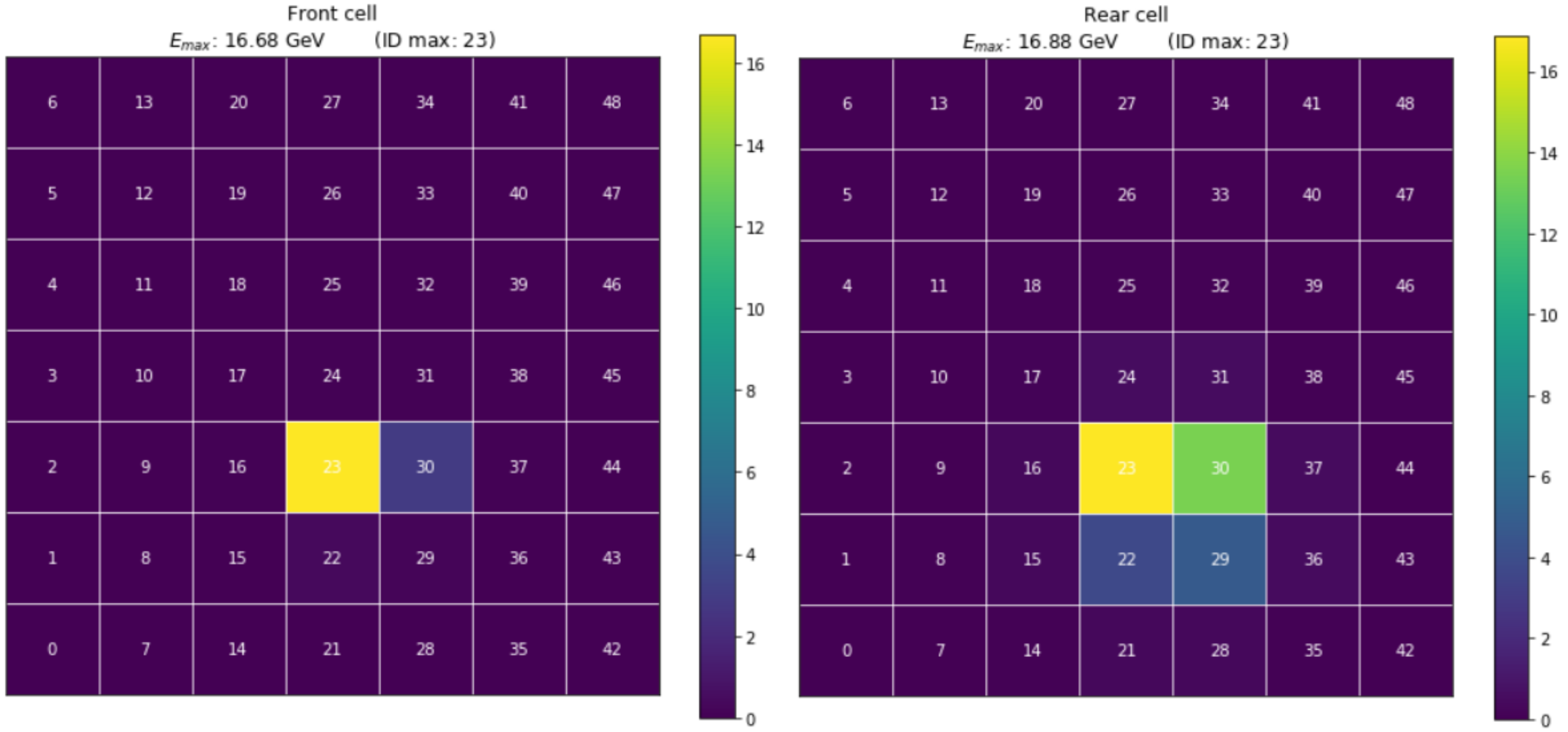
Ref:Geant4 collaboration, S. Agostinelli et al. Geant4: A simulation toolkit. Nucl. Instrum. Meth. A 506 (2003) 250.

SIMULATED DATA

SPACAL like calorimeter



e-

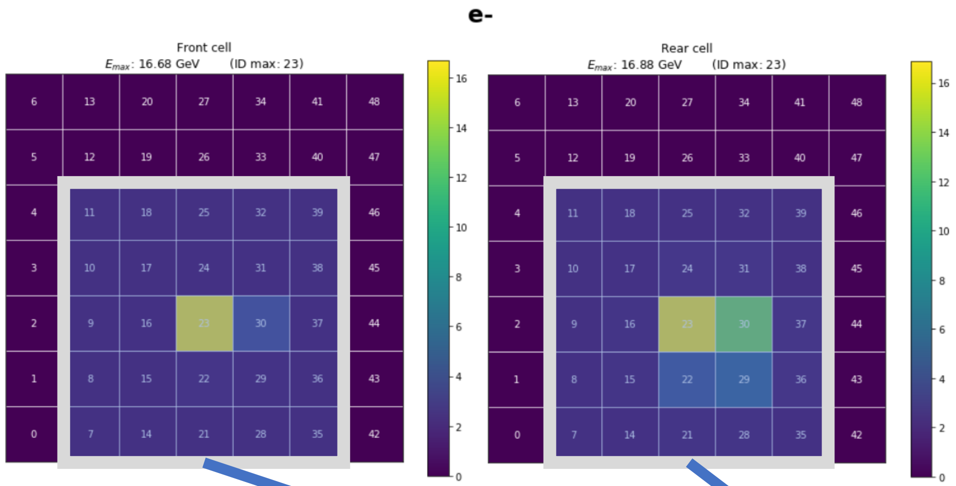


SIMULATED DATA

Classifications

Combination number	Alias	Purpose	Particles included
Combination 1	Neutral Particles	Limit the classification to neutral particles	Neutrons: n Photons: γ
Combination 2	Three Particles	Limit the classification to three particles with different behaviours in shower generation and energy deposit	Electrons: e^- Positive Muons: μ^+ Positive Pions: π^+
Combination 3	Particles without charge differentiation	Same purpose of "combination 4", without charge differentiation	Electrons and positrons: e^-, e^+ Photons: γ Muons: μ^+, μ^- Pions: π^+, π^- Kaons: K^+, K^- Protons and antiprotons: p, $\bar{p}$ Neutrons: n
Combination 4	All particles	Classification of 12 different particles	Electrons: e^- Positrons: e^+ Photons: γ Positive Muons: μ^+ Negative Muons: μ^- Positive Pions: π^+ Negative Pions: π^- Positive Kaons: K^+ Negative Kaons: K^- Protons: p Antiprotons: $\bar{p}$ Neutrons: n

ML APPROACH

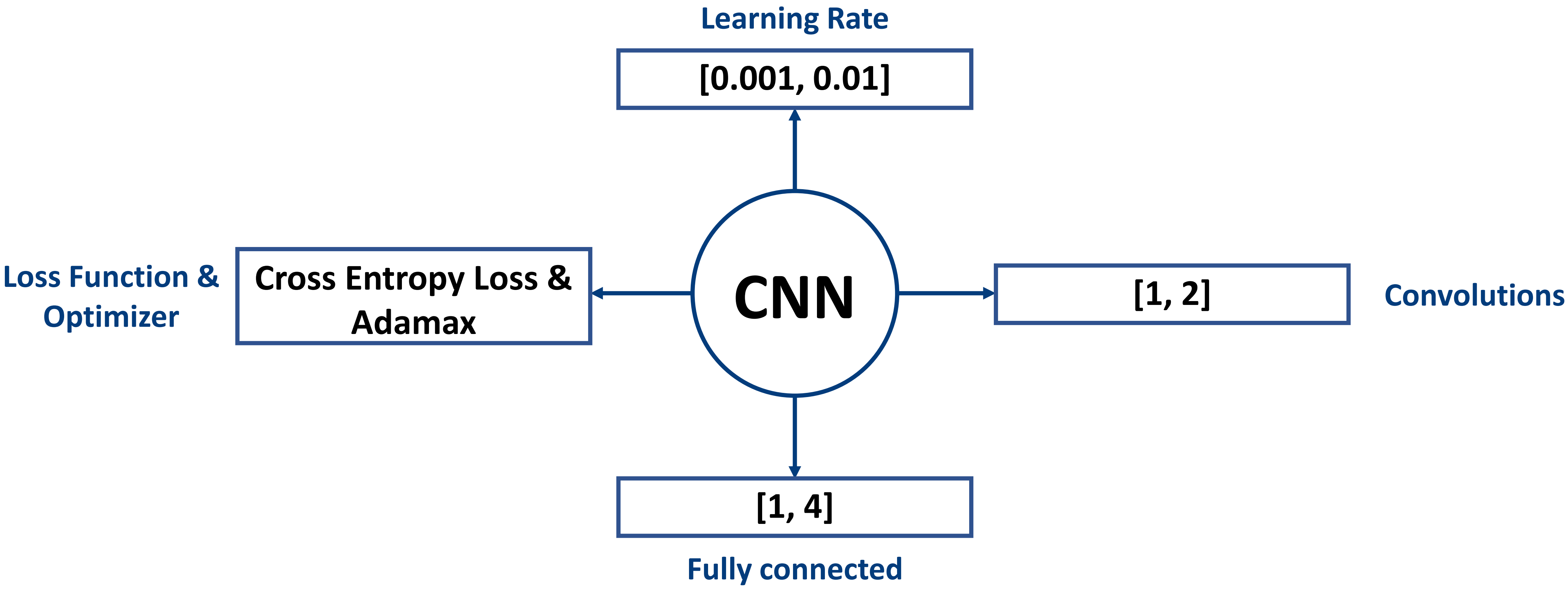


CNN
XGBoost
Image Centered XGBoost

Particle type

ML APPROACH

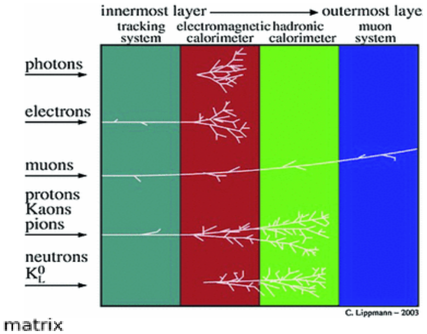
CNN Models

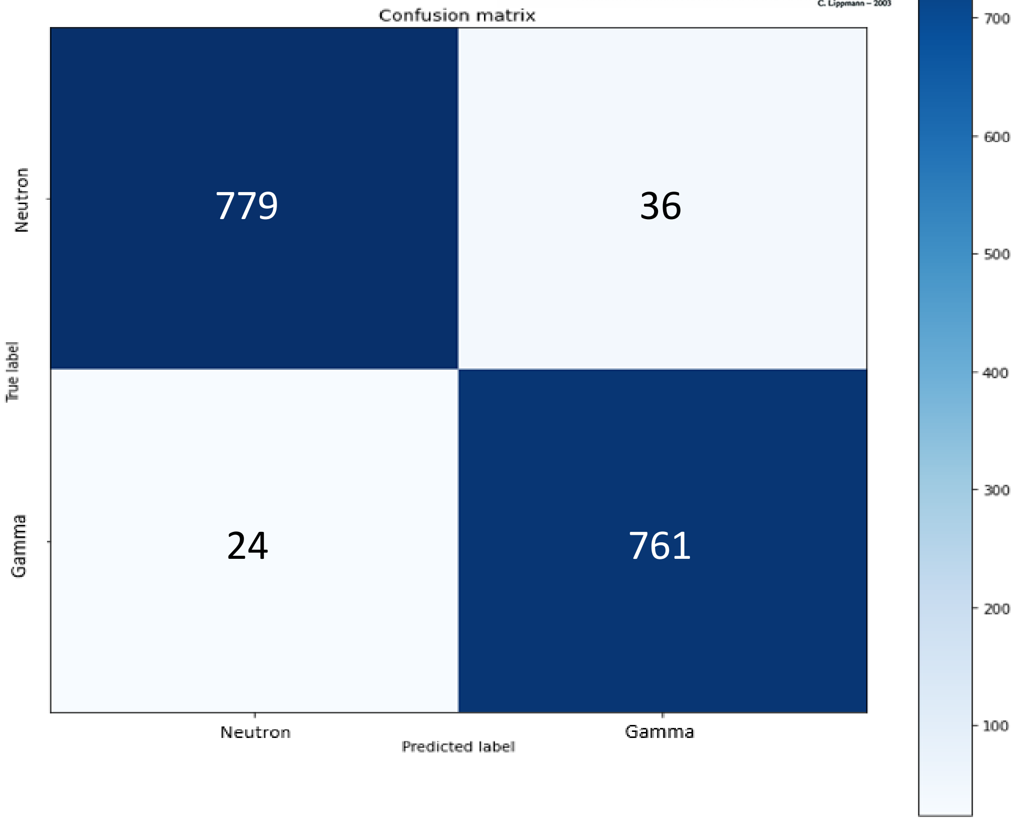


RESULTS

2 particle classification

Particle	Precision	Recall	False Positive Rate	F1-Score	Times seen
Neutron	0.97	0.956	0.03	0.963	815
Gamma	0.955	0.969	0.044	0.962	785

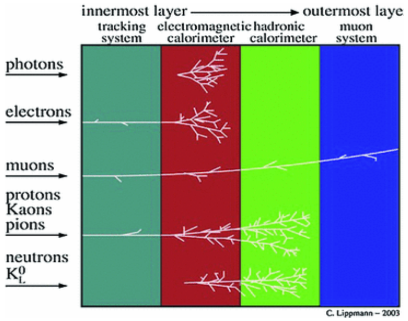


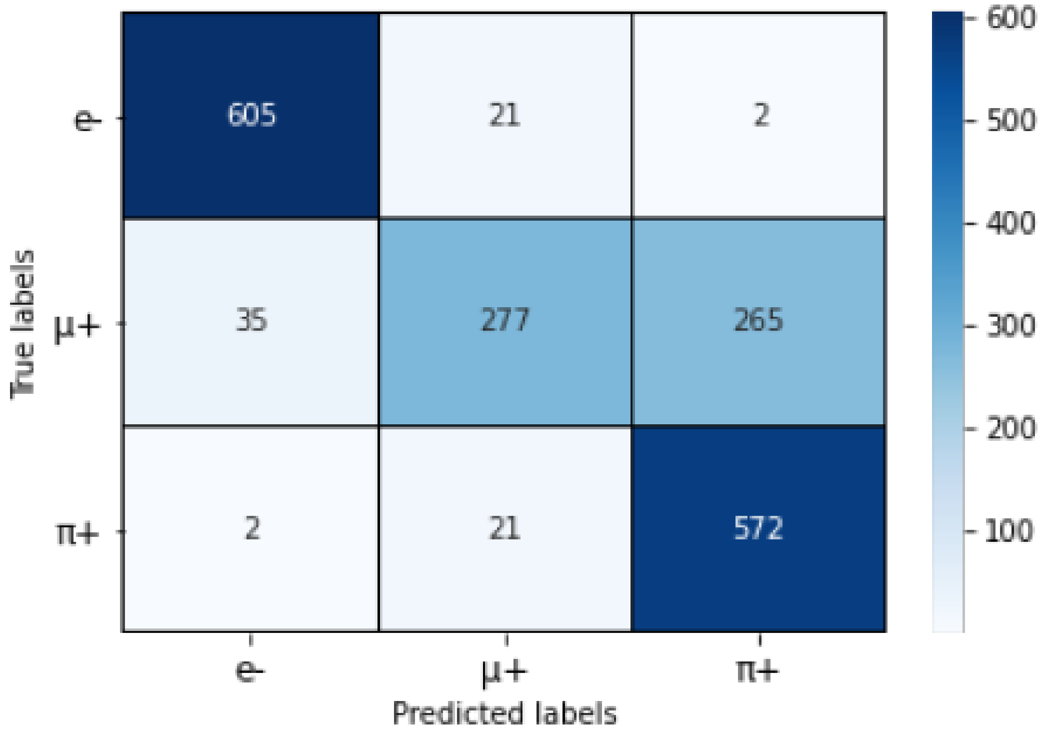


RESULTS

3 particle classification

Particle	Precision	Recall	False Positive Rate	F1-Score	Times seen
Electron	0.942	0.963	0.031	0.953	628
Muon	0.868	0.480	0.034	0.618	577
Pion	0.682	0.961	0.222	0.798	594

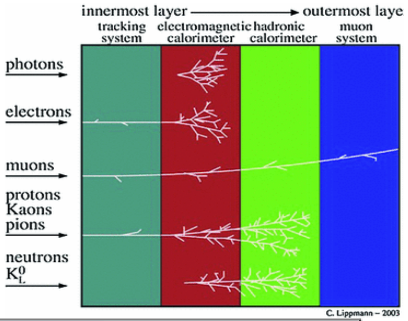


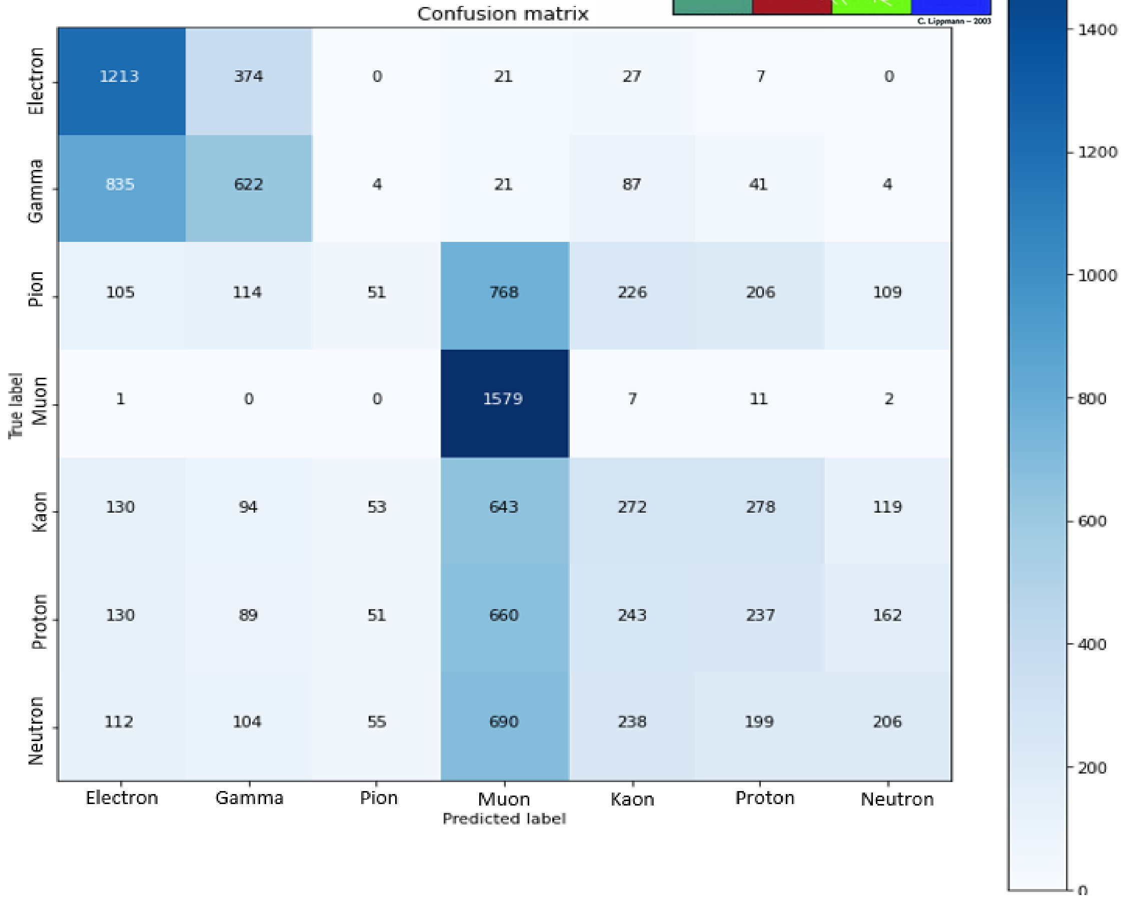


RESULTS

7 particles classification

Particle	Precision	Recall	False positive rate	F1-Score	Times seen
Electron	0.48	0.739	0.137	0.582	1642
Gamma	0.445	0.385	0.08	0.413	1614
Pion	0.238	0.032	0.017	0.057	1579
Muon	0.36	0.987	0.291	0.528	1600
Kaon	0.247	0.171	0.086	0.202	1589
Proton	0.242	0.151	0.077	0.186	1572
Neutron	0.342	0.128	0.041	0.187	1604

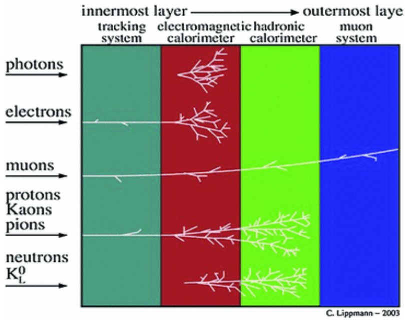


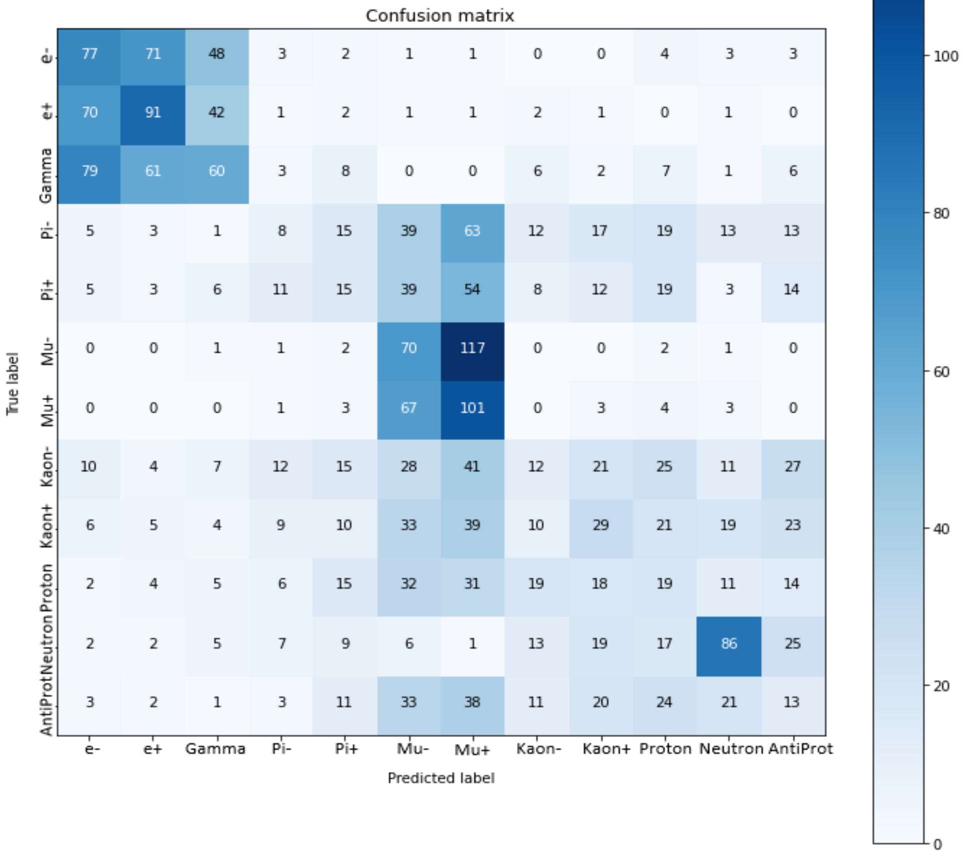


RESULTS

12 particle classification

Particle	Precision	Recall	False Positive Rate	F1-Score	Times seen
e-	0.297	0.362	0.083	0.326	213
e+	0.37	0.429	0.07	0.397	212
Gamma	0.333	0.258	0.055	0.291	233
Pi-	0.123	0.038	0.026	0.059	208
Pi+	0.14	0.079	0.042	0.101	189
Mu-	0.201	0.361	0.126	0.258	194
Mu+	0.207	0.555	0.174	0.302	182
Kaon-	0.129	0.056	0.037	0.078	213
Kaon+	0.204	0.139	0.051	0.166	208
Proton	0.118	0.108	0.063	0.113	176
Neutron	0.497	0.448	0.039	0.471	192
AntiProt	0.094	0.072	0.056	0.082	180





BEST RESULTS

Classification	CNN	XGBoost	XGBoost (Image centering)
Neutral particles	96.3%	85.4%	90.1%
Three particles	82.0%	77.2%	78.9%
Seven particles	37.0%	34.9%	38.35%
All particles	24.2%	21.9%	23.21%

Thank you

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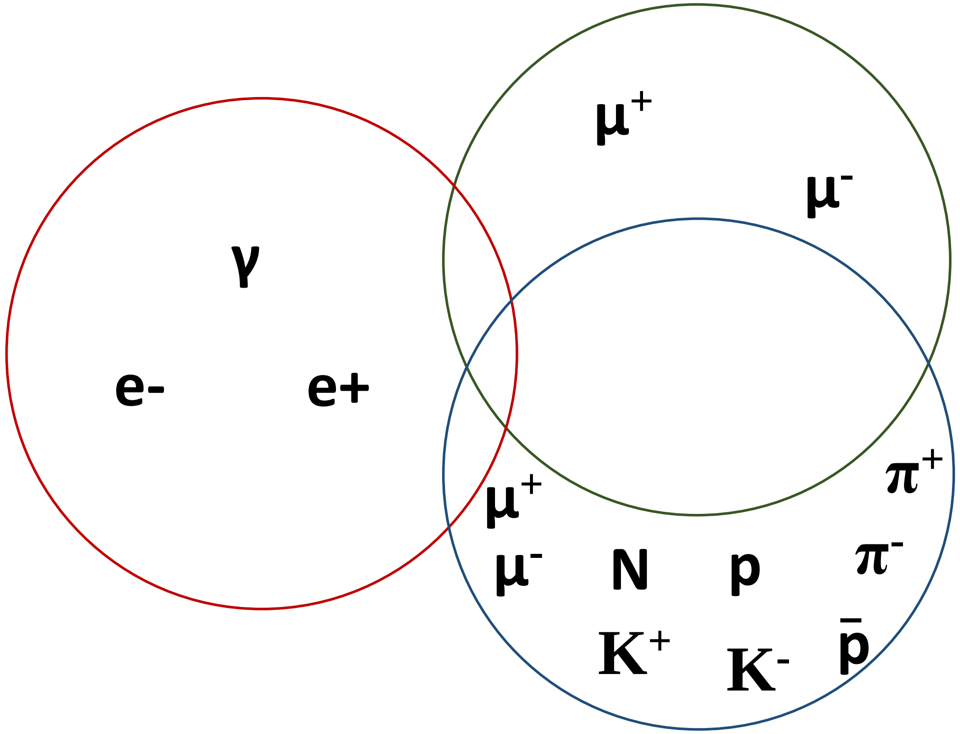
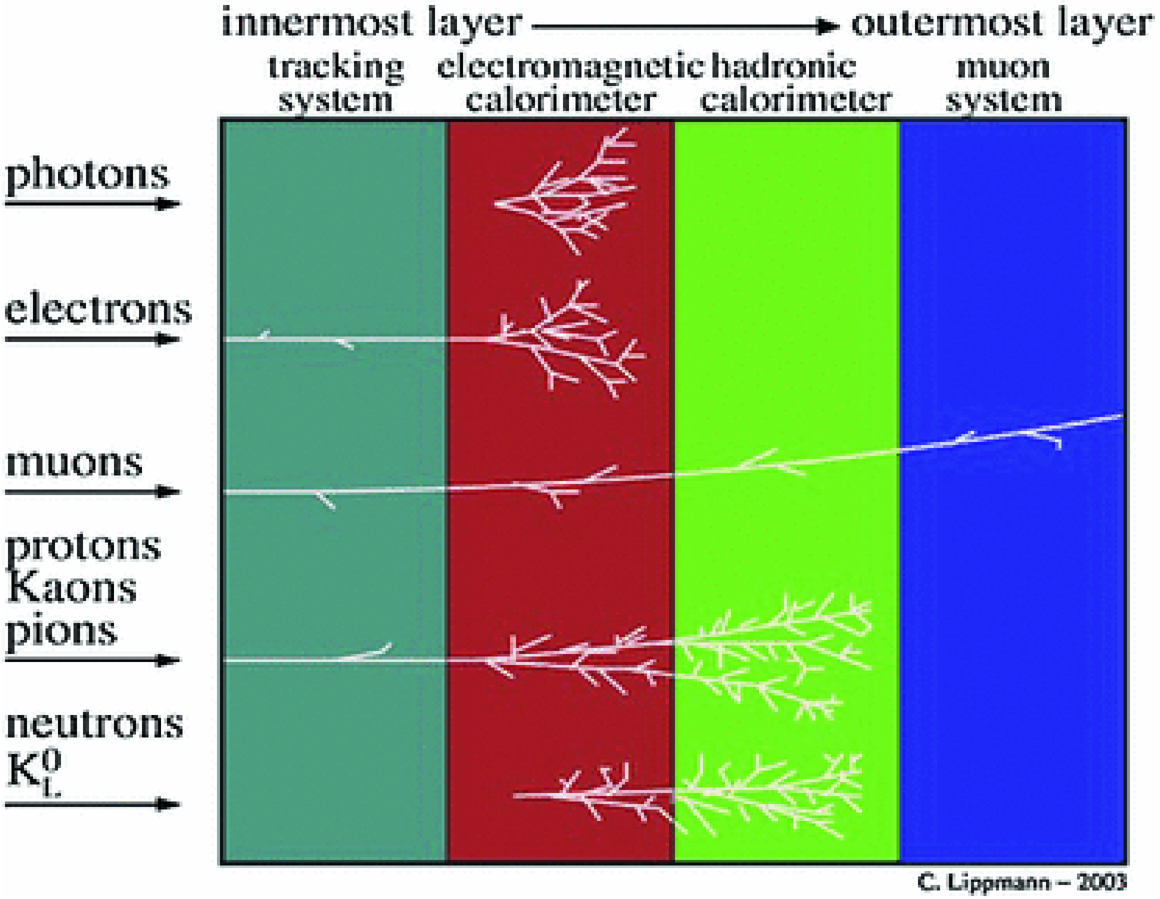
APPENDIX


μ+
μ-
γ
e-
e+
π+
μ+
μ-
N
p
π-
K+
K-
p̄


innermost layer
outermost layer
tracking system
electromagnetic calorimeter
hadronic calorimeter
muon system
photons
electrons
muons
protons
Kaons
pions
neutrons
K0L
C. Lippmann – 2003

APPENDIX

2 particle classification model

```
Net:
 Sequential(
  (0): Reshape()
  (1): Conv2d(2, 6, kernel_size=(2, 2), stride=(1, 1))
  (2): LeakyReLU(negative_slope=0.001)
  (3): MaxPool2d(kernel_size=2, stride=1, padding=1, dilation=1, ceil_mode=False)
  (4): Flatten()
  (5): Linear(in_features=294, out_features=128, bias=True)
  (6): ReLU()
  (7): Linear(in_features=128, out_features=32, bias=True)
  (8): ReLU()
  (9): Linear(in_features=32, out_features=2, bias=True)
  (10): Softmax(dim=1)
)

Learning rate:  0.01

Loss Function:  Cross Entropy Loss

Optimizer:  Adamax
```