deep learning for

tau decay ID
&
ECAL optimisation

a first report, 20 Dec 2019

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tau leptons

main decay modes:

tau → e ν ν
tau → μ ν ν
tau → pi+ ν
tau → pi+ pi0 ν
tau → pi+ pi0 pi0 ν
tau → ….

it is important to distinguish these decay modes for several analyses
which depend on tau polarisation measurement (L/R couplings, Higgs CP, …)

For high energy taus, decays products are in very narrow cone,
so not always easy to identify decay

	true MC decay $\tau^\pm \to \pi^\pm \nu$	$\tau^\pm \to \pi^\pm \pi^0 \nu$	$\tau^\pm \to \pi^\pm \pi^0 \pi^0 \nu$	$\tau^\pm \to$ other	purity
	IDR-L				
selected as $\tau^\pm \to \pi^\pm \nu$	89.27 ± 0.38	2.06 ± 0.12	0.87 ± 0.13	9.22 ± 0.29	82.11 ± 0.45
selected as $\tau^\pm \to \pi^\pm \pi^0 \nu$	6.47 ± 0.30	75.21 ± 0.36	13.32 ± 0.48	5.81 ± 0.23	86.79 ± 0.30
selected as $\tau^\pm \to \pi^\pm \pi^0 \pi^0 \nu$	2.20 ± 0.18	13.03 ± 0.28	64.32 ± 0.68	6.74 ± 0.25	53.86 ± 0.65

%

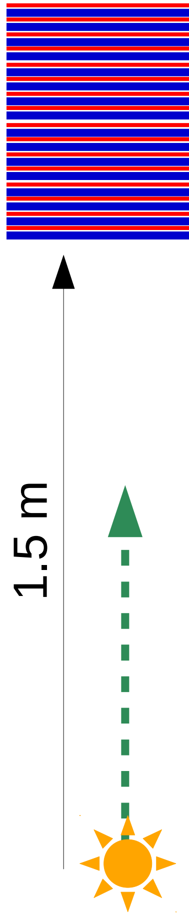
250 GeV taus, from IDR benchmark analysis (Yumino/Jeans) using PandoraPFA

the ECAL is the main detector to distinguish these decays modes

main question of this study:

can tau decay identification be helped by
- finer ECAL granularity ?
- better ECAL reconstruction ?

make a simplified detector (dd4hep, lcgeo)



30-layer Si-W calorimeter

3mm W, 0.5mm Si, 0.5mm air

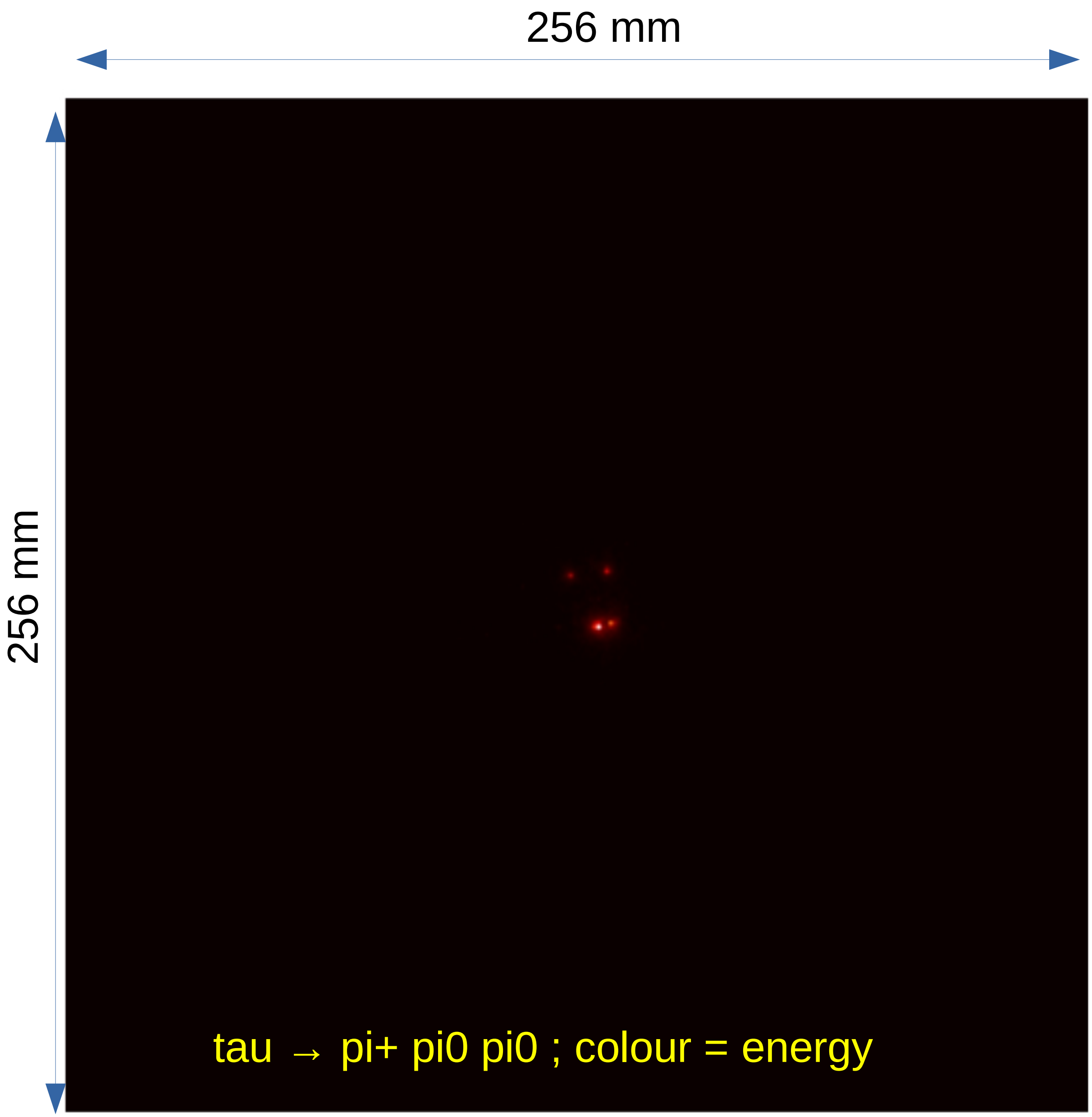
1x1 mm^2 readout segmentation

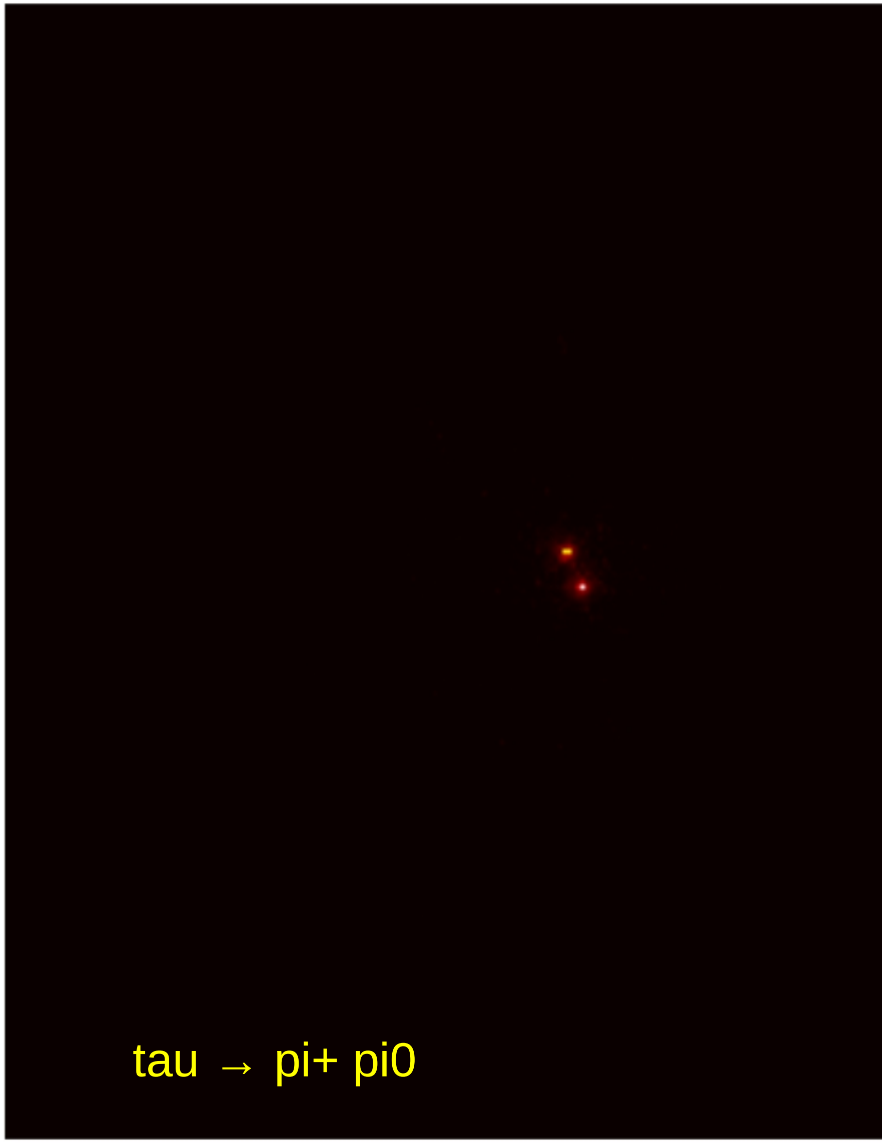
no B-field

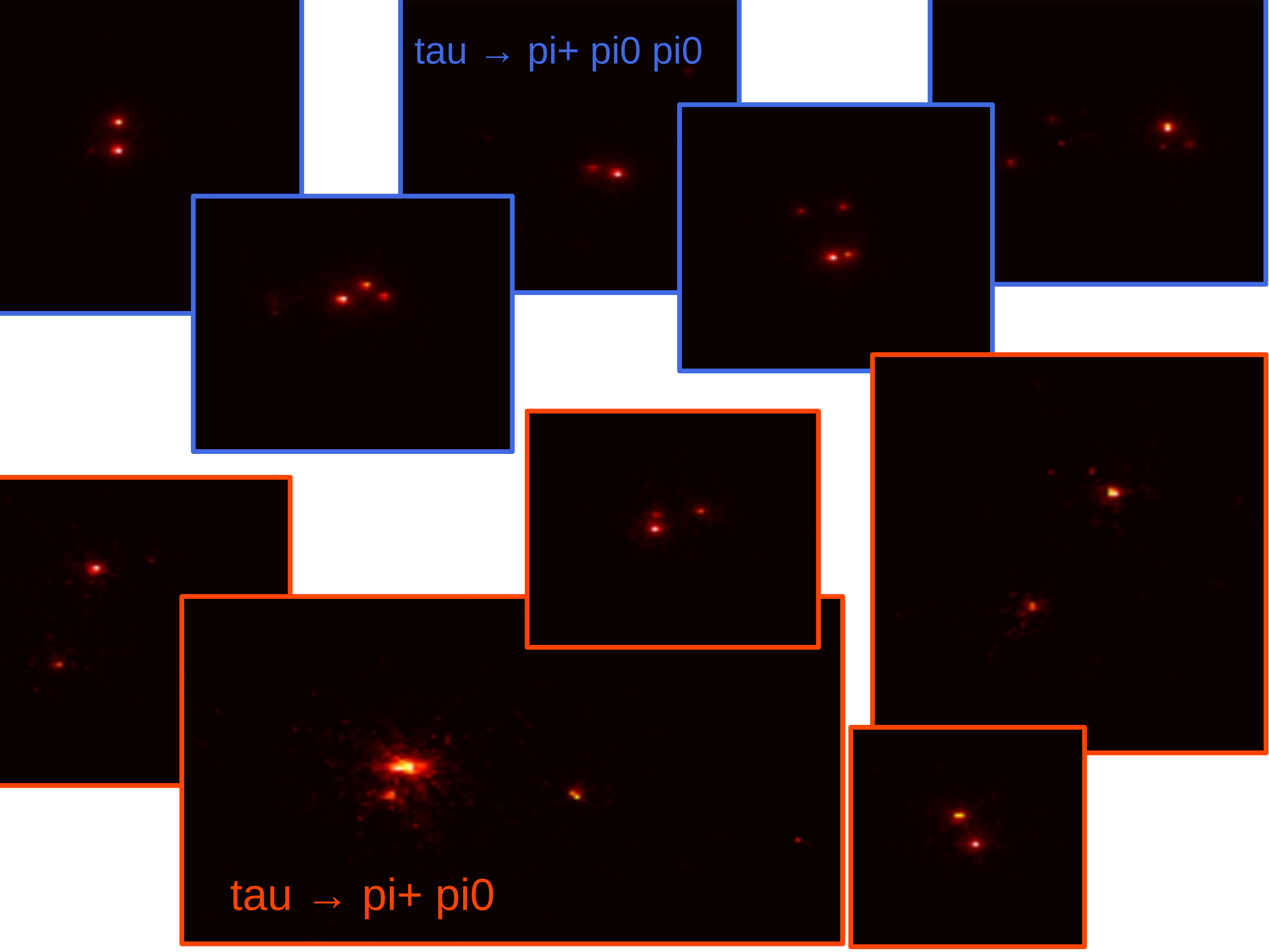
upwards-going 250 GeV tau,
constant energy, direction

decayed by tauola

transverse segmentation is probably most important aspect,
so for now combine all layers, project hit energies onto front face






tau → pi+ pi0 pi0
tau → pi+ pi0

now we can ask a neural network to analyse these images

convolutional neural network “CNN”

slides a small “filter” (eg 3x3 matrix) all over the image

convolute with the image pixels

→ generate a response

→ a CNN can find local features (same size as the filter)

→ a CNN is ~invariant against translations

we can make several CNN steps,

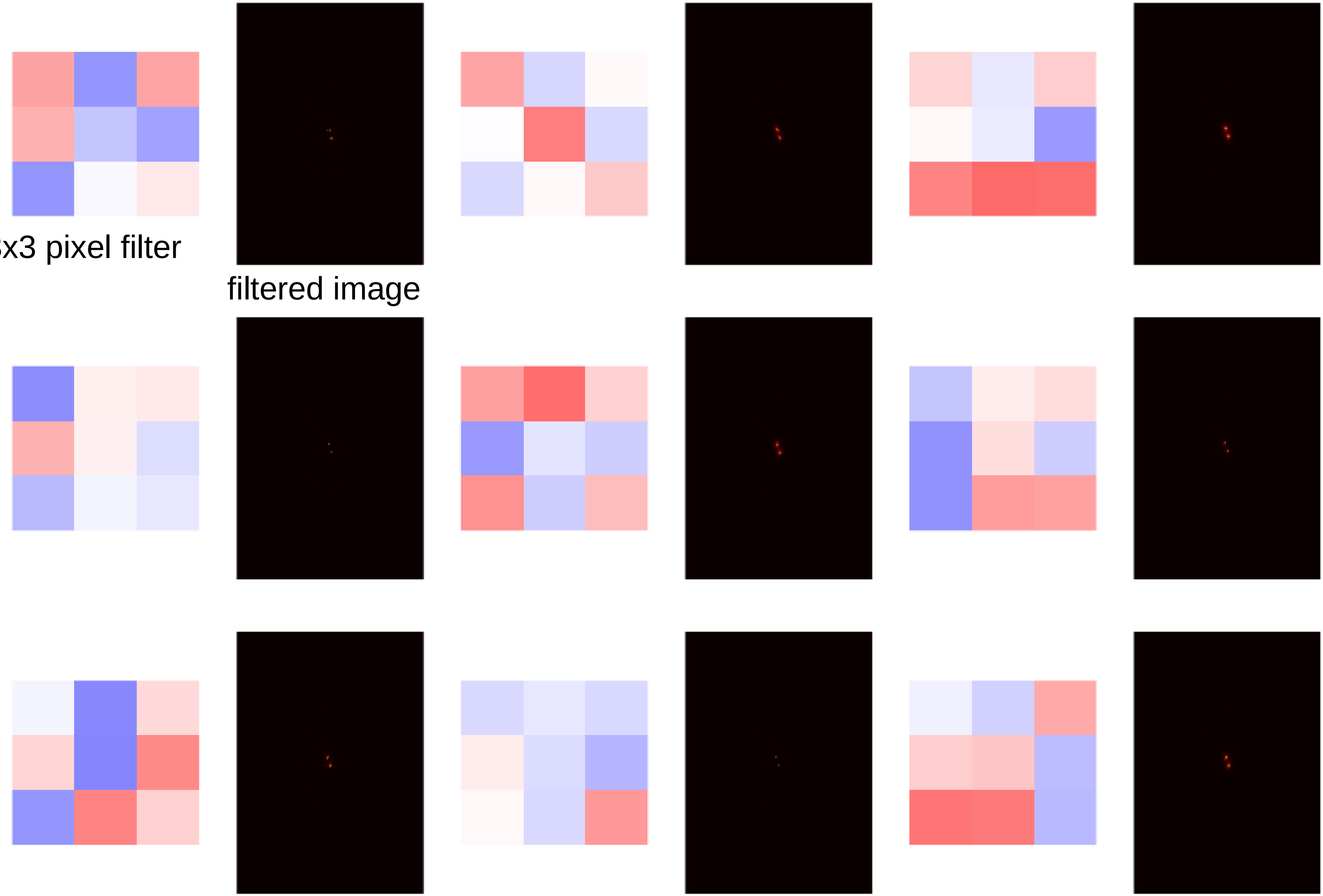
reducing the resolution between steps (eg “MaxPooling”)

→ look at picture at different scales

this can be trained to look for specific features in an image

(eg photon showers)

example



can repeat this procedure, applying new filters to the filtered images

→ "deep"

but many parameters to train → overtraining

to reduce # parameters

reduce resolution in later steps,

set small parameters to 0,

….

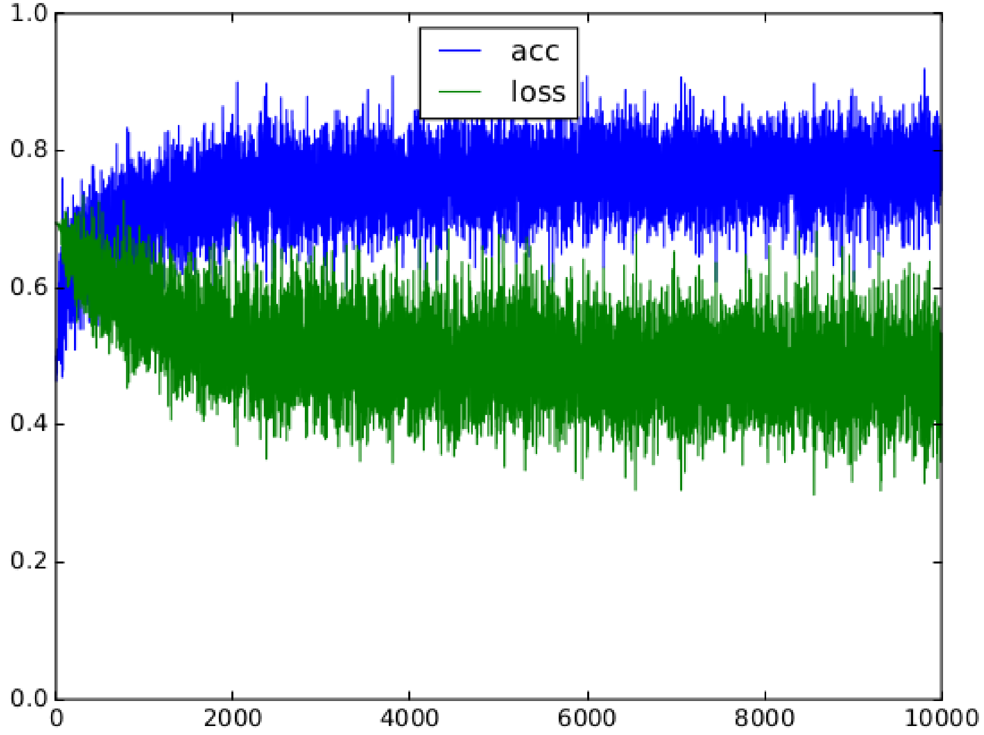
to train the networks, I'm using keras with tensorflow backend example configuration

```
inputs = Input( shape=imagedim )
x = Conv2D(filters=nFiltersPerStep, kernel_size=3, \
      strides=1, padding='same', activation='relu' )(inputs)
x = Dropout(0.33)(x)
x = Conv2D(filters=nFiltersPerStep, kernel_size=3, \
      strides=1, padding='same', activation='relu')(x)
x = MaxPooling2D(2)(x)
x = Dropout(0.33)(x)
x = Conv2D(filters=nFiltersPerStep, kernel_size=3, \
      strides=1, padding='same', activation='relu')(x)
x = MaxPooling2D(2)(x)
x = Dropout(0.33)(x)
x = Flatten()(x)
predictions = Dense(ncategories, activation='sigmoid')(x)
```

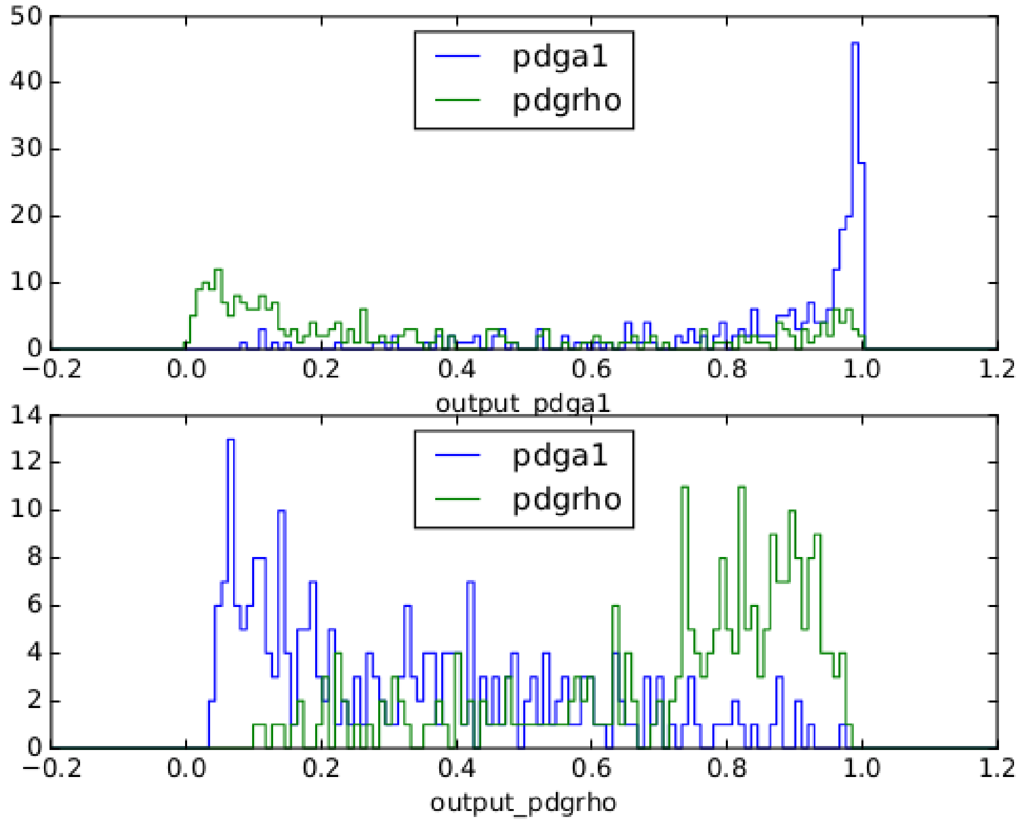
try to separate (pi+ pi0 pi0) from (pi+ pi0) decays

200 training epochs, “randomly” selected 50+50 event samples/epoch

sometimes training works nicely...



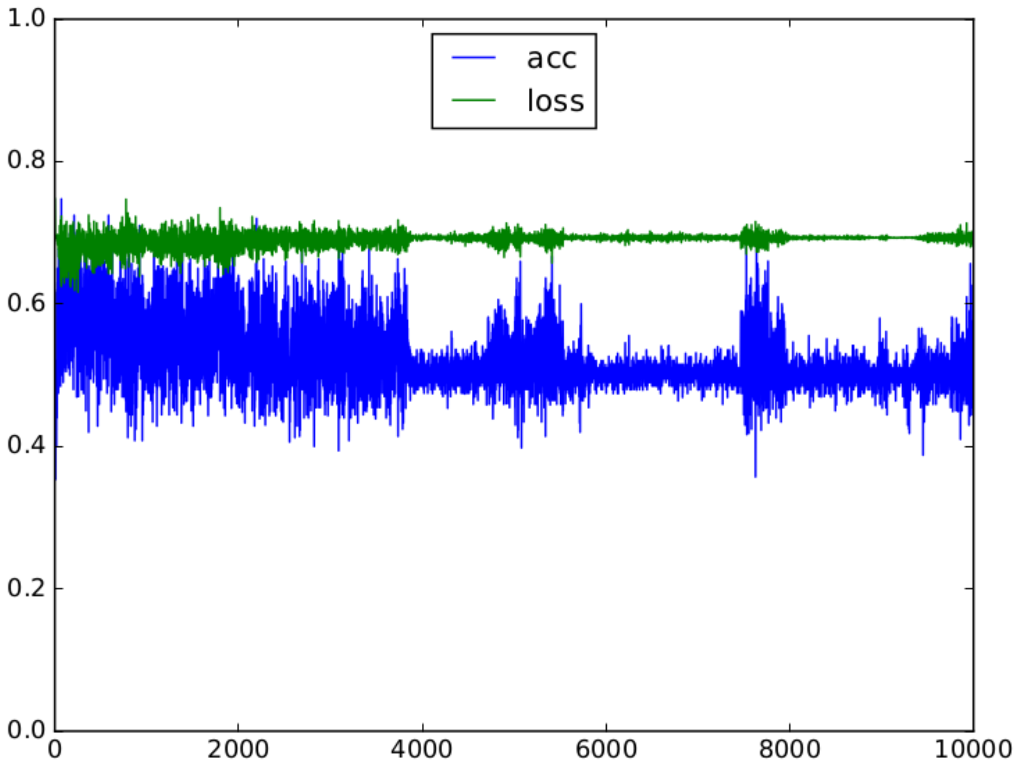
training epoch



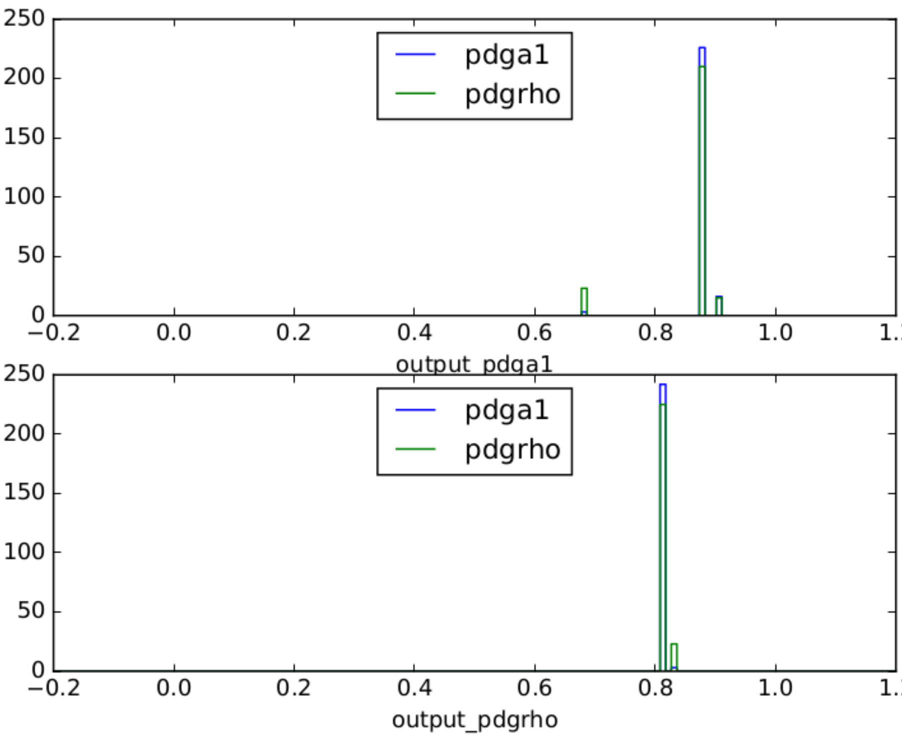
outputs

...other times not

→ I need to understand why!

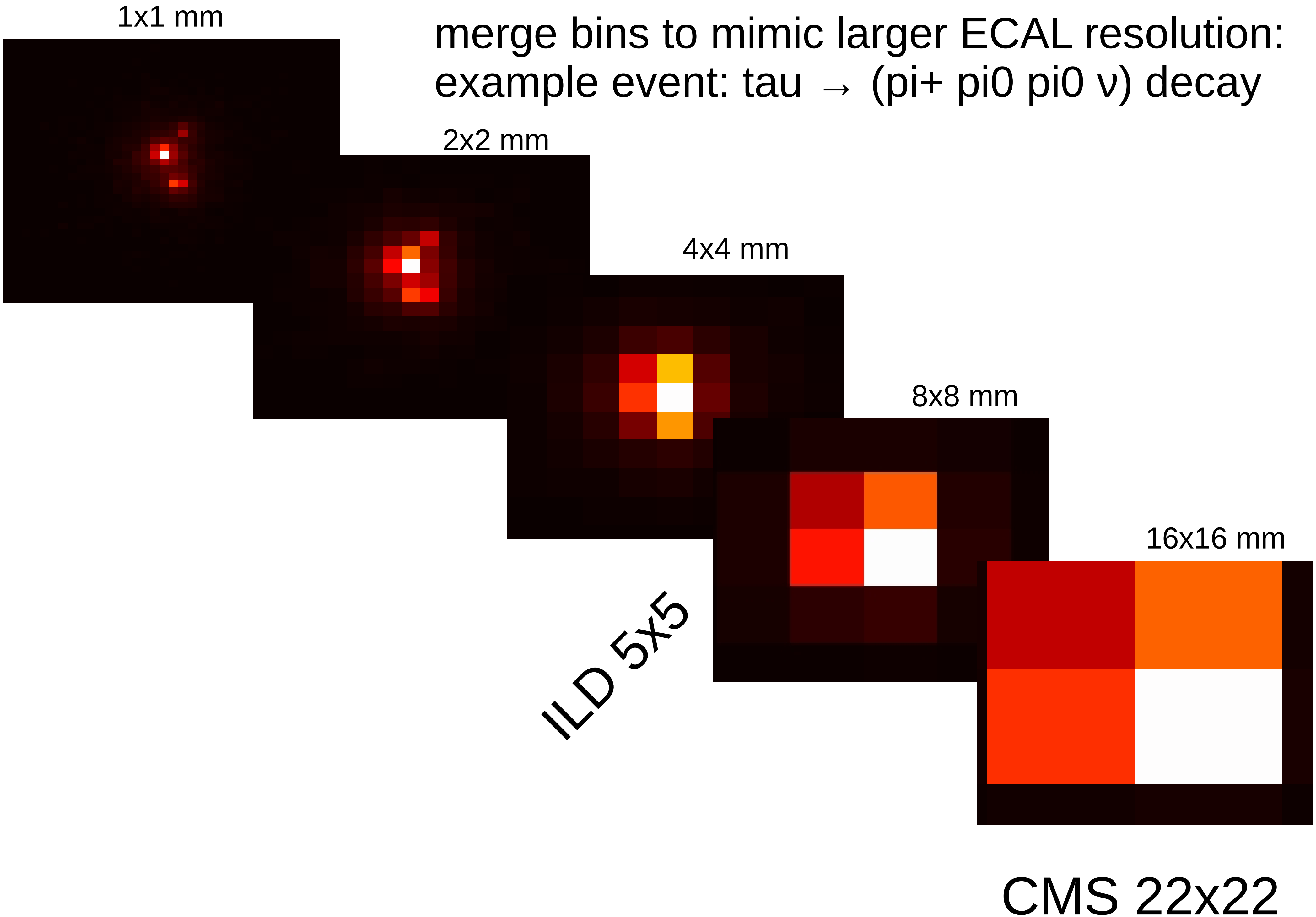


training epoch



outputs

merge bins to mimic larger ECAL resolution:
example event: tau → (pi+ pi0 pi0 ν) decay



started study:

DNN to reconstruct tau decay mode

→ use to optimise ECAL geometry

still things to learn about DNN framework/training

future plans:

include longitudinal information