LHAASO机器学习项目简介

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Contents

Large High Altitude Air Shower Observatory (LHAASO)

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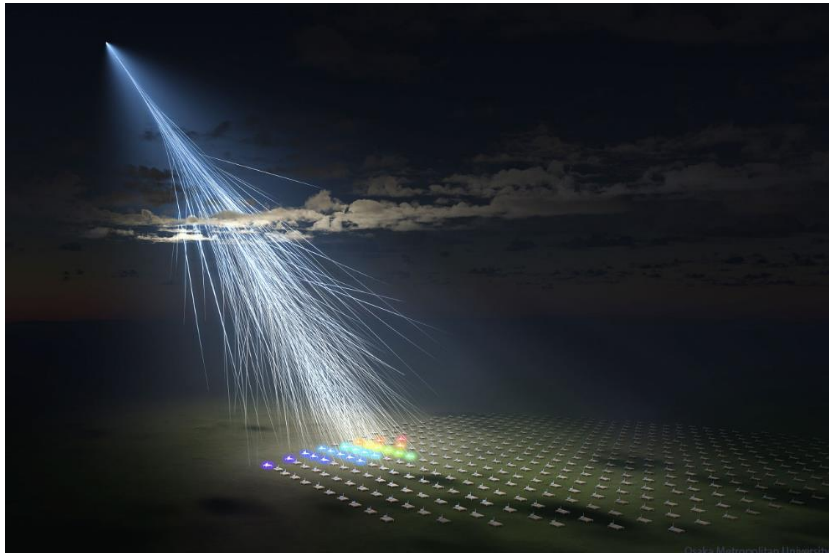
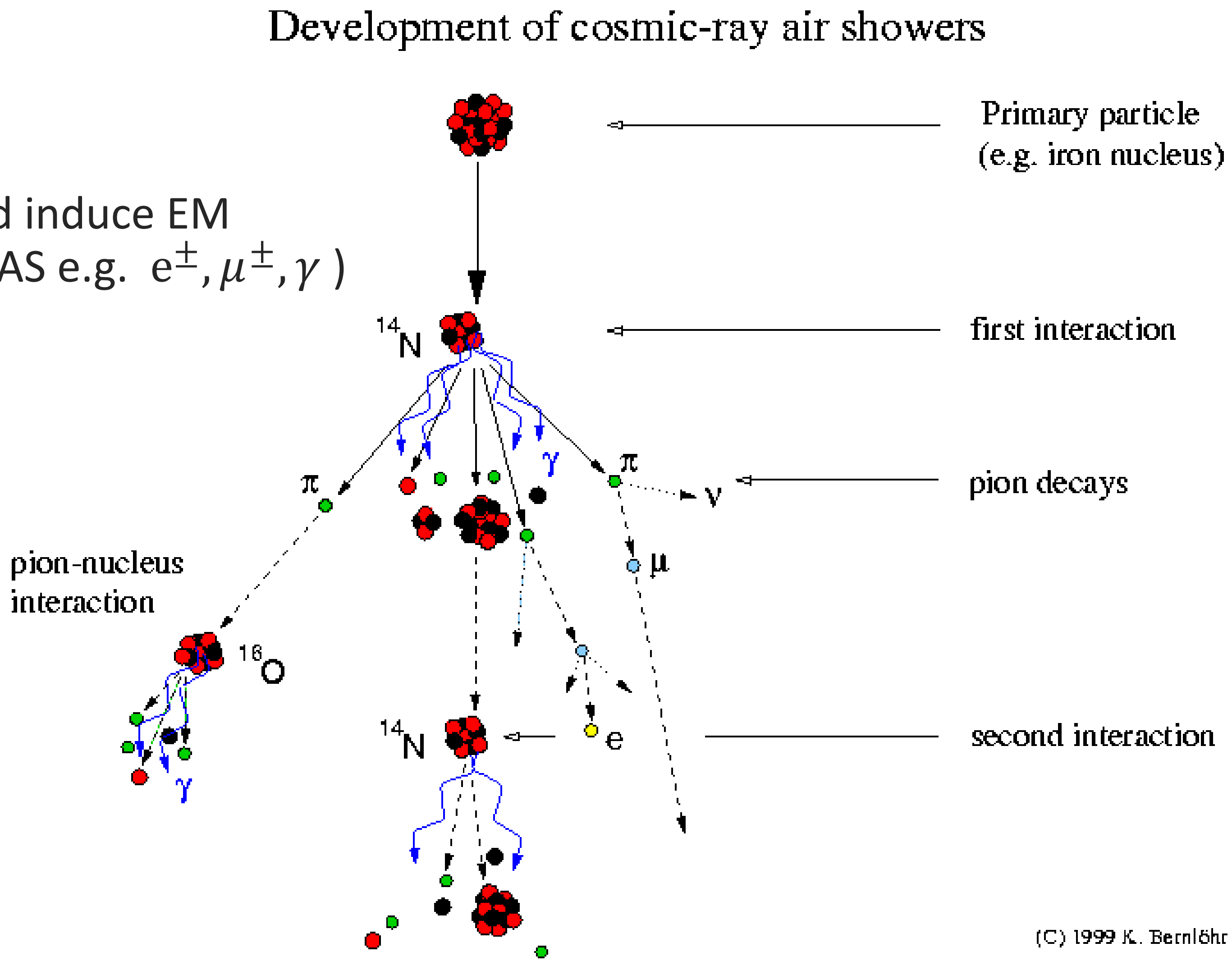
Air Shower

- Extensive Air Shower (EAS)
  - Particle collide with atmosphere and induce EM cascade (secondary particles from EAS e.g. $e^{\pm}, \mu^{\pm}, \gamma$)





Instruments

KM2A

Gamma-ray > 30 TeV (3×10^{12}eV)

Cosmic ray 10TeV – 100PeV

Electromagnetic particle detector (ED)

Muon detector (MD)

Water Cherenkov Detector Array (WCDA)

100 GeV -30 TeV ($10^{11} - 3 \times 10^{12}$eV)

WCDs

Wide Field Cherenkov Telescope Array (WFCTA)

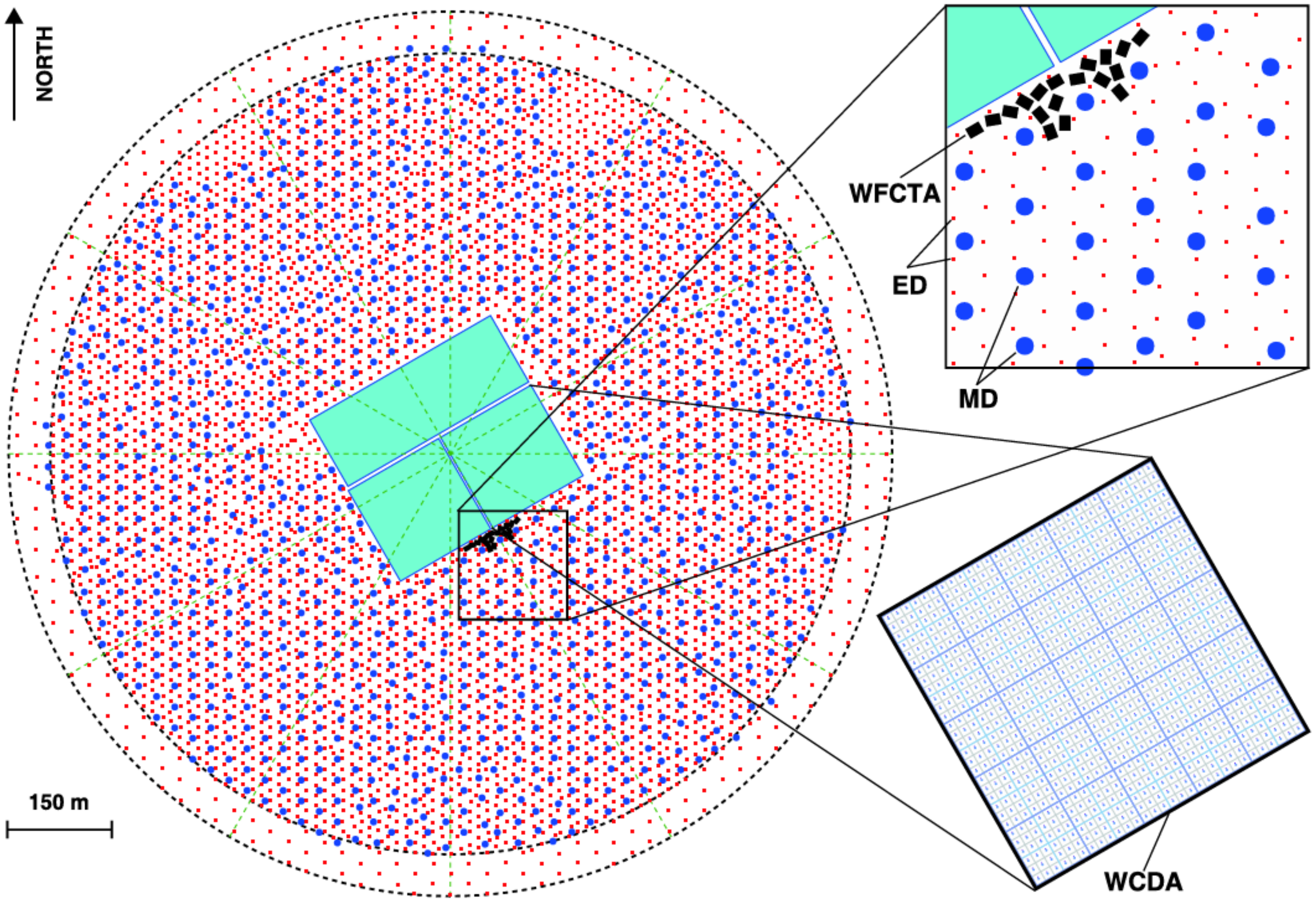


Fig. 1. (color online) Layout of LHAASO.

LHAASO Collaboration

[Chapter 1 LHAASO Instruments and Detector technology - IOPscience]

Instruments

- ED
  - Detection of secondary particles from EAS: $e^{\pm}, \gamma$
- MD
  - $e^{\pm}, \gamma$ with low energy shielded by soil
  - Detect $\mu^{\pm}$ with Cherenkov light in water
- EM – muon ratio helps categorize the primary particle:
  - Gamma-induced muon-poor shower
  - CR-induced muon-rich shower

Fig. 6. (color online) Photo of an installed ED.

[Chapter 1 LHAASO Instruments and Detector technology - IOPscience]

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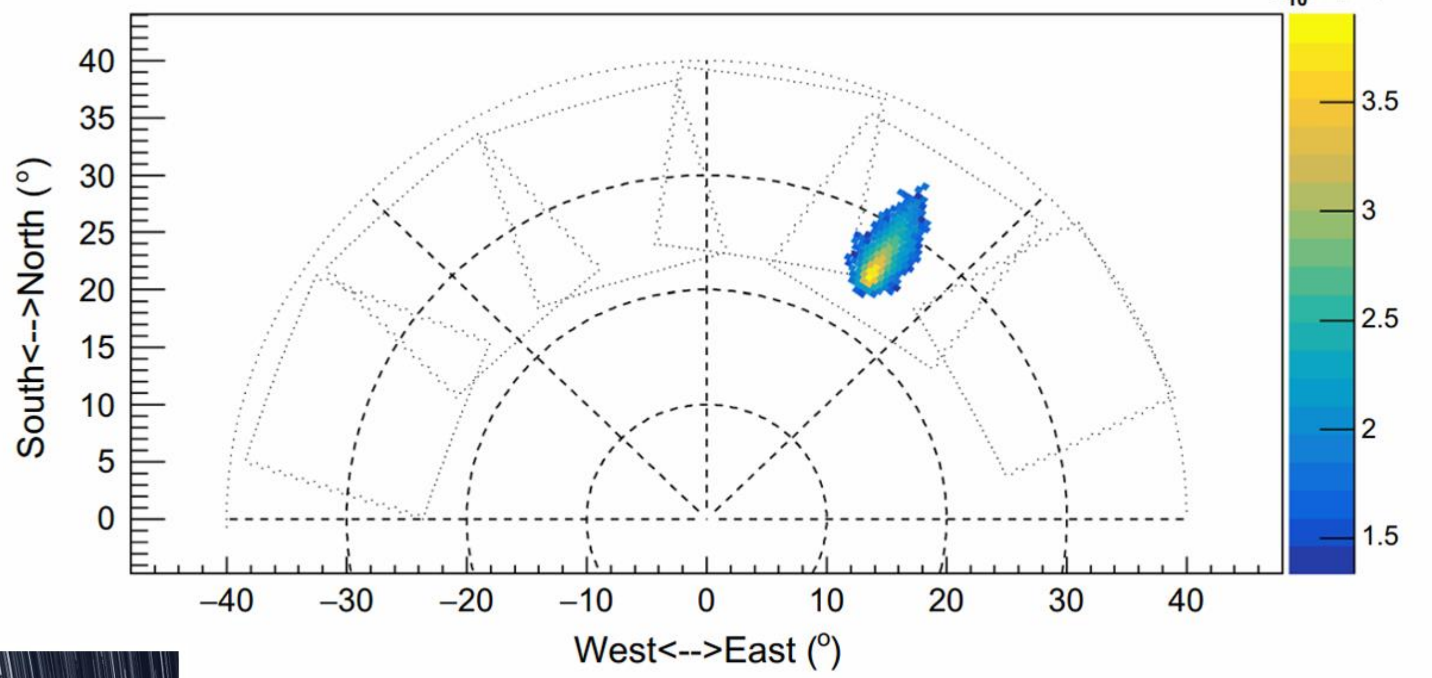
Instruments

- WFCTA
  - Direct observation of the Cherenkov radiation

WFCTA observation of an EAS event



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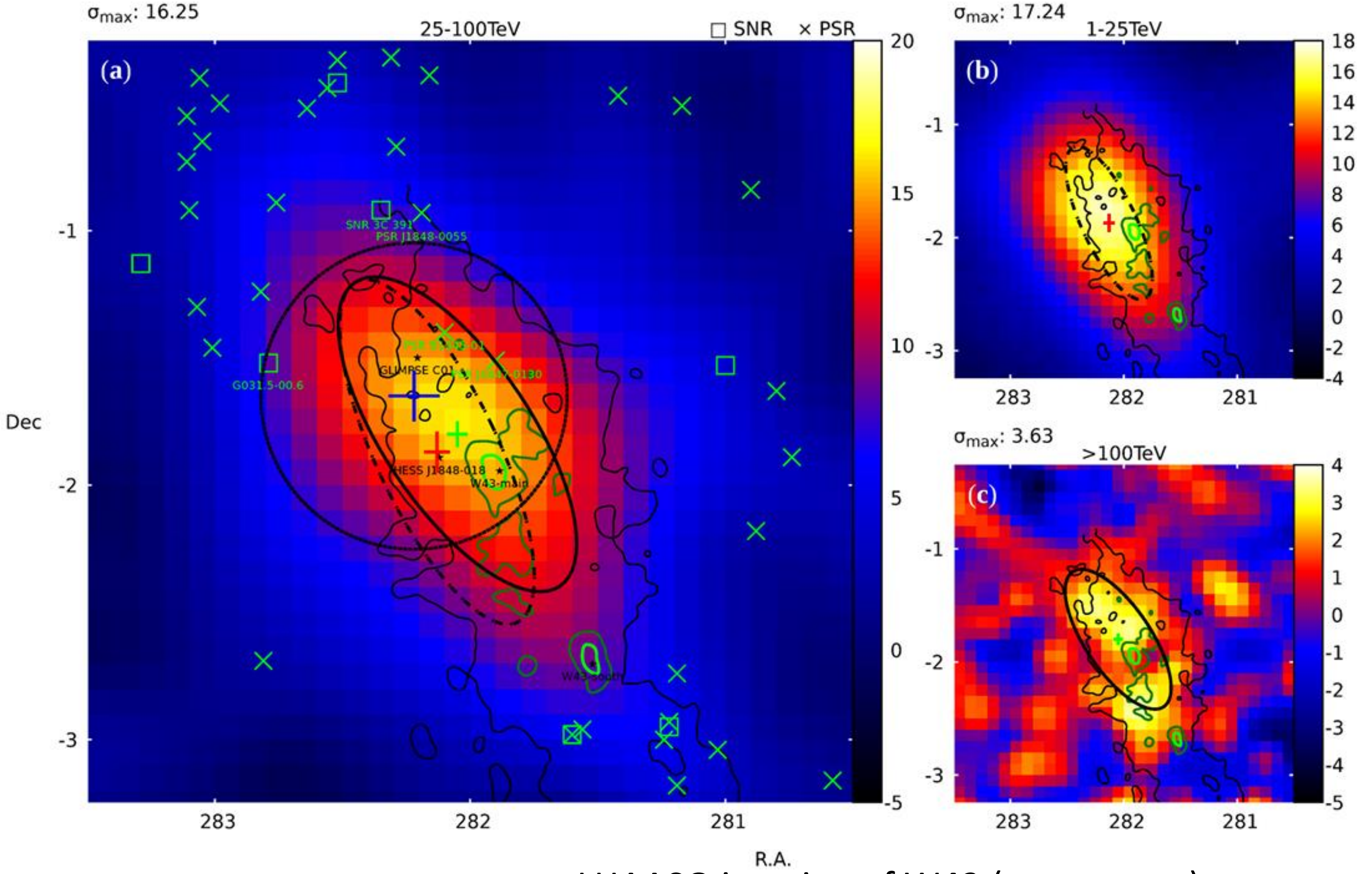
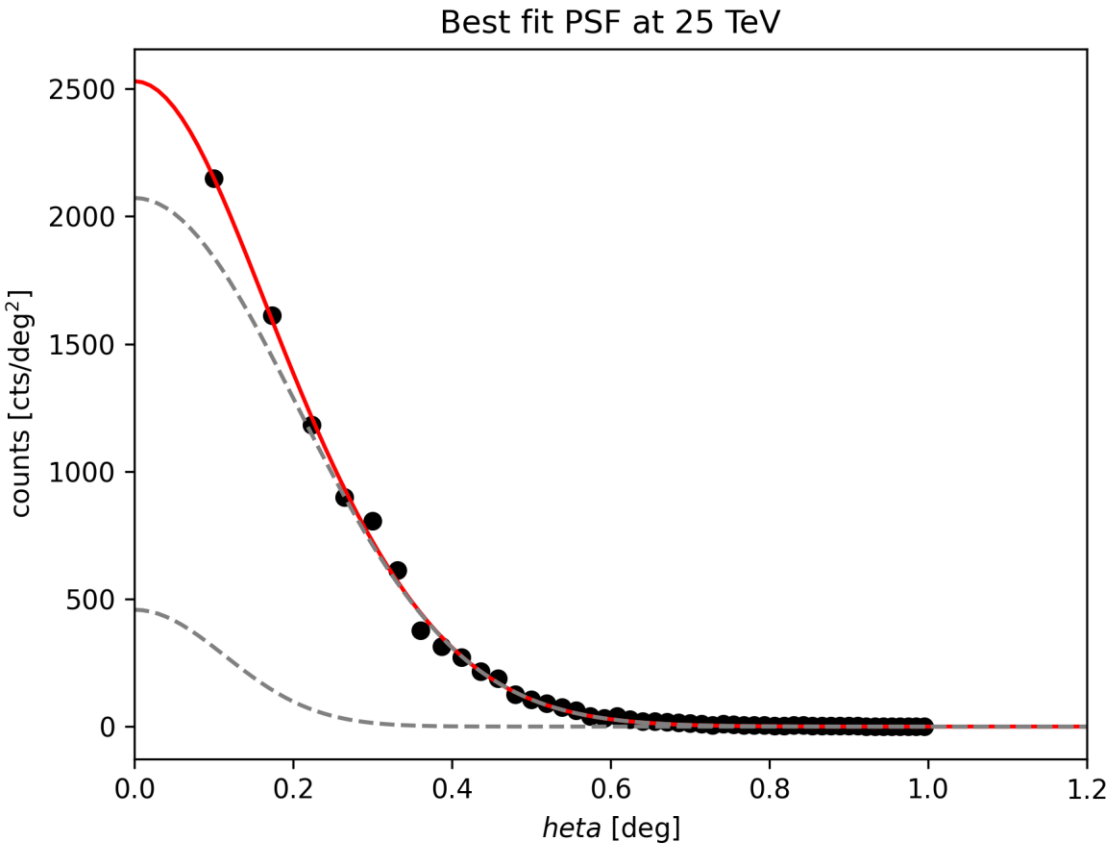
Imaging

- Significance Map
  - Likelihood Ratio Test
- Bin size: $0.1° \times 0.1°$



LHAASO imaging of W43 (gamma-ray)
[2408.09905 (arxiv.org)](https://arxiv.org/abs/2408.09905)

PSF of LHAASO



How To Enhance Resolution?

-- Denser detector configuration

d: distance between detectors

Cost: $\mathrm{C} = C_1 n \propto d^{-2}$

Resolution: $\mathrm{R} = \frac{1}{\theta} \propto d^{-1}$

$C \propto R^2$! **Expensive!!!**

--Machine Learning (our project)

Cost: GPU cluster is all you need.

Machine learning approach

- ML in microscopy

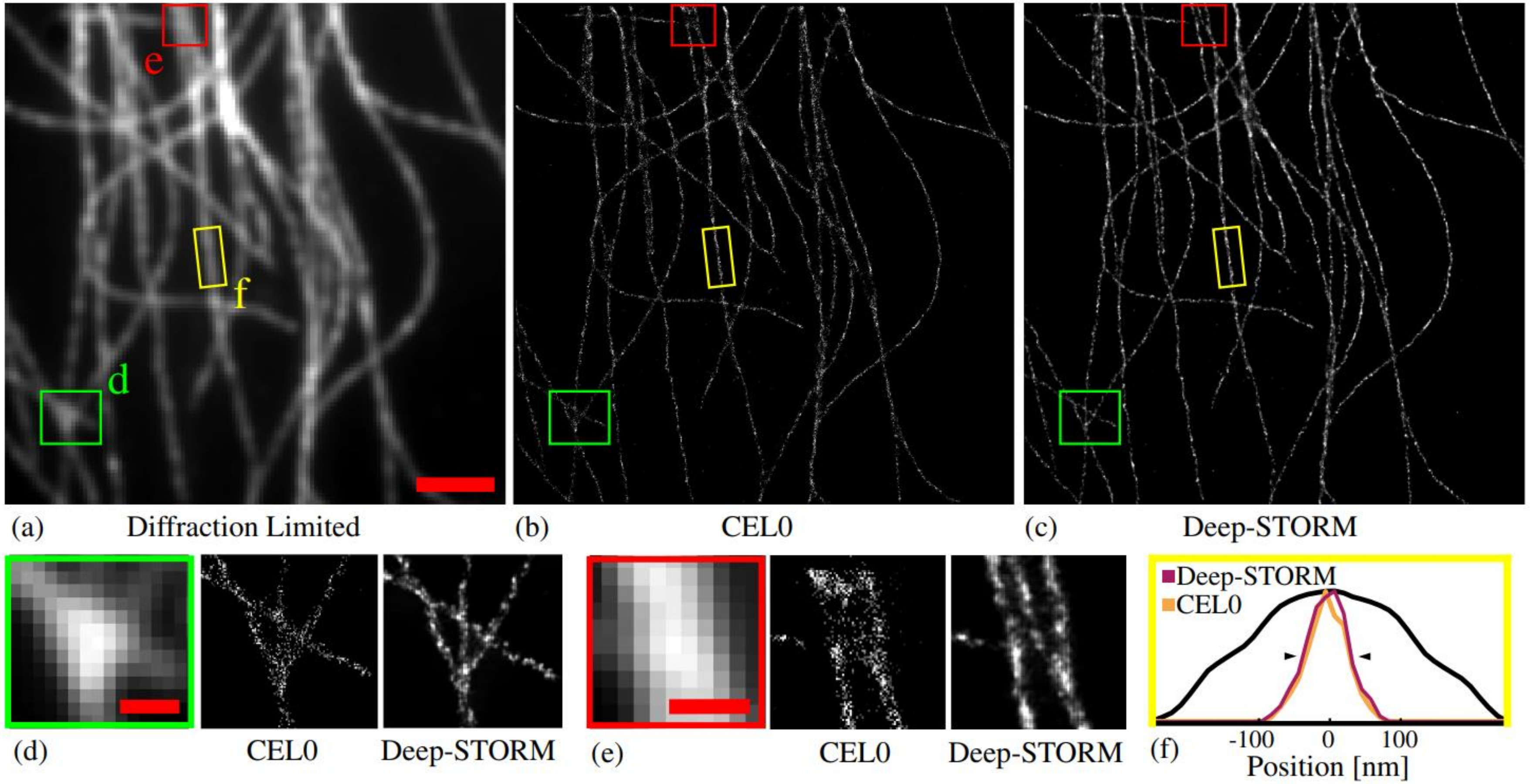
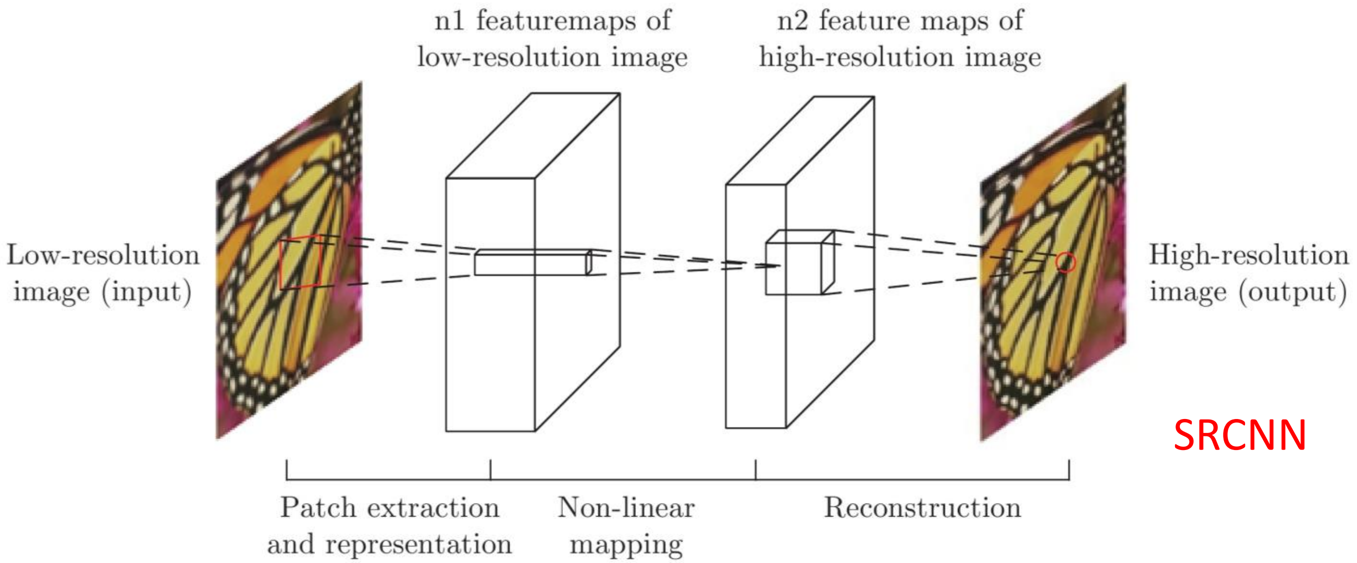


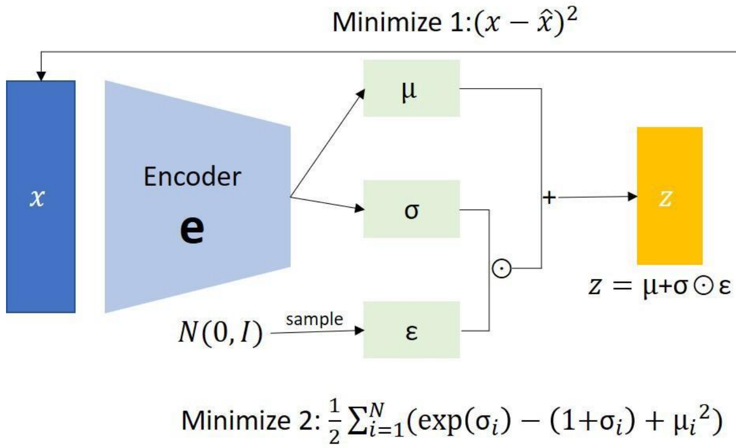
Fig. 6. Experimentally measured microtubules. (a) Sum of the acquisition stack. Scale bar is 2 μm. (b) Reconstruction by the CEL0 method. (c) Reconstruction by Deep-STORM. (d), (e) Magnified views of two selected regions. Scale bars are 0.5 μm. (f) The width projection of the highlighted yellow region. The attained FWHM (black triangles) for CEL0 was 61 nm and 67 nm for Deep-STORM. The black line shows the diffraction-limited projection.

ML Models

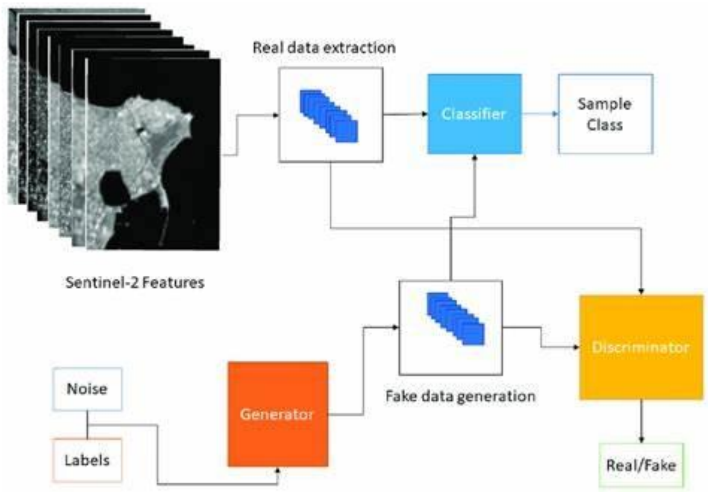
- Convolutional Neural Network (CNN)
  - (Best for de-convolution)
- Generative Adversal Network (GAN)
- Variational Auto-Encoder (VAE)



SRCNN



VAE

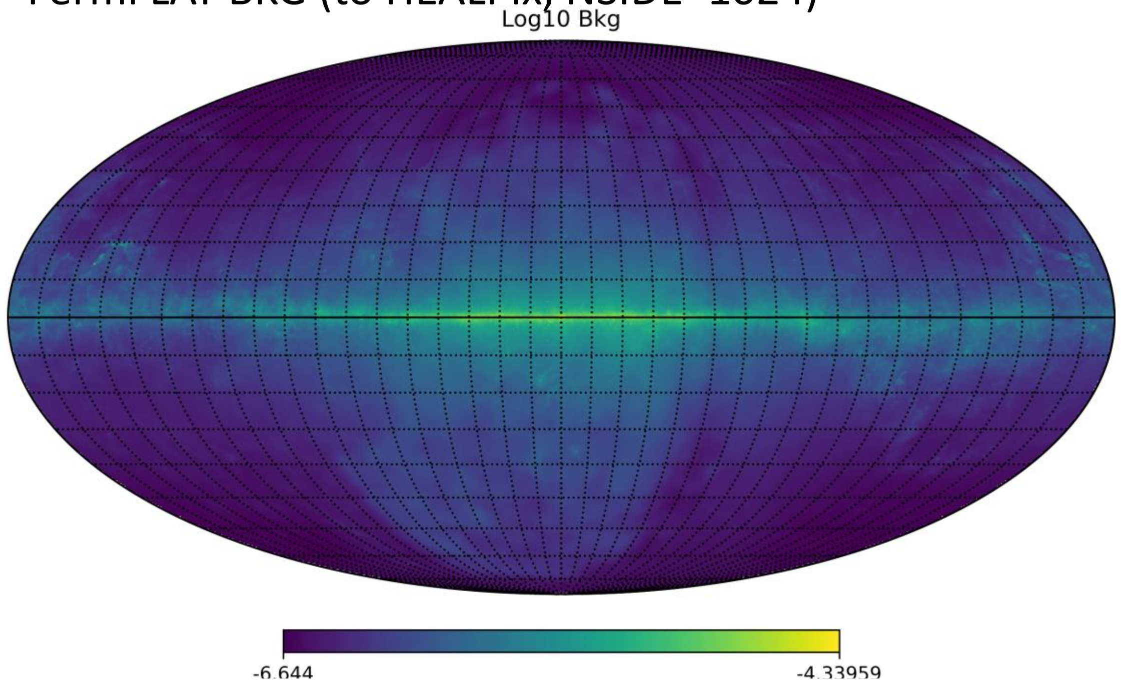


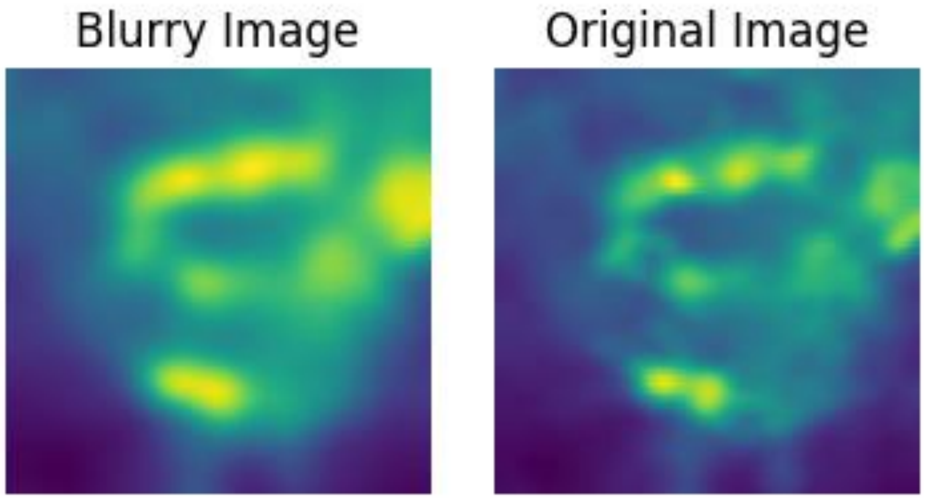
GAN

Training Dataset

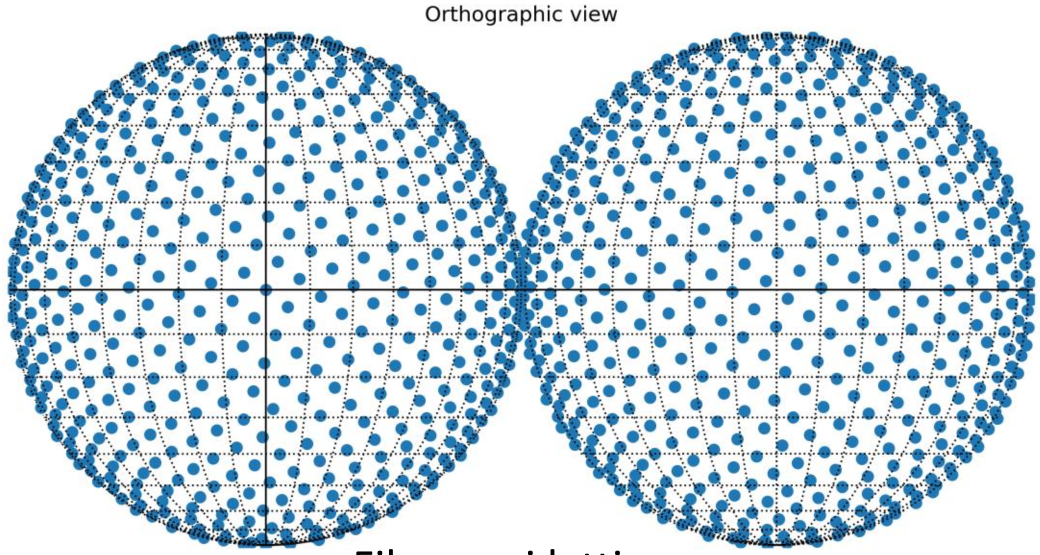
- Fermi LAT diffuse gamma-ray background
- Select ROIs with Fibonacci lattice
- Extract Sky Map from HEALPix ($6.4° \times 6.4°$)
- Bin to $0.1° \times 0.1°$
- Perform 2d convolution with PSF function

Fermi LAT BKG (to HEALPix, NSIDE=1024)





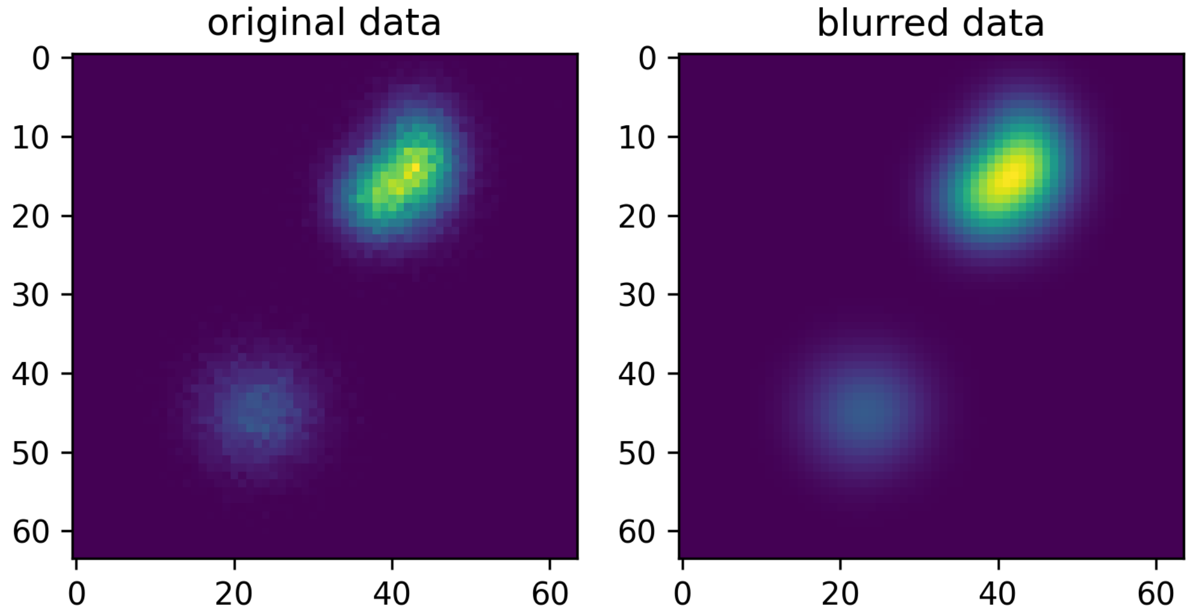
Generated Training Dataset



Fibonacci lattice

Training Dataset

- Randomly generated gaussian-like extensive src
  - Parameters saved in a XML file
- Simulate observation with Fermitools
  - gtobssim
  - gtbin
- Perform 2d convolution with PSF function



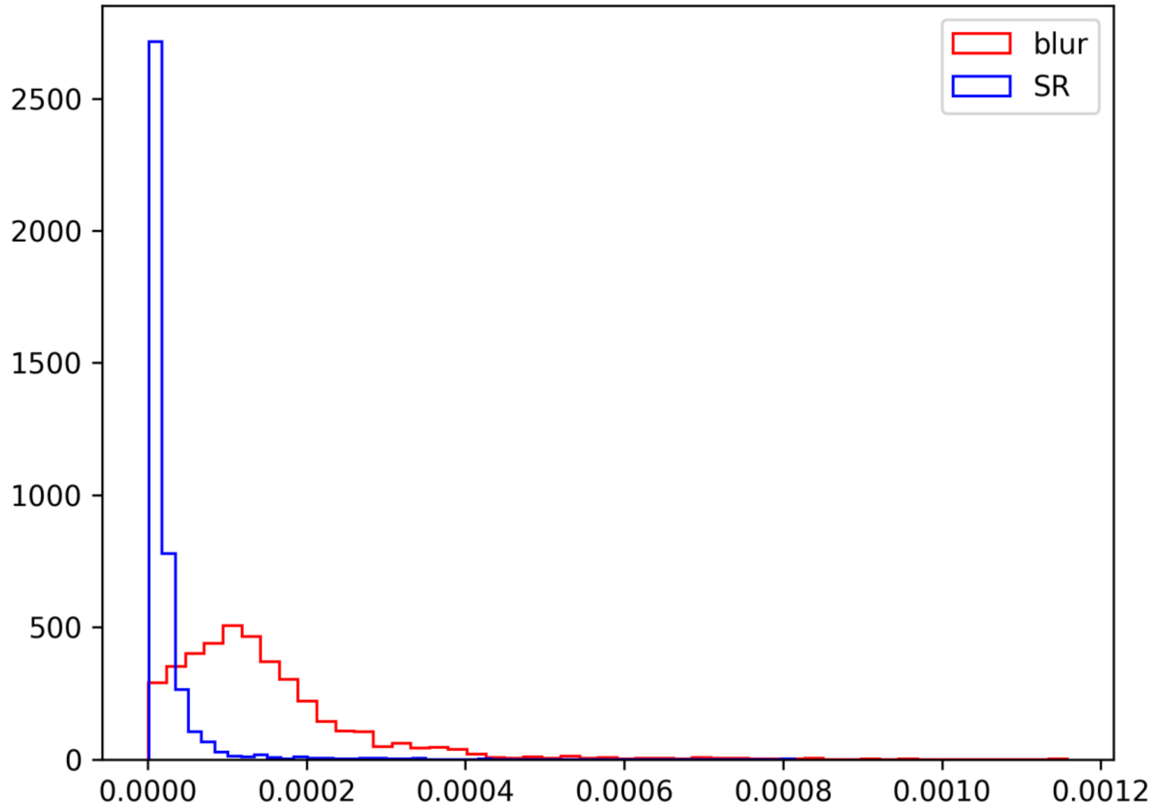
Generated Training Dataset

Training Results

- Model Performance Characterization
  - Jensen-Shannon Divergence
    - Cross-Entropy of two distribution
    - Symmetric
    - 0-1
    - $JSD(P||Q) = \frac{1}{2}KL(P||M) + \frac{1}{2}KL(Q||M)$,

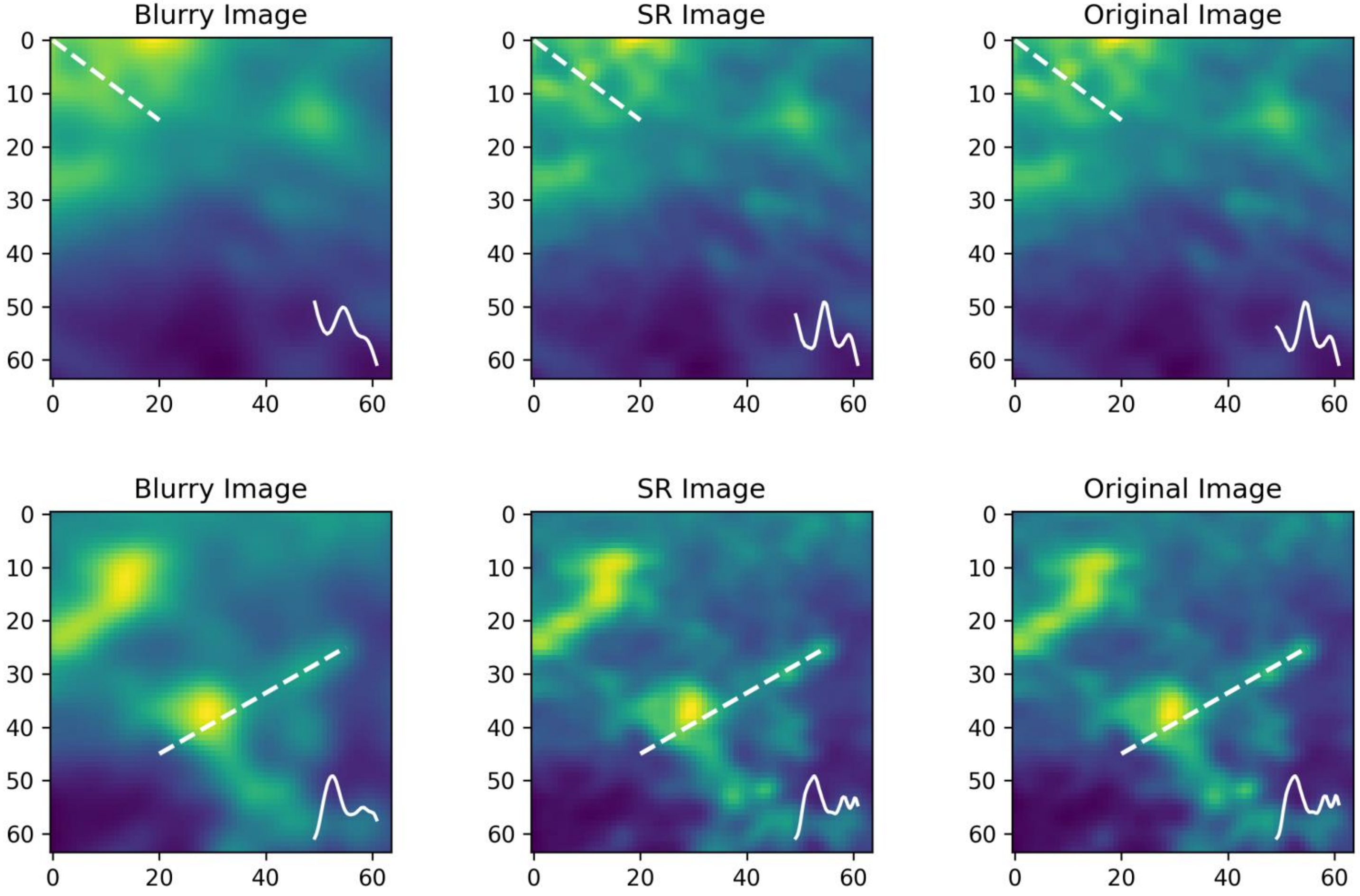
      where $M = \frac{1}{2}(P + Q)$,

      and $KL(P||Q) = \sum_i p_i \log\frac{p_i}{q_i}$.

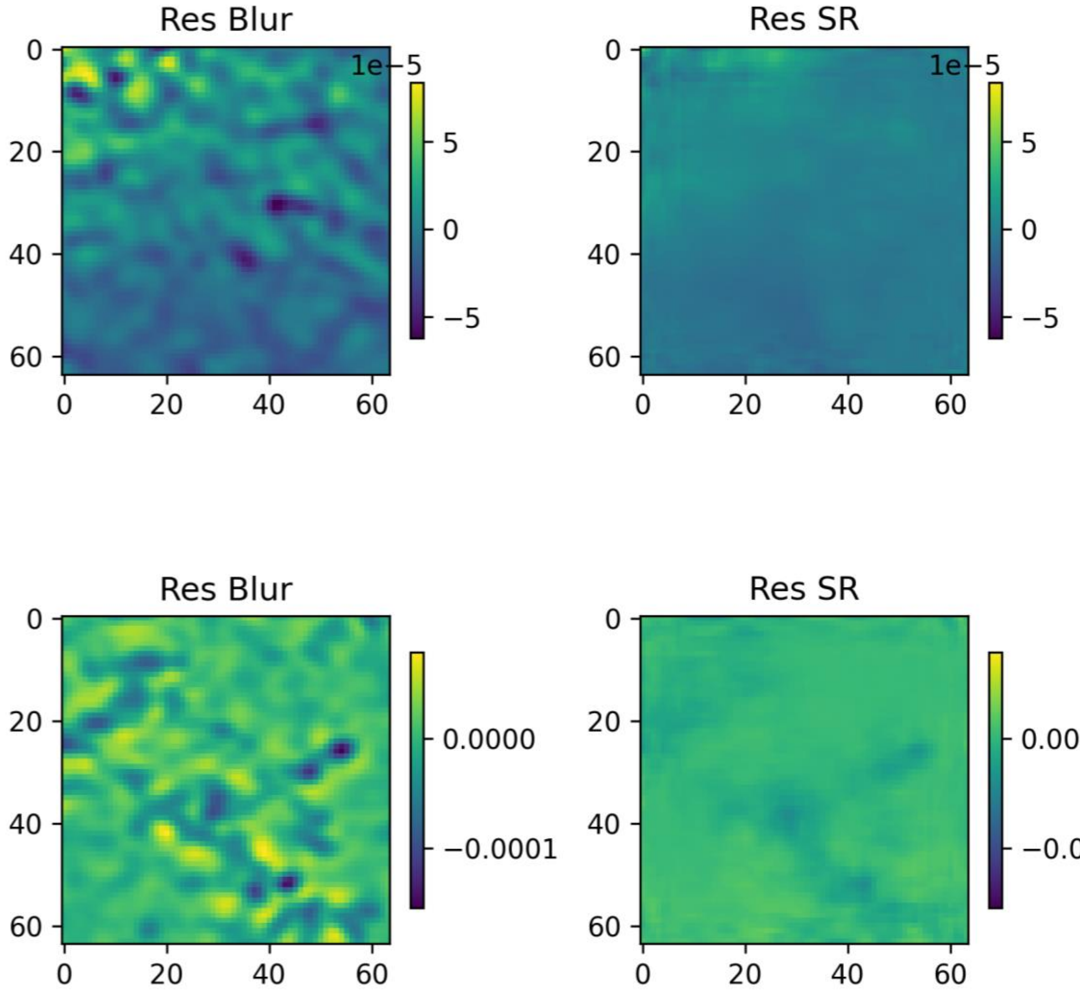


Trained by SRCNN, only on Fermi bkg dataset.
Other models (VAE and GAN) were not as good.

Training Results

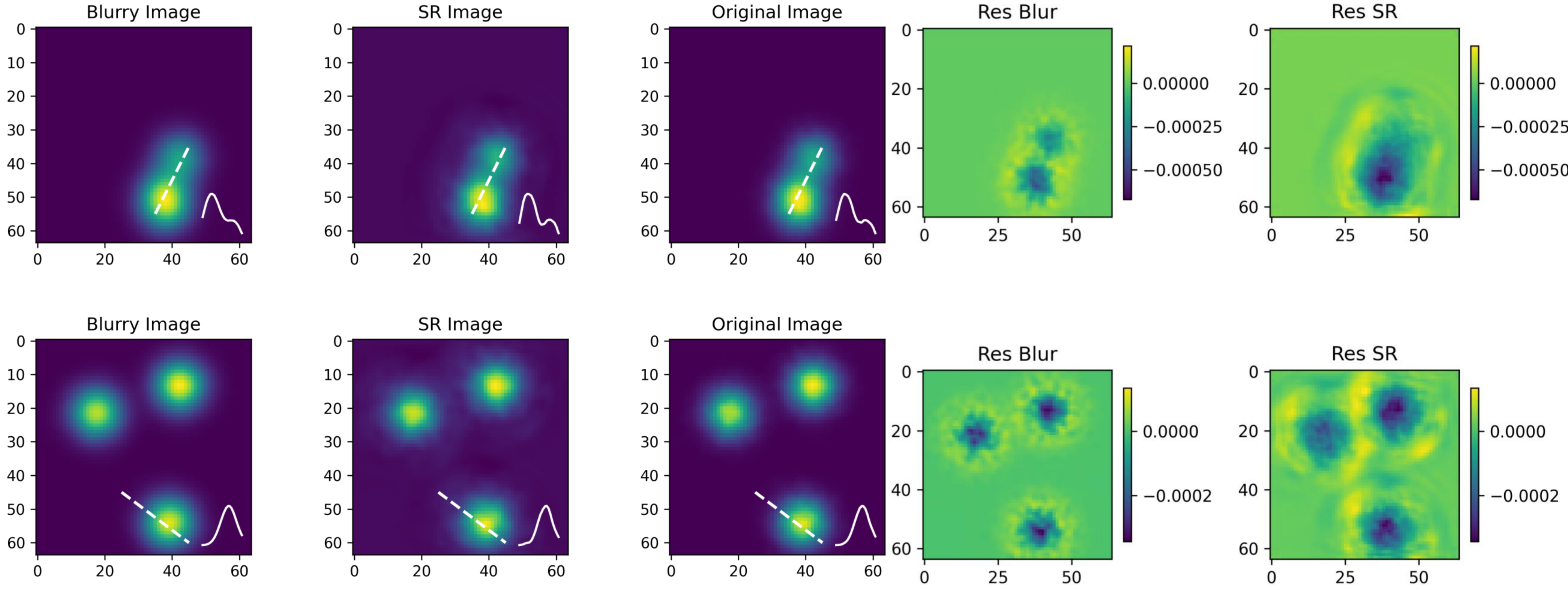


Reconstruction of SRCNN, tested on Fermi BKG dataset



Residual map to original map

Training Results –Generalization Test

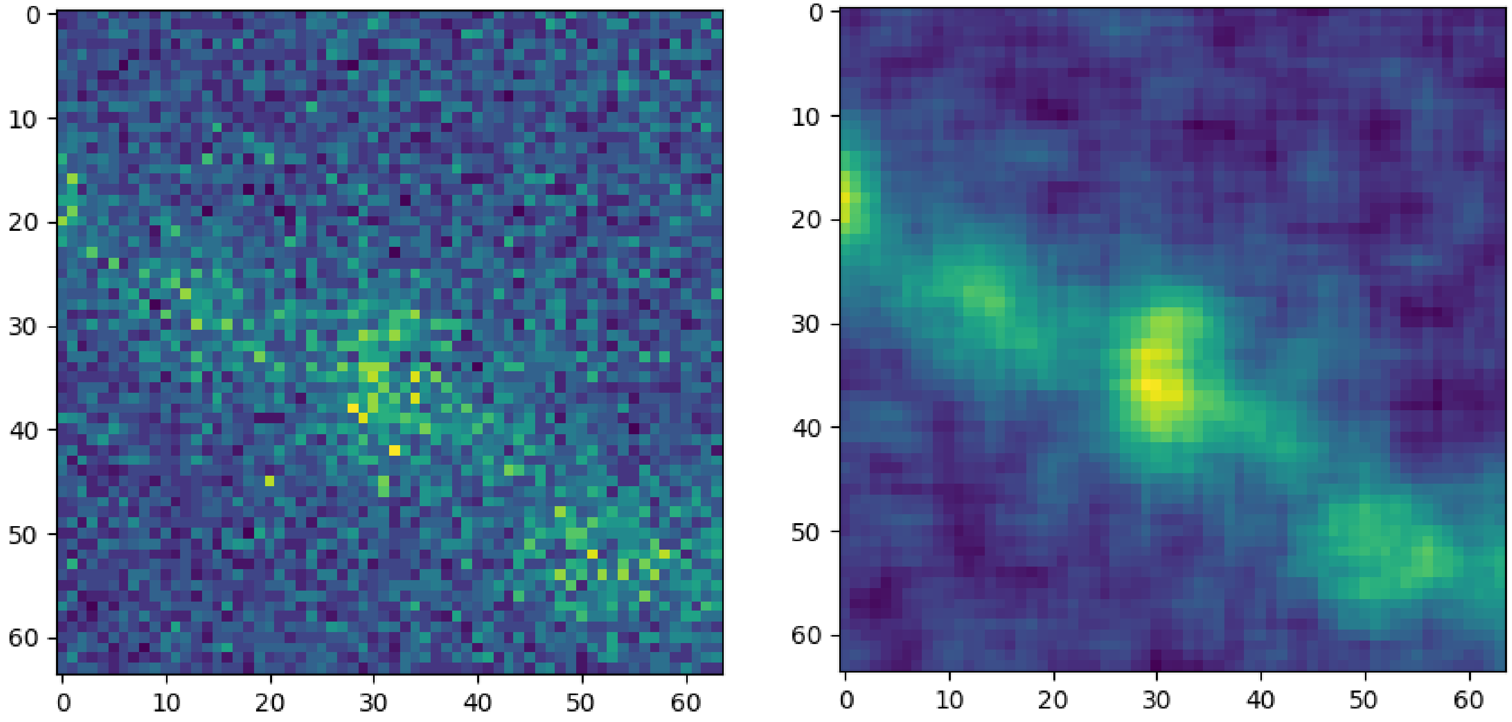


Reconstruction of SRCNN, tested on Gaussian SRC dataset

Residual map to original map

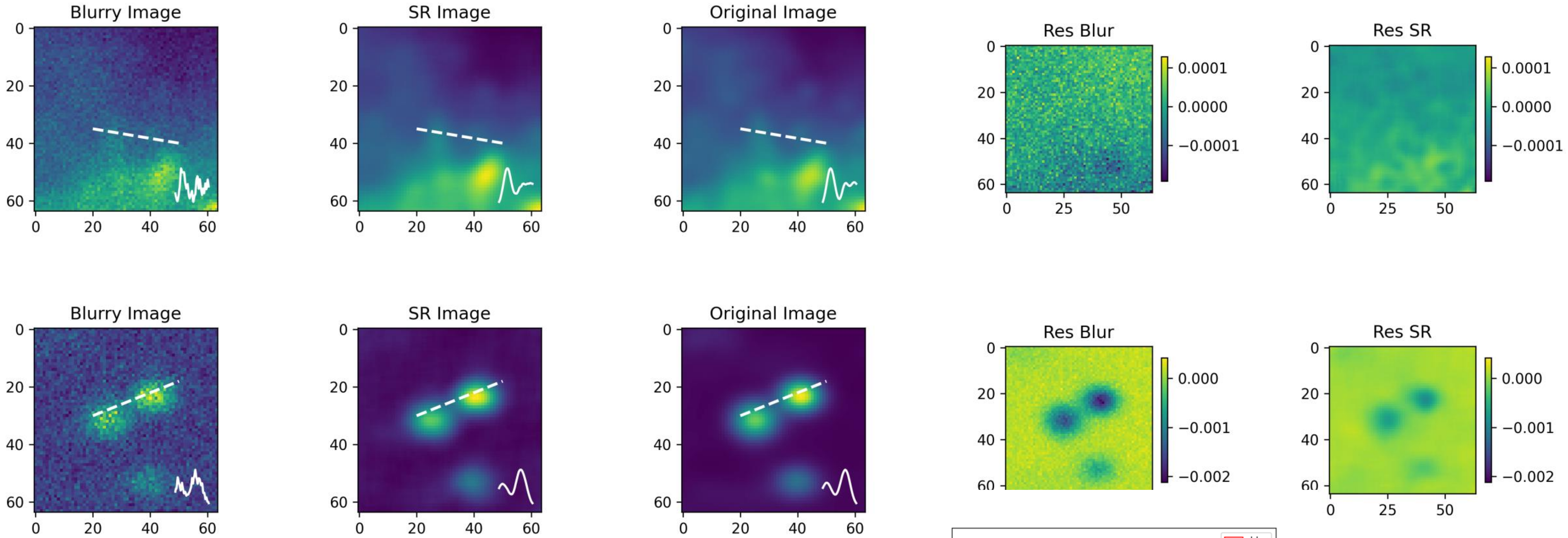
Real Data

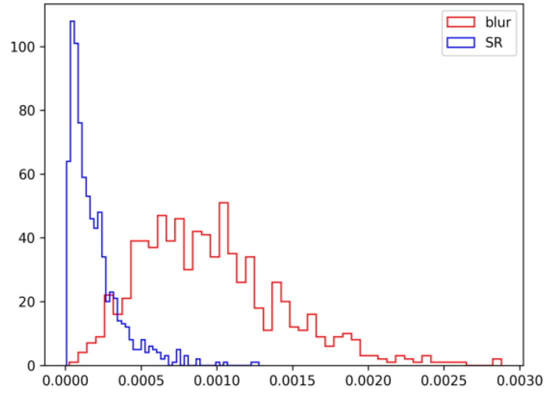
- Counts Map
  - Strong Poisson noise
- TS Map
  - Data smoothed first
  - Larger PSF, not suitable for training
- Training set with Poisson noise
  - Superposition of Extend Fermi SRC and Fermi diffuse background (Smooth)
  - Use smooth map as parameter for poisson noise



J1849-0003 Counts Map and TS Map(radius 2.95 deg)

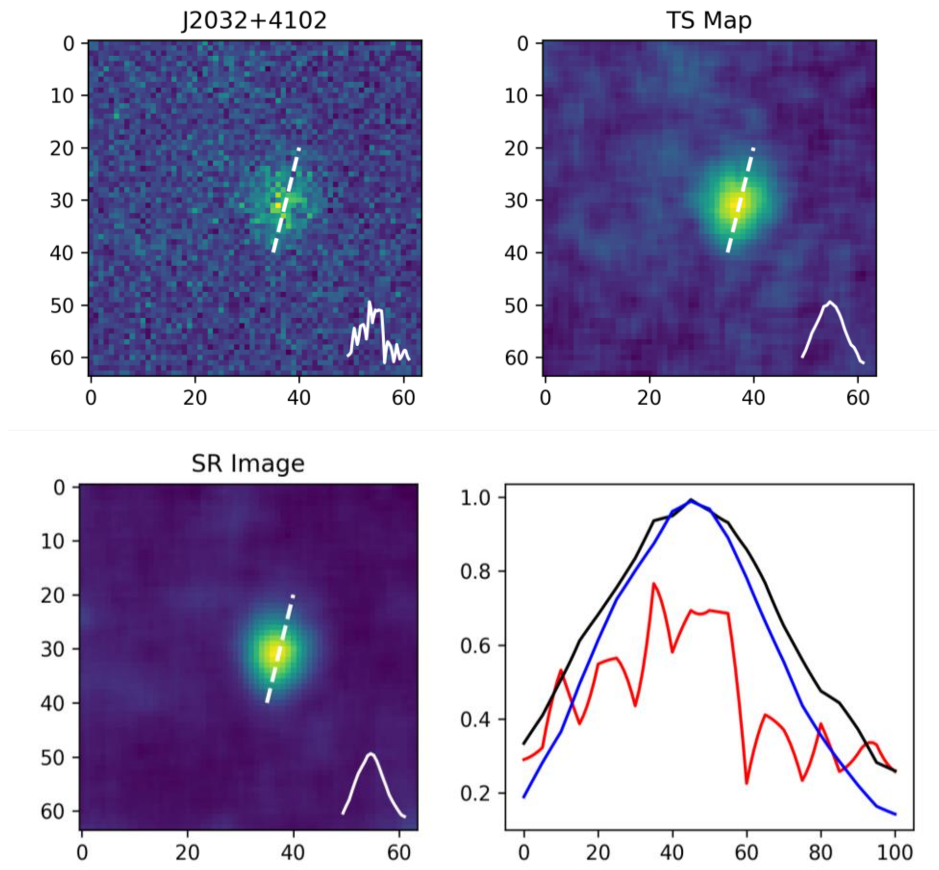
Model on Data with Noise

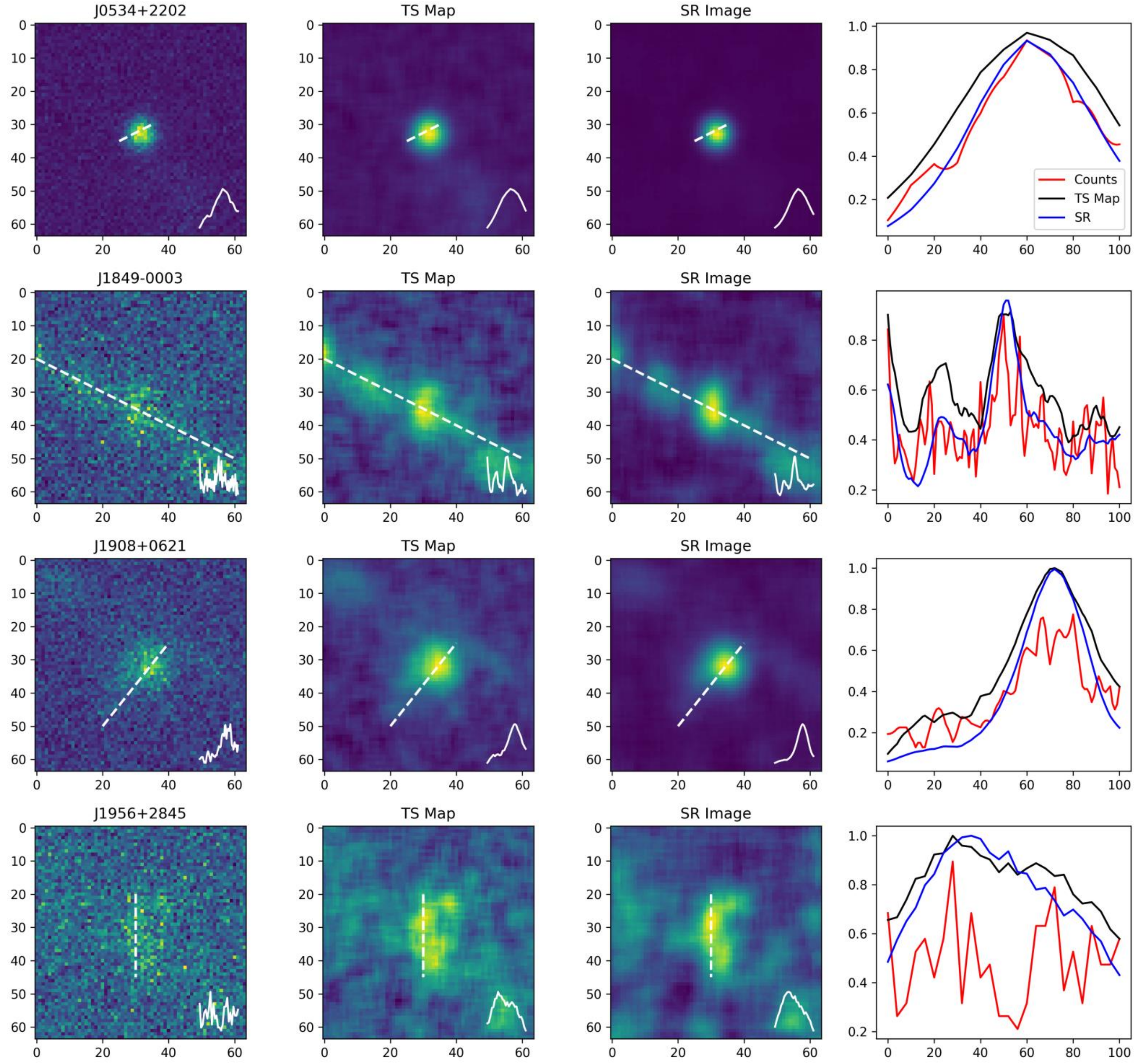




Trained for 400 epoch, with noise. Not as good but not bad.
Loss Func: 0.8* J-S divergence (small scale),
0.2* MSE (large scale)

CNN on real data





Questions are welcome