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Deep learning methods for gamma event selection in TAIGA-IACT image analysis in stereo-mode

Elizaveta Gres[1,2], A. Kryukov[2], P. Volchugov[2], A. Demichev[2], Ju. Dubenskaya[2], D. Zhurov[1], S. Polyakov[2], E. Postnikov[2], A. Razumov[2]

1 - Applied Physics Institute of Irkutsk State University, Irkutsk;
2 - Lomonosov Moscow State University, Skobeltsyn Institute of Nuclear Physics, Moscow.

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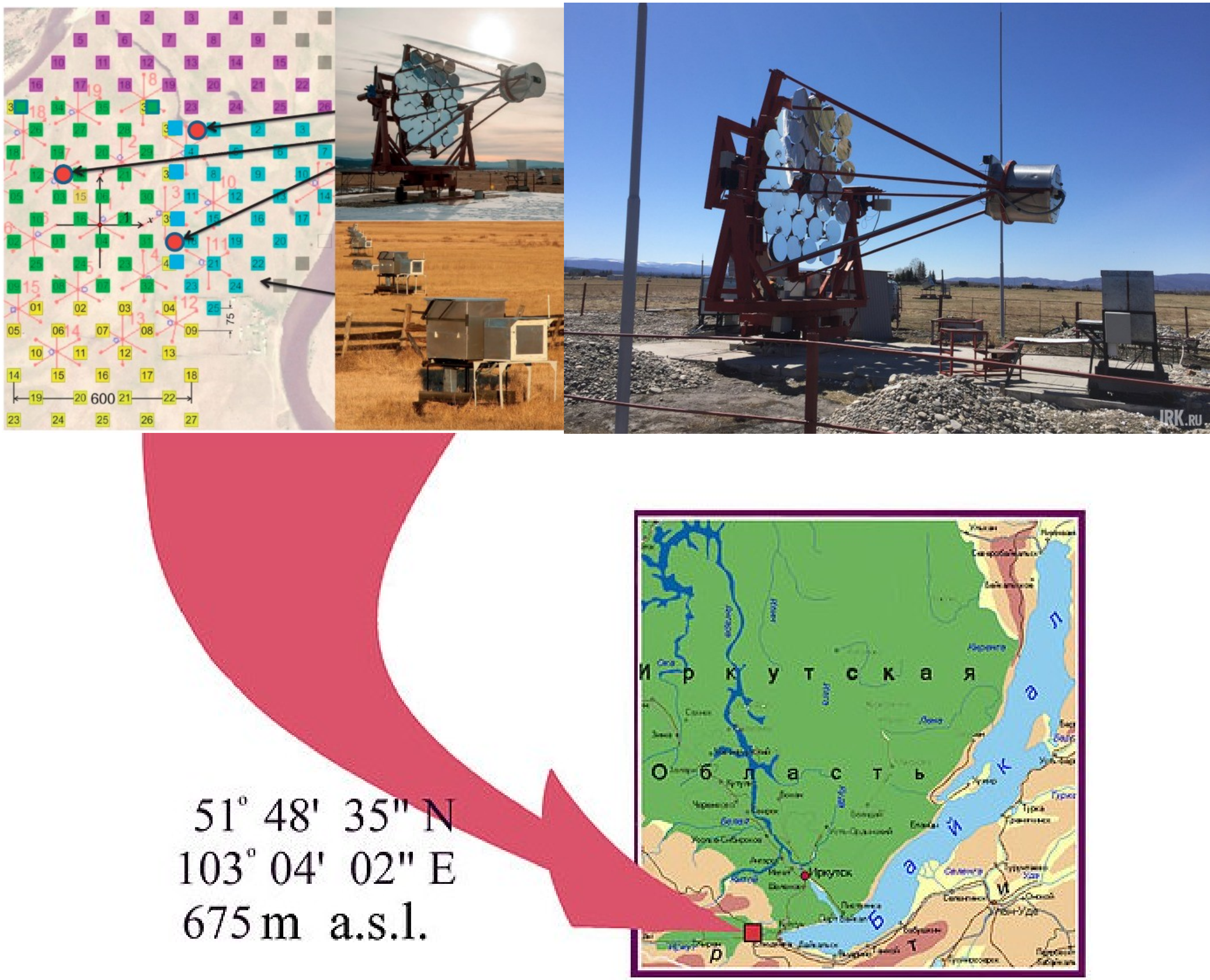
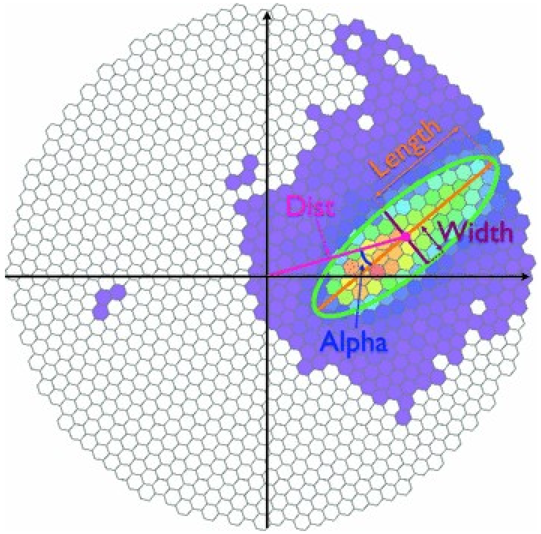
TAIGA-IACT

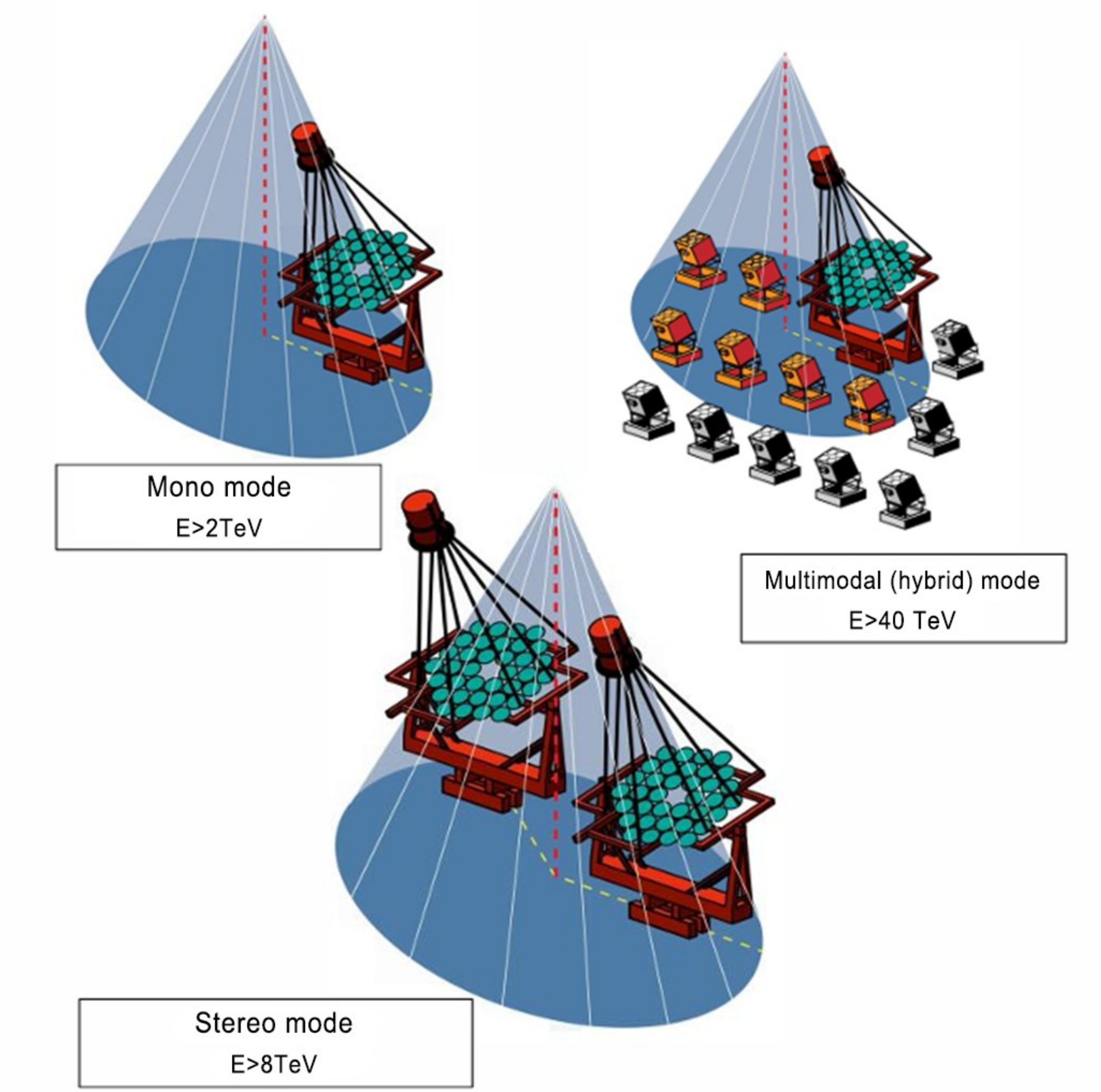
- Imaging Air Cherenkov Telescopes (IACT) are located in Tunka Valley, Republic of Buryatia, at the astrophysical gamma observatory TAIGA of the API ISU.
- Mirror diameter: 4.3m
- FoV: 9.6°
- Camera: 600 PMT XP1911, grouped into 22 clusters.
- Four TAIGA-IACT are in operation mode.



Stereo mode

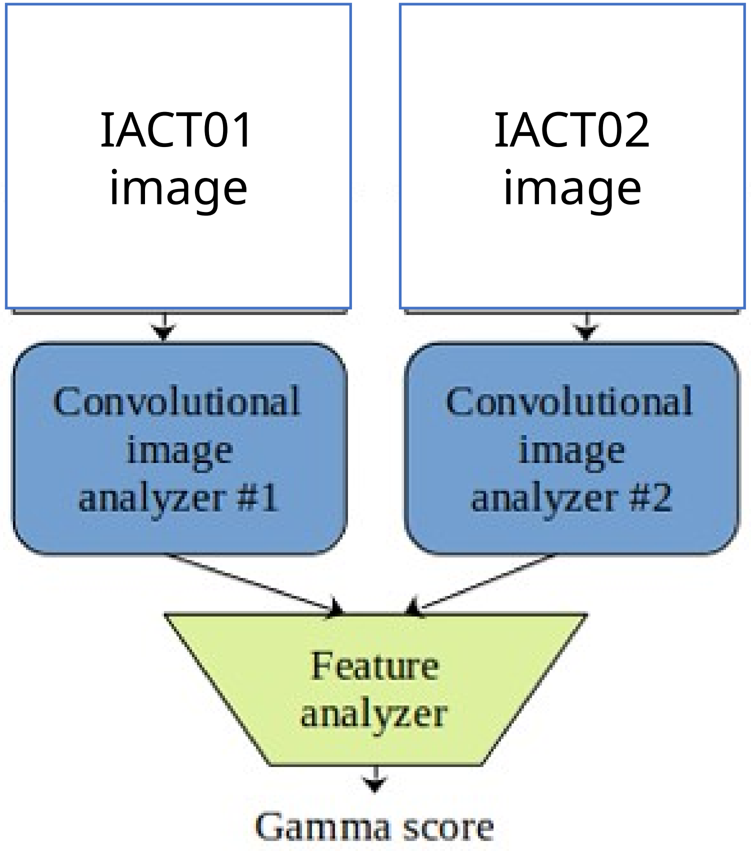
- Every telescope detects the Cherenkov light from EAS.
- Since telescopes is located near each other (250-350 m), Cherenkov light cone can trigger multiple telescopes.
- Classical approach is based on the analysis of normalized Hillas parameters extracted from the images.



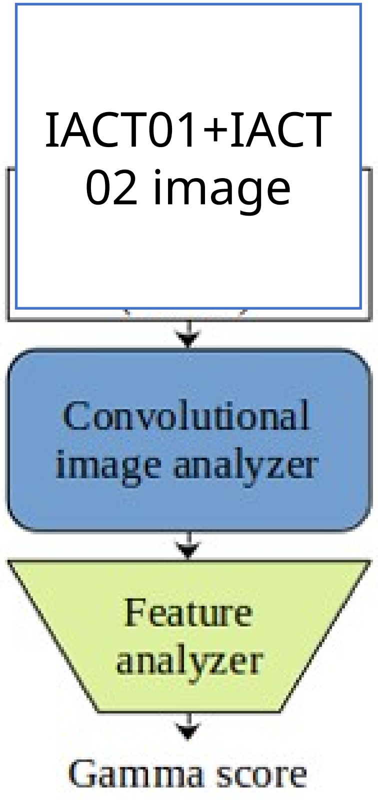


Proposed deep learning approaches for IACT stereo-mode

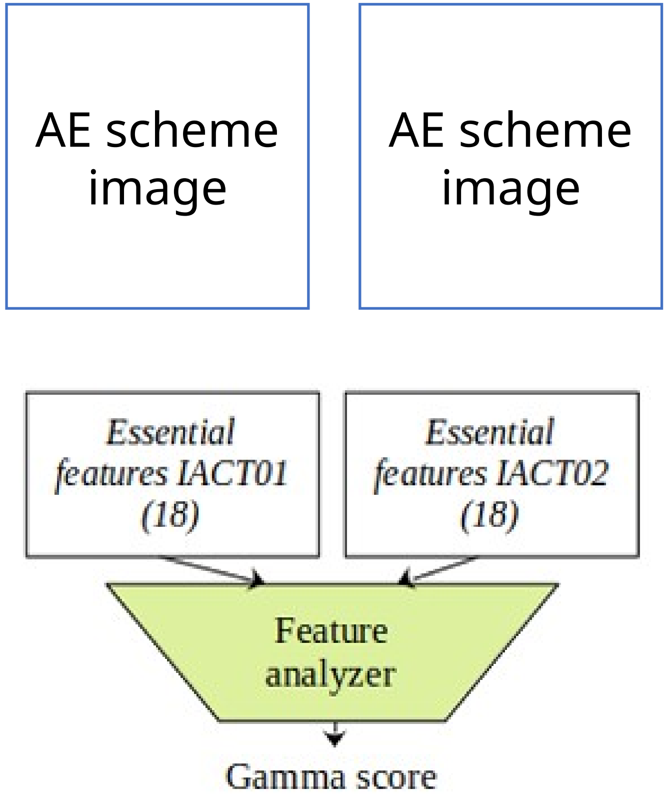
1. Medium fusion:



2. Early fusion:



3. Essential feature analysis



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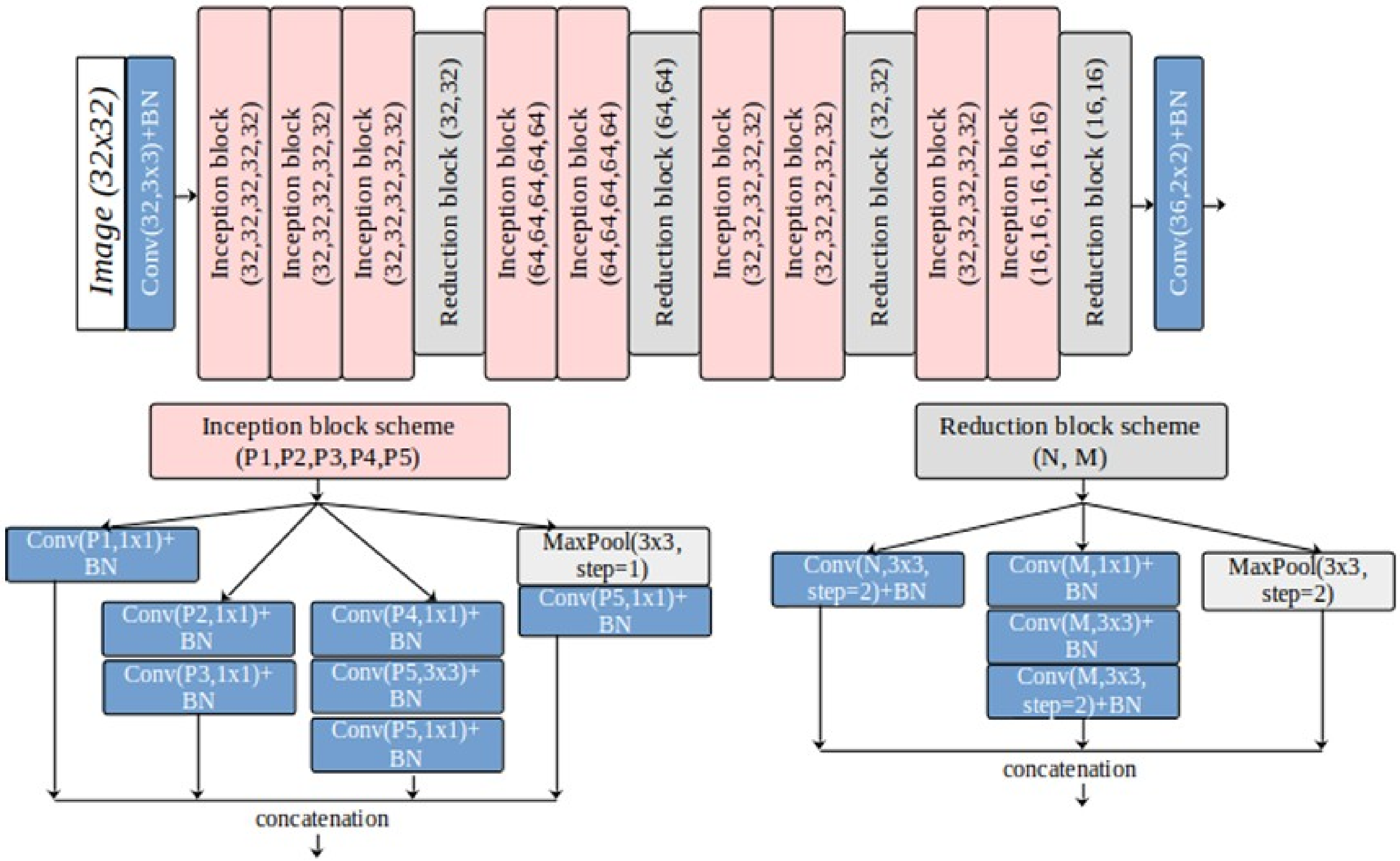
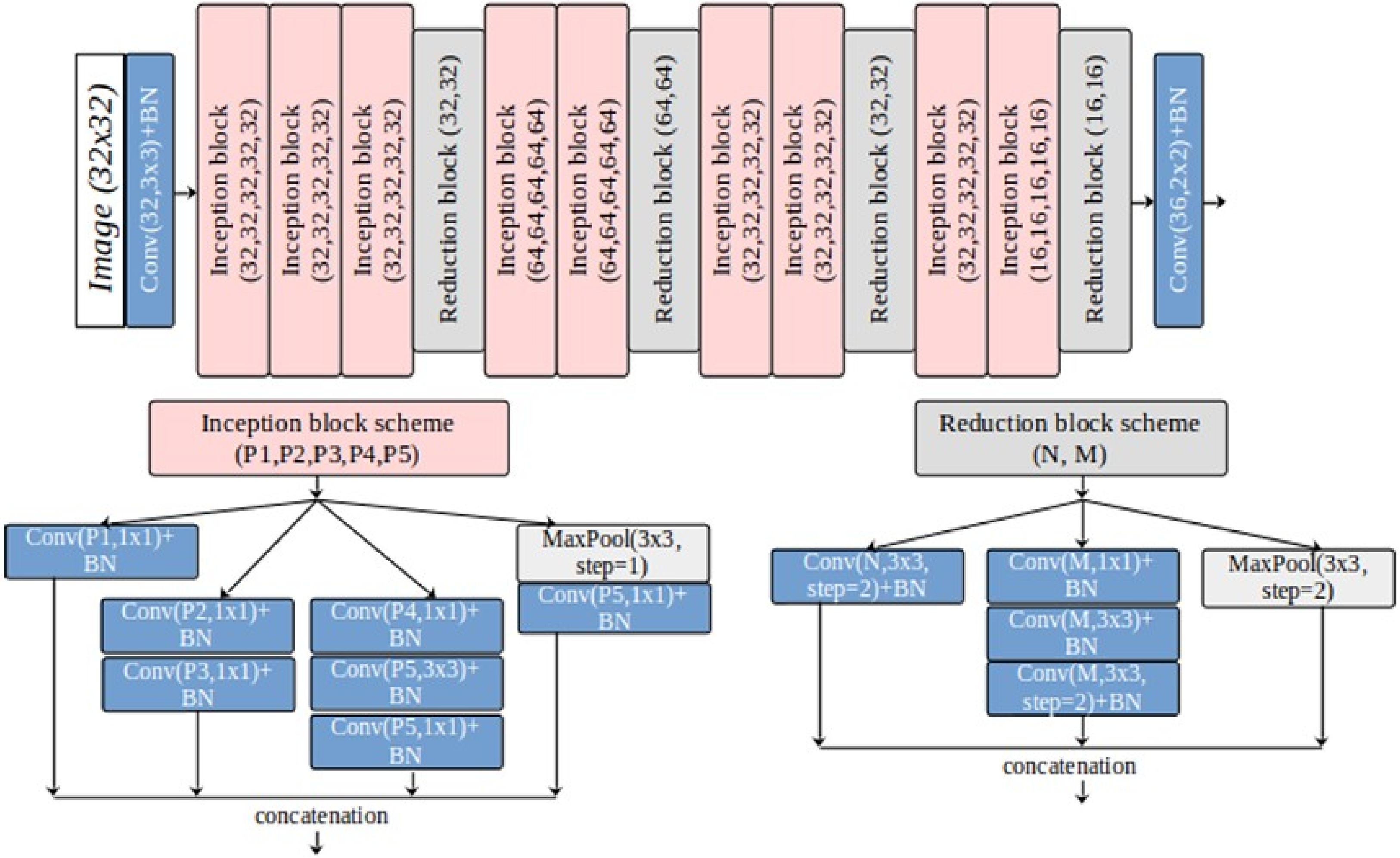


- Simplified Inceptionv4 CNN
- Total trained weights: ~1.1 million
- In case of medium and early image fusion, 1 dense layer is feature analyzer
- For AE latent space analysis feature analyzer structure:
- Input(36) -> dense(2048) -> reshape(8,8,32)-> conv2d(2x2,128, s=2) -> conv2d(2x2,256 , s=2) -> conv2d(2x2,512 , s=2) -> dense(512) -> dense(1)

Proposed deep learning approaches for IACT stereo-mode



- Classification loss function: binary crossentropy, *focal loss*.
- Image reconstruction loss function: MSE.
- Activation function: silu
- Epoches: ~10
- Learning rate: 0.0001

Training and Validation

- MC data was generated with CORSIKA. Simulation includes relative PMT sensitivity, PMT's Winston cone, background noise, etc.
  - Gamma and proton events spectrum slope: -1
  - Energy range: 40-400 TeV.
- <u>Gamma training events:</u> 29 900
- <u>Proton training events:</u> 157 000
  - AE was trained on proton events.
  - Augmentation for stereo-mode CNN: class weights, input channel switch.

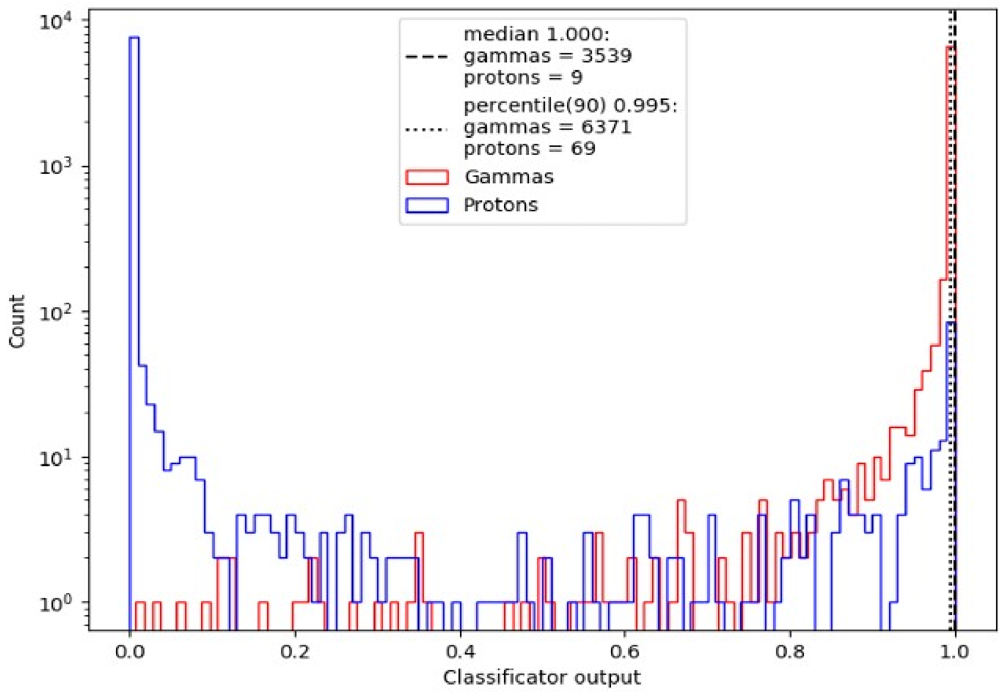
- <u>Image preprocesing</u>:
  - Image cleaning;
  - Image transformation to square form;
  - Logarithmic amplitude scaling.

Пример преобразований

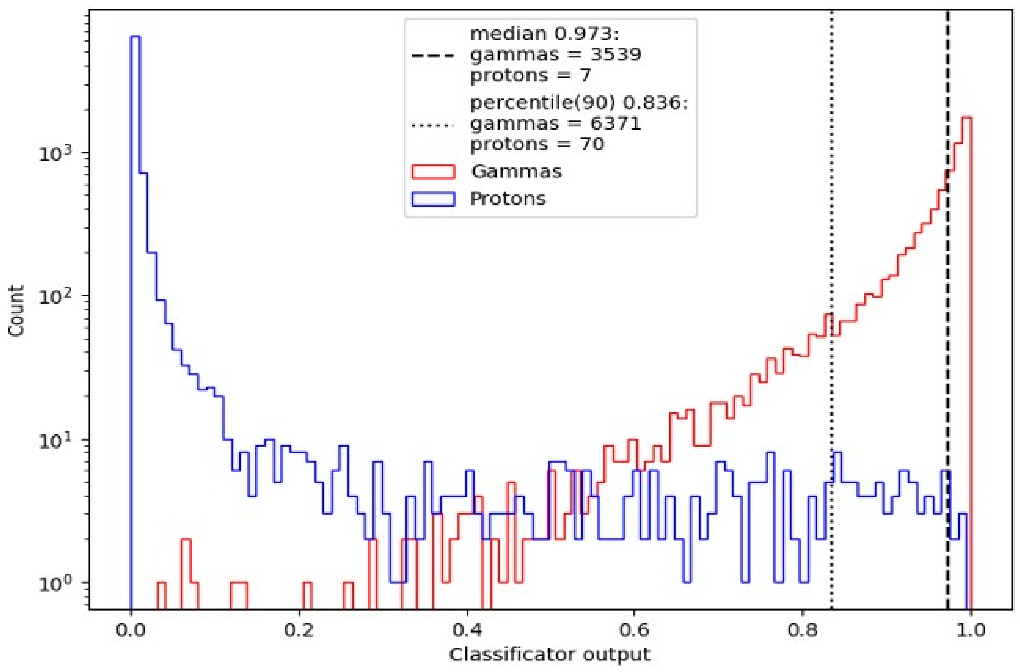
Training and Validation

- Validation gamma events: 7 100
- Validation protons events: 7 600
- Class threshold: 50% gamma remaining

Binary crossentropy (0.99994)

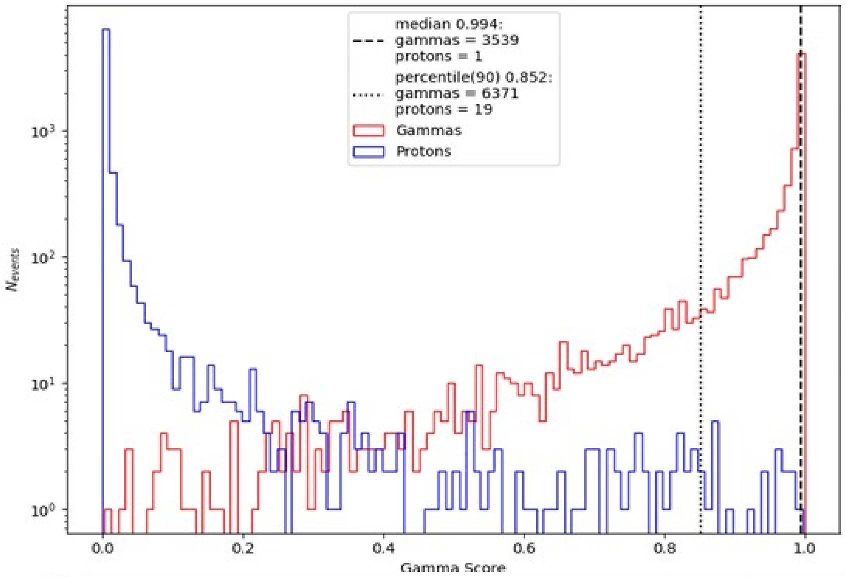


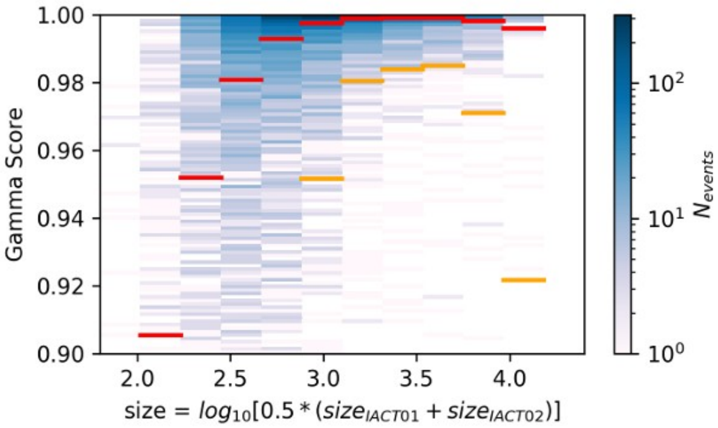
Focal loss (0.973)

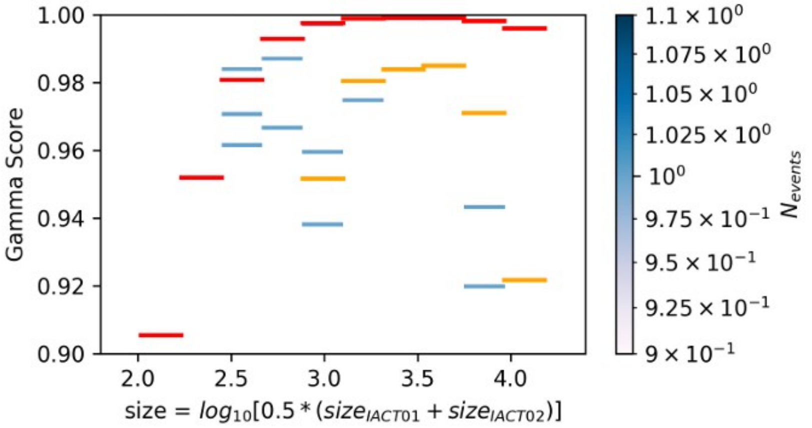


Training and Validation

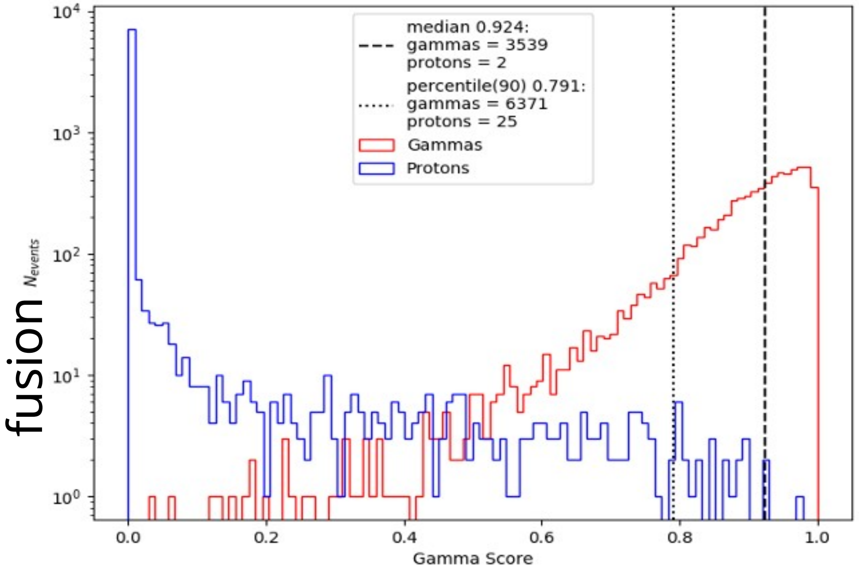
Medium

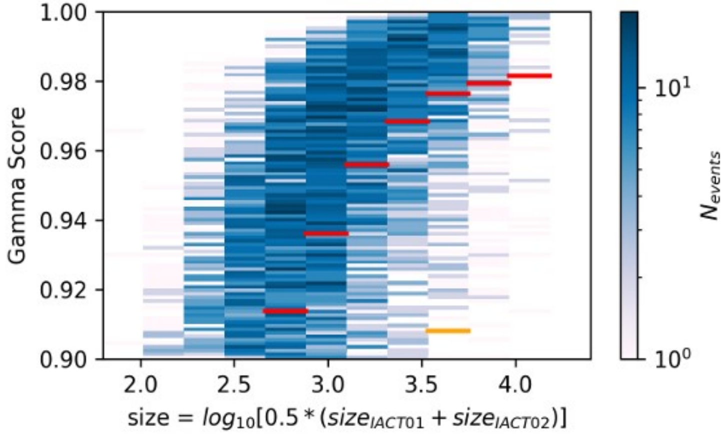


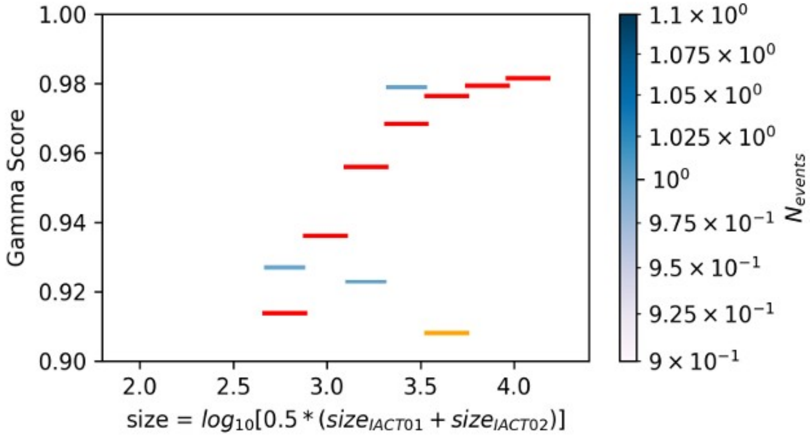




Latent space analysis fusion







Selection in case of class imbalance

- For the most gamma sources, significant gamma/hadron imbalance (1/10000) are observed in TeV energy range.
- Thus, test imbalance was around 1/100 to investigate the CNN capibilities. Also, test results for mono-mode are presented. Class thresholds obtained from CNN validations.

Table to recompile: add results for size-depended classification

DL methods (augmentation)	Total gamma	Total hadrons	selected gamma	selected protons	Gamma remained	Hadron suppression
mono (class weights)	320	35000	147	41	45.9%	854
medium fusion (initial bias)	400	39600	188	9	47.0%	4400
early fusion (class weights)	400	39600	206	3	51.5%	13200
early fusion (oversample)	400	39600	188	5	47.0%	7920
early fusion (initial bias)	400	39600	186	10	46.5%	3960
early fusion (1:1 train set)	400	39600	200	47	50.0%	843
LP analysis (oversample)	400	39600	199	16	49.8%	2475

Conclusion

- Multiple deep learning methods was proposed and studied in the gamma/hadron classification task: medium fusion (separate IACTs images analysis in CNN before concatenation), early fusion (concatenated IACTs images are fed to CNN) and autoencoder-derived essential feature analysis.
- Test results demonstrated that for highly imbalanced classes early fusion is the most promising method.
- Stereo-mode classification results demonstrated significant improvement in comparison to neural network mono observations with background noise suppression close to the gamma/hadron imbalance observed in the experiment.

Thank you for your attention!