Using Conditional GAN to Control the Statistical Characteristics of the Generated Images from Imaging Atmospheric Cherenkov Telescopes

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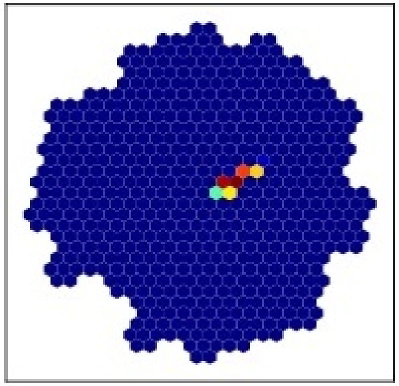
Air showers and event images

Charged cosmic rays and high energy gamma rays interact with the atmosphere

The result is extensive air showers of secondary particles emitting Cherenkov light

Imagine Atmospheric Cherenkov Telescopes (IACT) detect the light



Detected data form "images" of the air shower

Image generation task

For each IACT to operate correctly a large amount of experimental data, including simulated data, is required

Traditionally, event images are modeled using a special programs that perform detailed direct simulation of extensive air showers, thereby producing reasonably accurate but resource-intensive and time-consuming results

Machine learning techniques such as generative adversarial networks (GANs) significantly reduce the time to generate images

The quality of image generation using GAN is quite good. Most of these images are indistinguishable from images generated by the traditional method when checked by third-party tools

Statistical characteristics of the generated sample

GAN is trained on examples, namely on a set of input images

Important task for GAN is to reproduce the statistical characteristics from the training set in the output sample of generated images

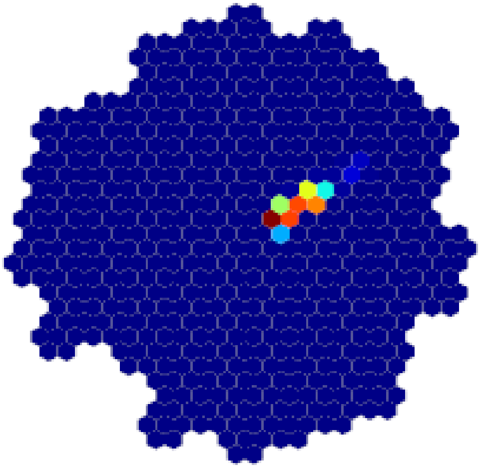
For images from Cherenkov telescopes, it is important to reproduce the energy distribution

Restoring the energy of the original particle from the generated images is a separate complex issue

As a first approximation, instead of energy, it is convenient to use the image size

Image size

- Image size is the total sum of all image pixel values in photoelectrons
- Image size can be easily calculated
- Image size correlates with the energy of the primary particle



Size distribution of reference images

As reference, we use a sample of two-dimensional images obtained using TAIGA Monte Carlo simulation software

The plot shows the distribution of these images by size

This distribution is very uneven and asymmetrical

This is the distribution that we are trying to reproduce when generating new images using machine learning

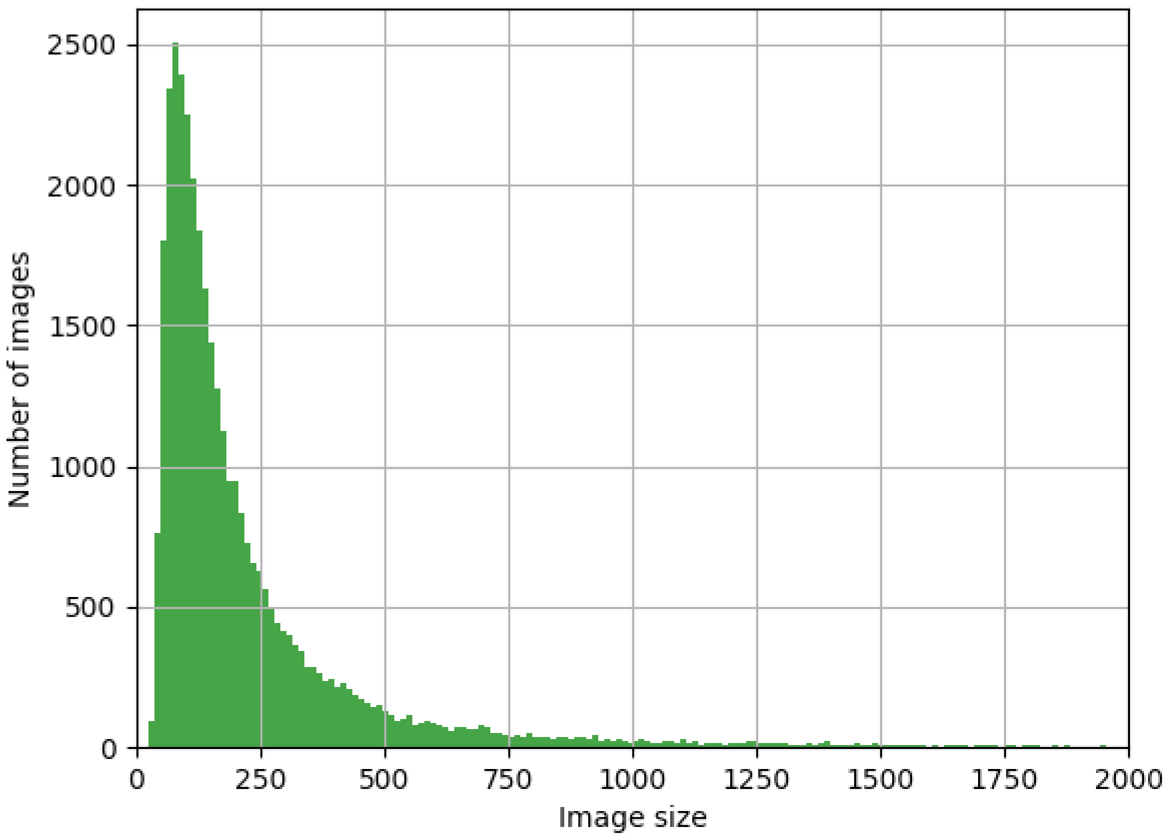
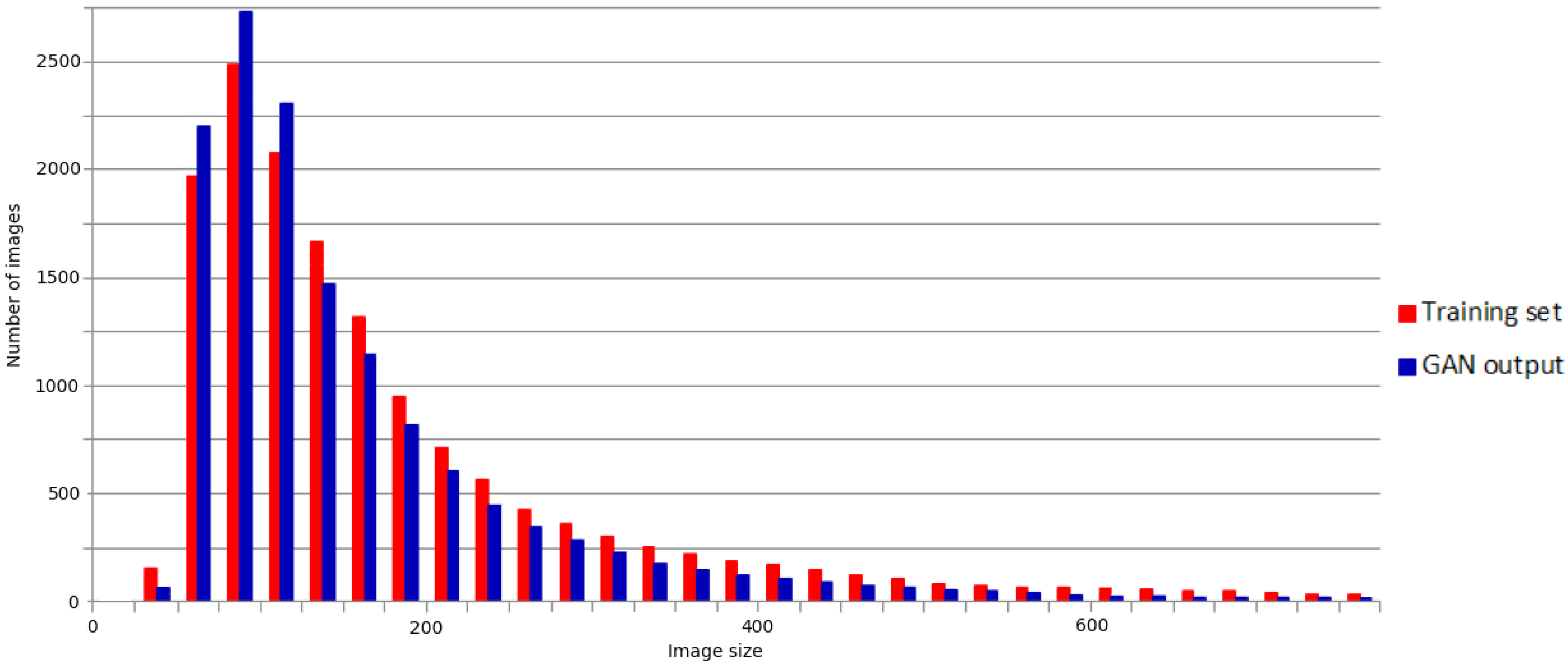


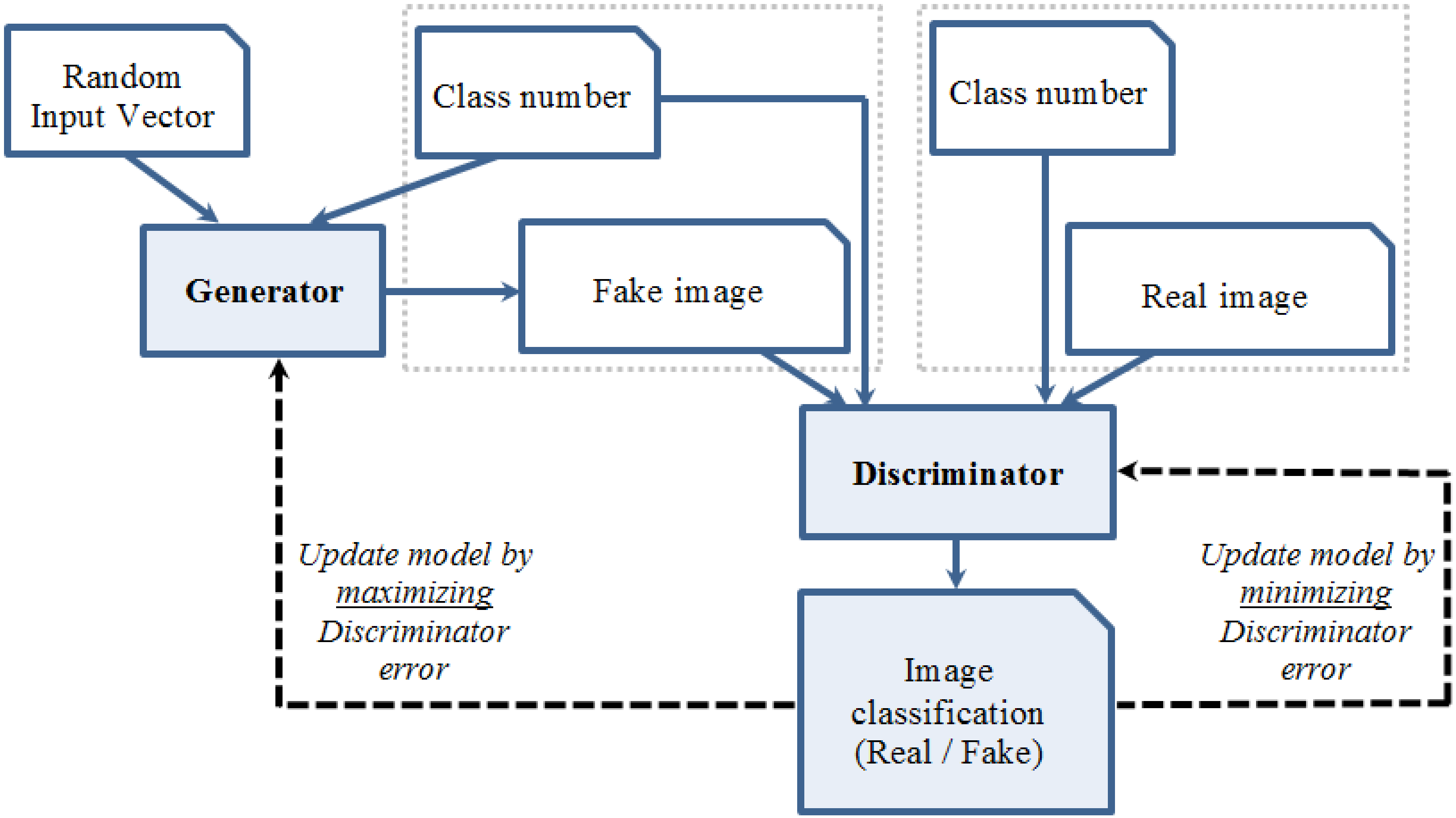
Image size distribution for samples generated by classical GAN

Problem: the size distribution for the generated sample is different from the distribution of the training set



Conditional generative adversarial network (CGAN)

CGAN is a modification of a traditional GAN that allows you to <u>divide images</u> into <u>multiple classes</u> according to the value of some property of the image



Conditional GAN features

- CGAN is trained in an unsupervised manner on a set of real images (a training set)
- Each training image must have a class label
- A set of labeled real images is passed to Discriminator

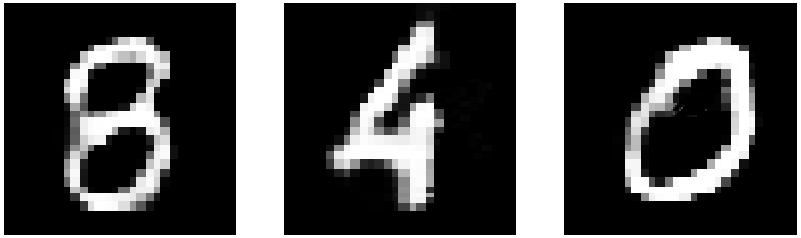
- Discriminator is trained to distinguish whether an image is real or fake with respect to the class label

- Generator tries to create fake images of the requested class
- Generator is not trained to minimize the distance to a specific image, but rather to fool the Discriminator
- Generator does not produce images exactly like the training ones, but just similar to them

Classical application of a CGAN

CGAN do very well when images from different classes differ significantly

Example – a set of a handwritten digits

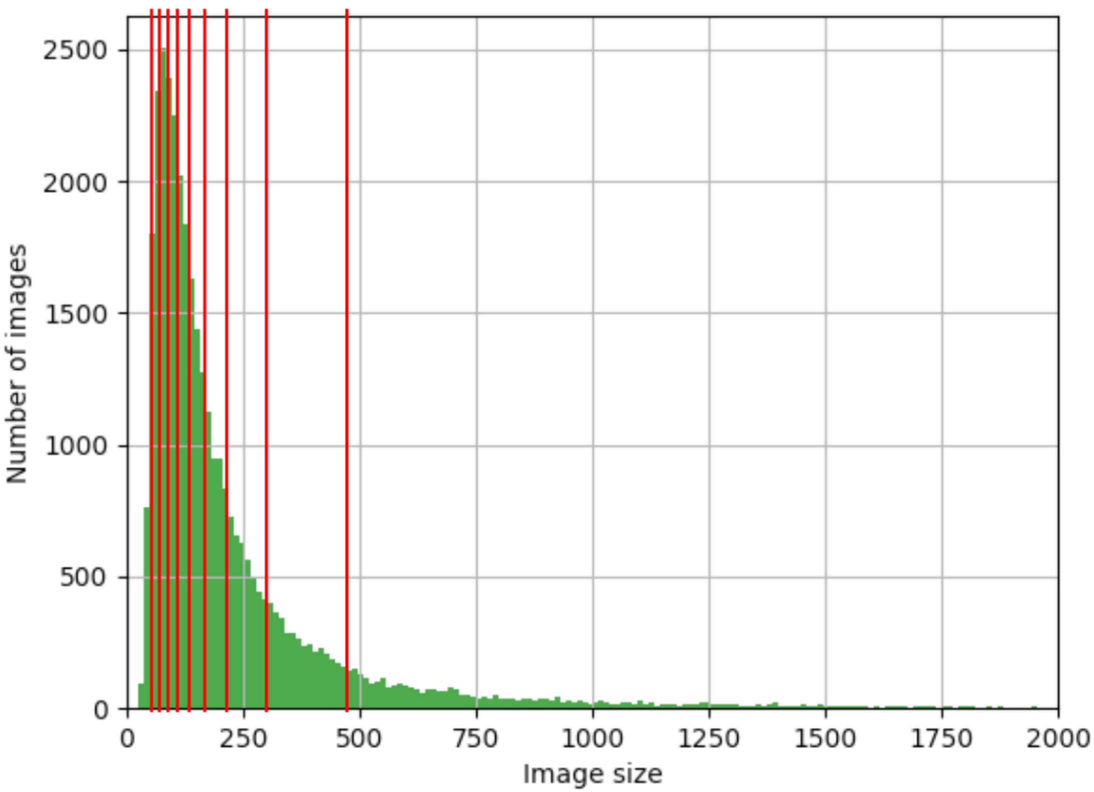


- Each digit can always be attributed to a particular class
- No “transition” digits between classes

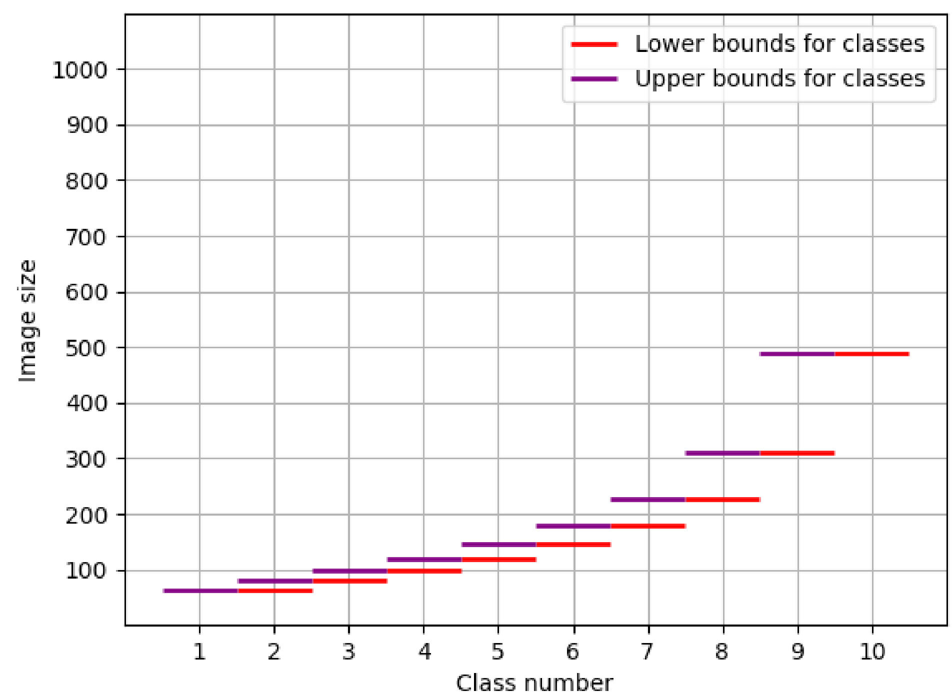
CGAN easily learns to generate images of the specified digits

Artificial classes for the IACT images

The training set was artificially divided into 10 classes by image size so that each class has the same number of images

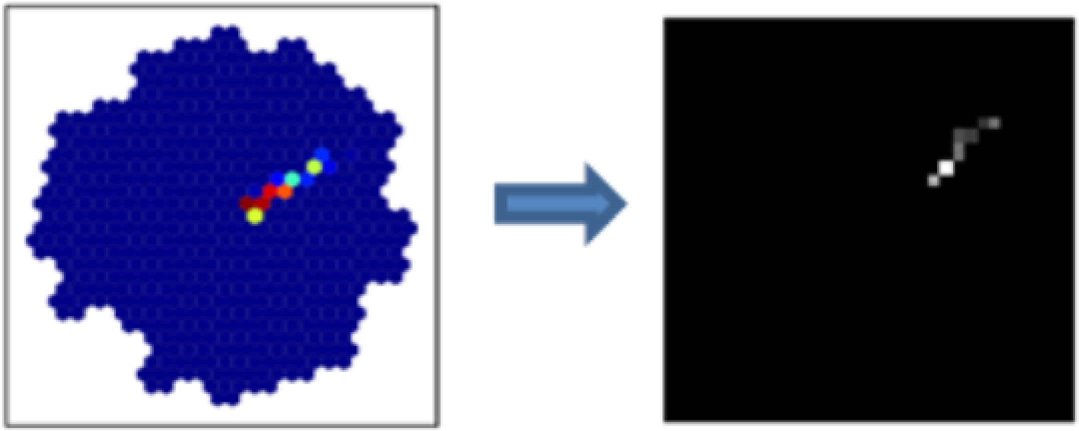


Thanks to this:
- we do not lose rare events
- training becomes more balanced and stable



CGAN training set preparation

The original hexagonal images were transformed into images with a size of 32 by 32 pixels by transition to an oblique coordinate system



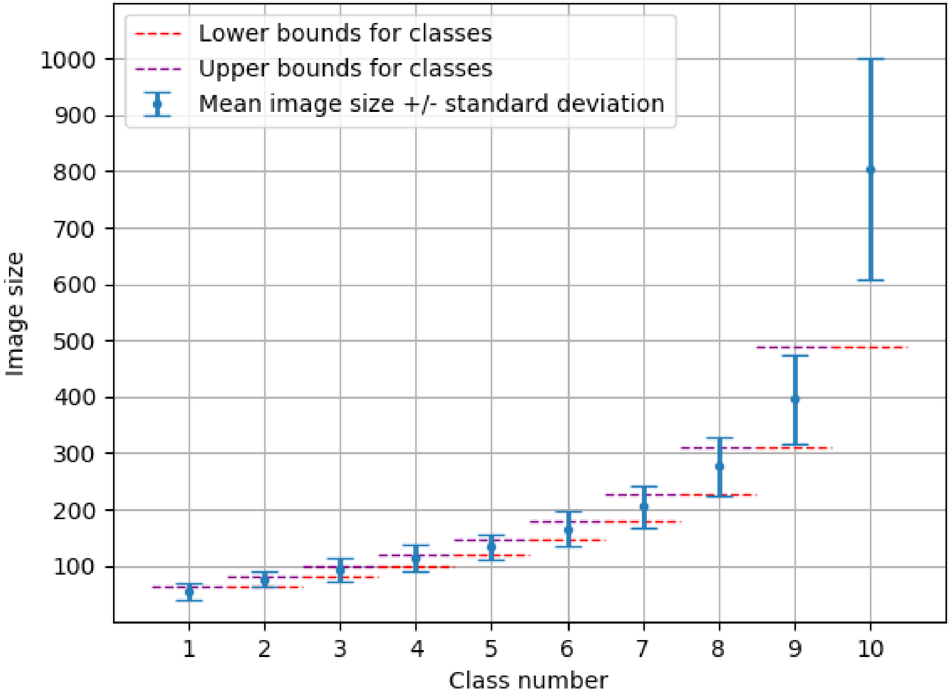
Each image was labeled with a class number according to its size

Image generation results

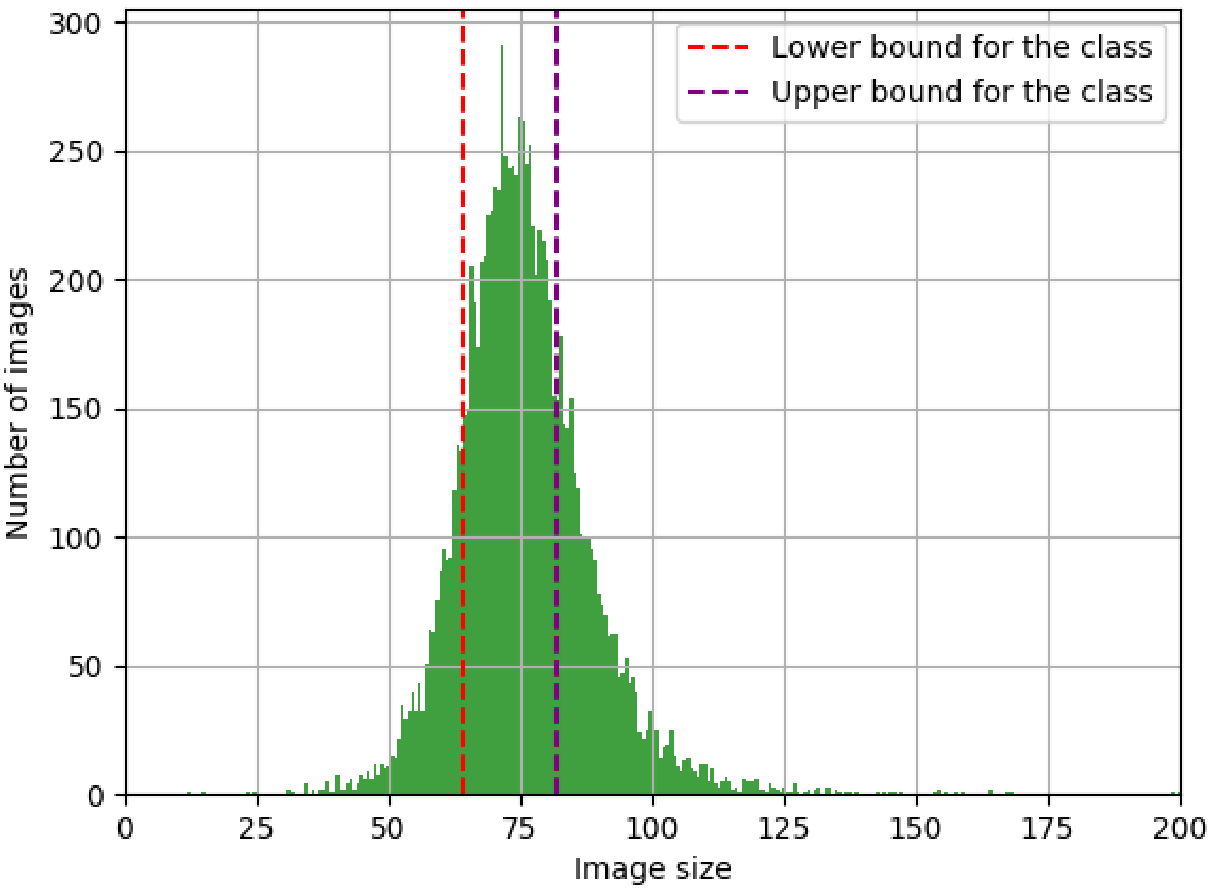
We used the 10 artificial classes while training our CGAN

After training we used our Generator to create the same number of images of each class

For each class, the size distribution is close to normal with the mean located approximately in the middle of the corresponding class

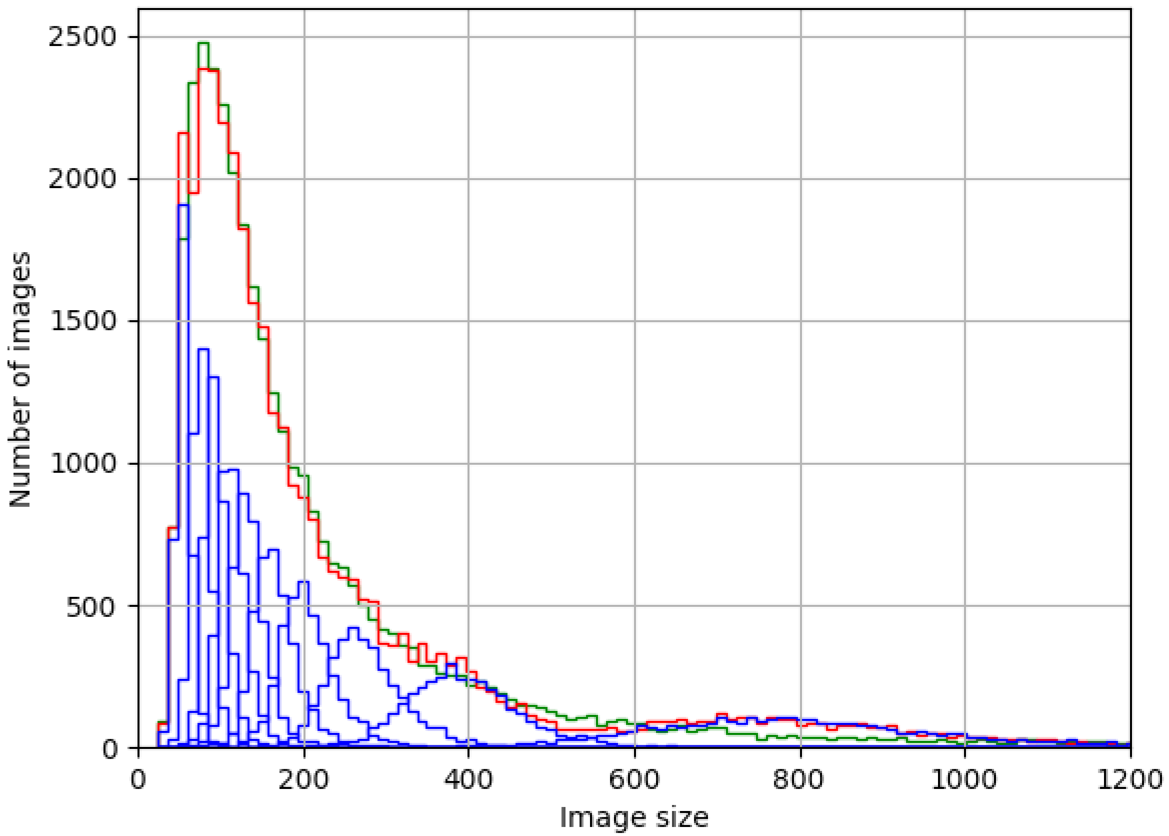


Example: size distribution for the class #2



Summed size distribution

The size distribution summed over all classes is close to the original distribution in the training set



The Chi-Square test statistic is 949. The critical value corresponding for a 5% significance level with 100 degrees of freedom is 124,34

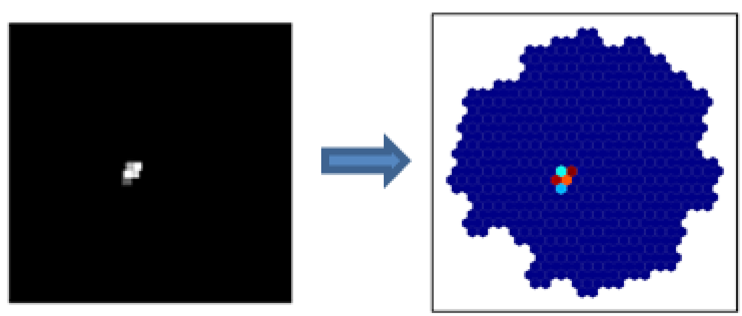
The chi-square test still shows that the difference is significant

But the resulting distribution is much closer to the input one than the distribution for the classical GAN

Training set distribution Summed distribution Distribution for each class

Images generated by CGAN

Every generated image can be easily converted back to hexagonal form:



Conclusion

A conditional generative adversarial network simulate images for the TAIGA-IACT experiment with a very good degree of accuracy

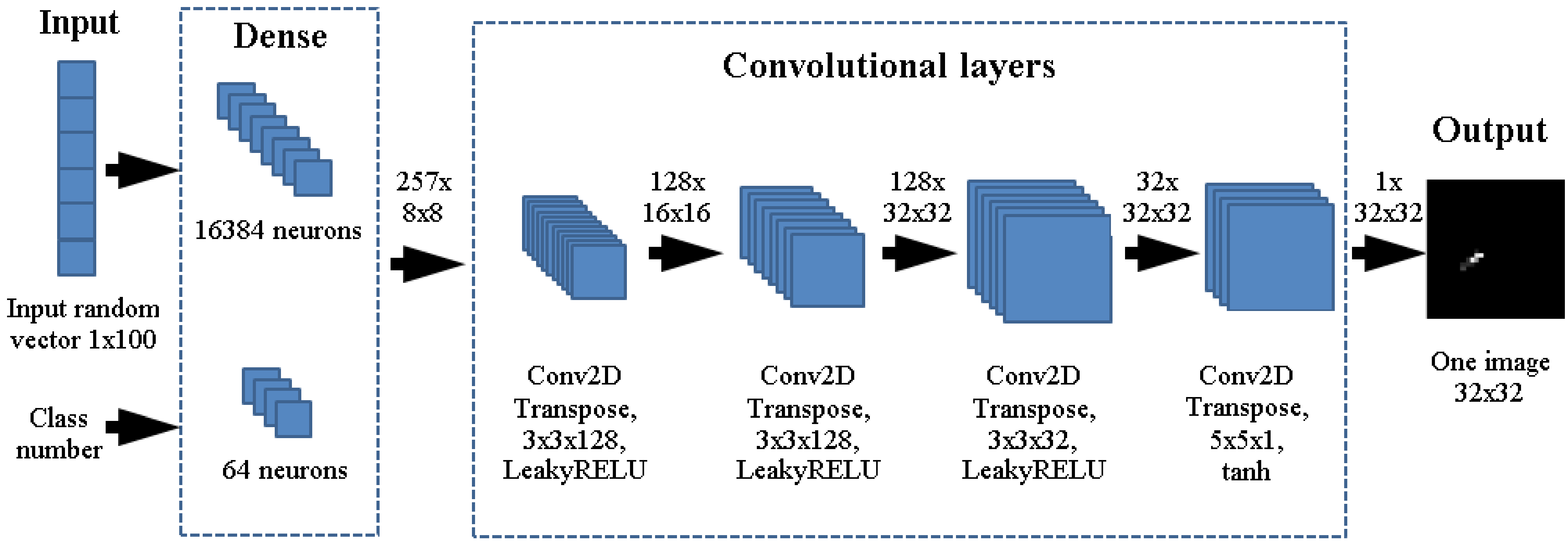
CGAN helps to generate images with a size value that falls within the boundaries of the requested class with a high degree of probability

CGAN helps to generate an output sample of images with a distribution close to that of the training set

The rate of images generation using CGAN is more than 1000 times higher than the rate of generation by the traditional method

Thank you for attention!

Generator architecture



Discriminator architecture