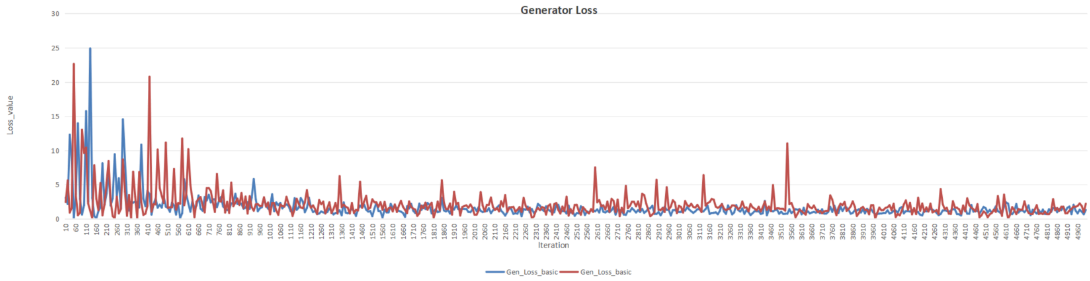
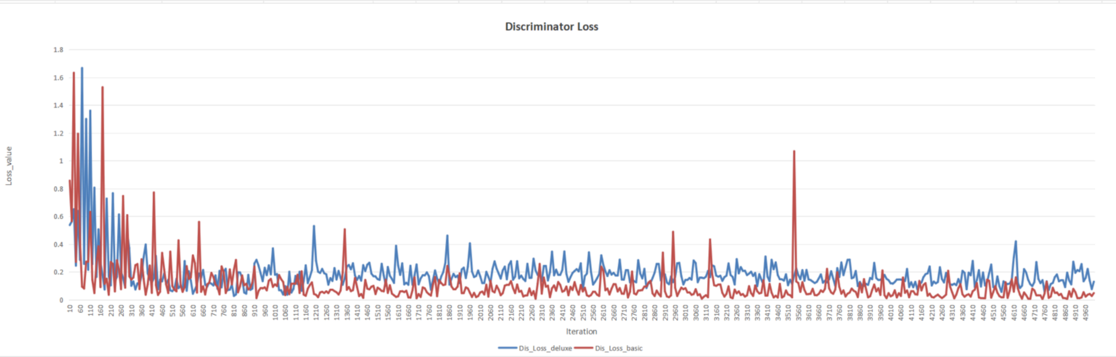
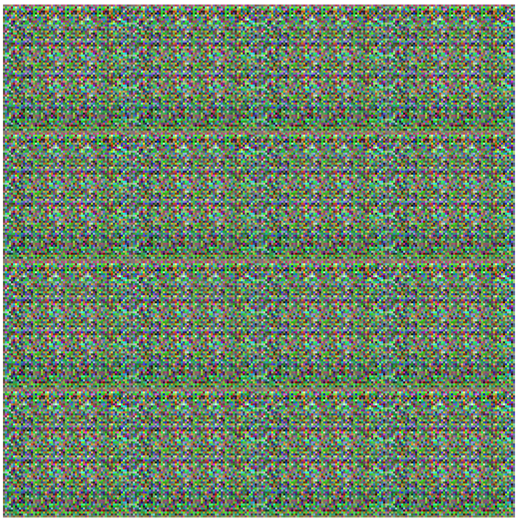
CS172 - Computer - Version

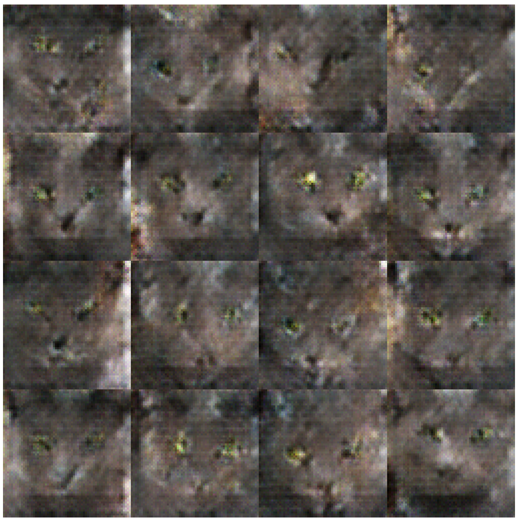
Problem 3 DCGAN

1. discriminator and generator training loss with both data aug=basic/deluxe





2. samples when data augmentation = 'deluxe'
   - iteration = 200
   - 
   - iteration = 5000

- 
- From the above pictures, we can find that when iteration increases, the samples will have a better performance. Also, from the comparison, we can find that in the samples, the DCGAN can generate flip, crop pictures as well, which is different from the samples generated when data augmentation = 'basic'.
- In the training process, it can be divided into two parts, and there are different loss function. But what we need to do is same, that is calculate the gradient of the loss function to get the updated hyper parameters of `G` and `D` so that `G` can generate more realistic images and `D` can improve its ability to recognize fake images.

3. Problems in DCGAN
    - Vanishing Gradient: In some cases, the gradients in GAN training can vanish especially for the generator, leading to slow or stalled learning. Through the `Gen_Loss` shown above, the loss is continuously decrease instead of increasing. Thus, generator can not produce more realistic fake images.
    - Unstable Training: While DCGAN is more stable than traditional GANs, it can still suffer from instability, especially in the early stages of training. From the picture above, we can find that the up-and-down oscillation of the curves is obvious.
4. Improvement
    - Architectural Modifications: Modifying the architecture of the generator and discriminator, such as using different activation functions, normalization techniques, or adding skip connections, can help stabilize training.
    - Loss Function Modifications: Using alternative loss functions, such as Wasserstein loss or hinge loss, can improve training stability and mitigate mode collapse.
    - Regularization Techniques: Applying regularization techniques, such as weight regularization or gradient penalty, can help prevent the generator from collapsing to a few modes.
    - Advanced Training Techniques: Techniques like curriculum learning, where the model is first trained on easier examples before moving to harder ones, can help stabilize training.
5. Other models
    - Other generative models like VAE (Variational Autoencoder) and Diffusion models also face similar challenges, but each has its own set of strengths and weaknesses.
    - VAEs, for example, are known for their ability to generate diverse samples but may struggle with generating high-fidelity images.
    - Diffusion models, on the other hand, are capable of generating high-quality images but can be computationally expensive to train.

- Each model has its own trade-offs, and the choice of model depends on the specific requirements of the task at hand.