RBE 474X
Project 4

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I. Part 1 - Diffusion Training

We trained the diffusion model to generate new images from a provided dataset. This training is done over linear betas. Below are the hyperparameters used for training:

- Batch size: 80
- T: 500 (number of steps)
- Channel: 128
- Channel-multiplier: [1, 2, 2, 2]
- Learning rate: 1e-4
- Beta 1: 1e-4
- Scheduling: linear
- Beta T: 0.028
- Loss Function: MSE loss

For training, we are using the CIFAR10 dataset. Figure 1 is the loss plot of the training:

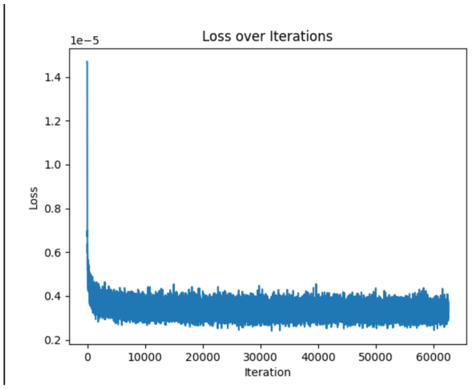


Fig. 1. Plot

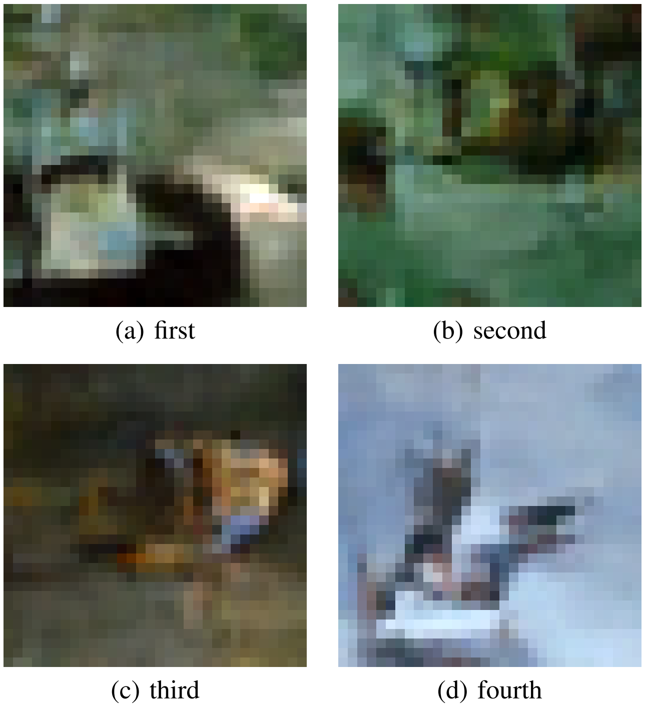
Figure 2 to 11 show the images for every class generated by the diffusion model.

II. Part 2 - Data augmentation using diffusion

For this section, we are augmenting the cifar10 dataset with 5000 extra images per class (examples are shown in Figure 2 to 11).

The network used for this is a custom implementation of MLP. The hyperparameters used for training are:

- Learning rate: 1e-4
- Epoch count: 40
- Batch size: 32



(a) first

(b) second

(c) third

(d) fourth

Fig. 2. Bird images, generated from the diffusion model

A. Results for non-augmented data

The accuracy for the non-augmented data is 44.05%. Figure 12 is the loss plot for the training.

And the confusion matrix for the training is shown in Figure 13.

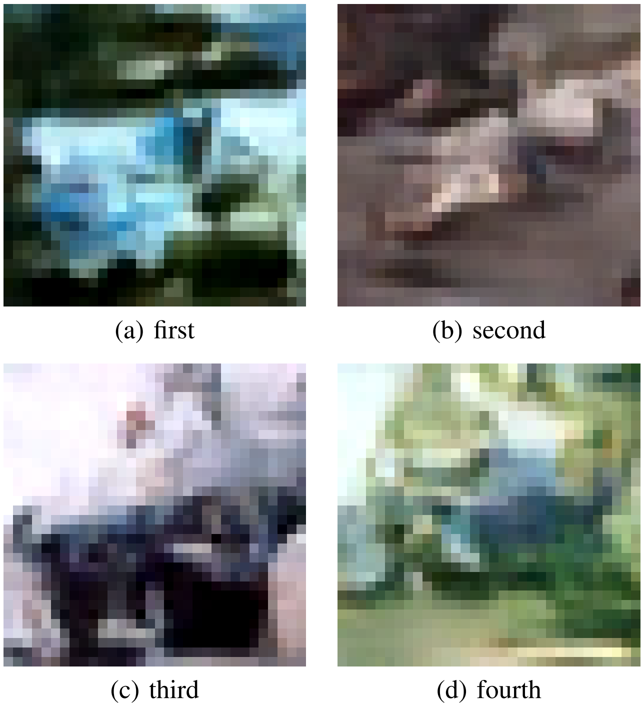
B. Results for augmented data

The accuracy for the augmented data is 41.14%. Figure 14 is the loss plot for the training.

And the confusion matrix for the training is shown in Figure 15.

C. Comparison

The accuracy for the non-augmented data is 44.05%, while the accuracy for the augmented data is 41.14%. Although the augmented data includes additional images generated by the diffusion model, it does not improve the accuracy. This is likely because the generated images are somewhere between



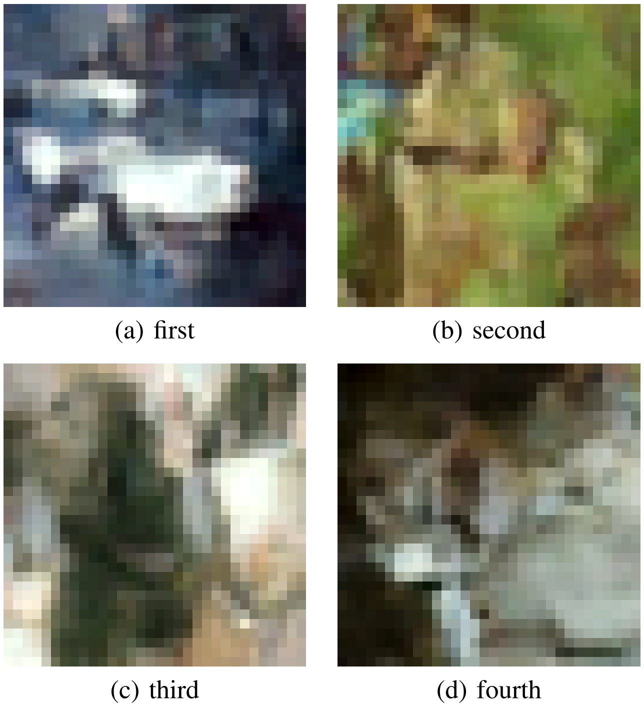
(a) first

(b) second

(c) third

(d) fourth

Fig. 3. Car images, generated from the diffusion model



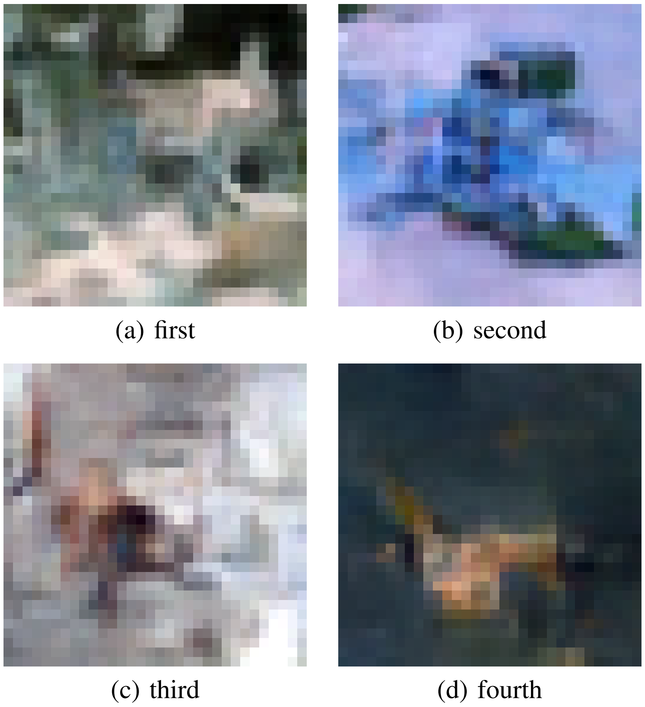
(a) first

(b) second

(c) third

(d) fourth

Fig. 4. Cat images, generated from the diffusion model



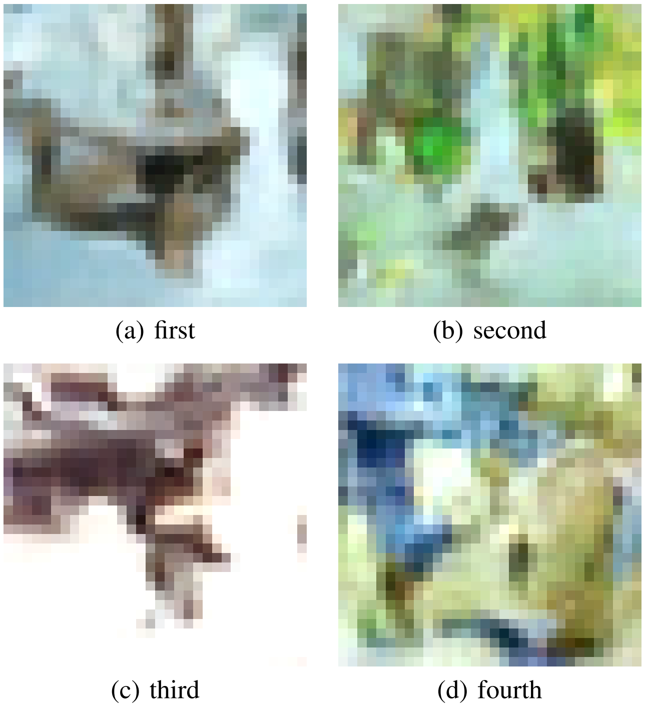
(a) first

(b) second

(c) third

(d) fourth

Fig. 5. Deer images, generated from the diffusion model



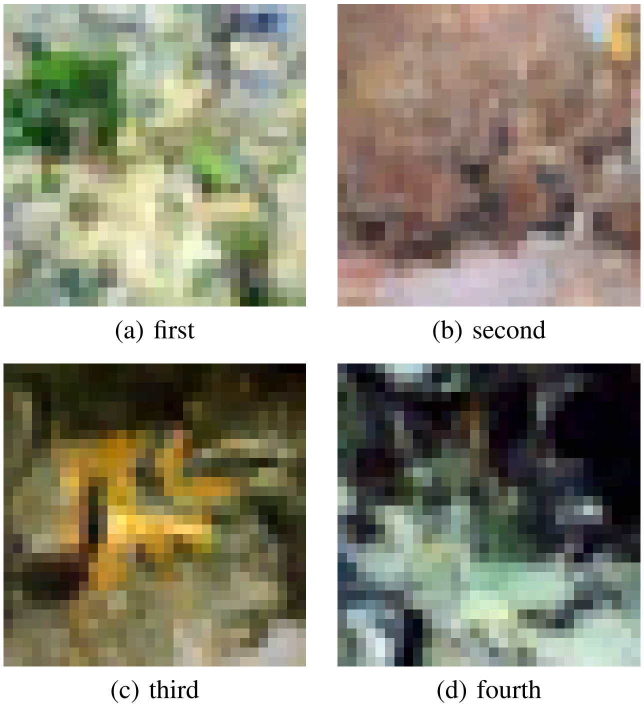
(a) first

(b) second

(c) third

(d) fourth

Fig. 6. Dog images, generated from the diffusion model



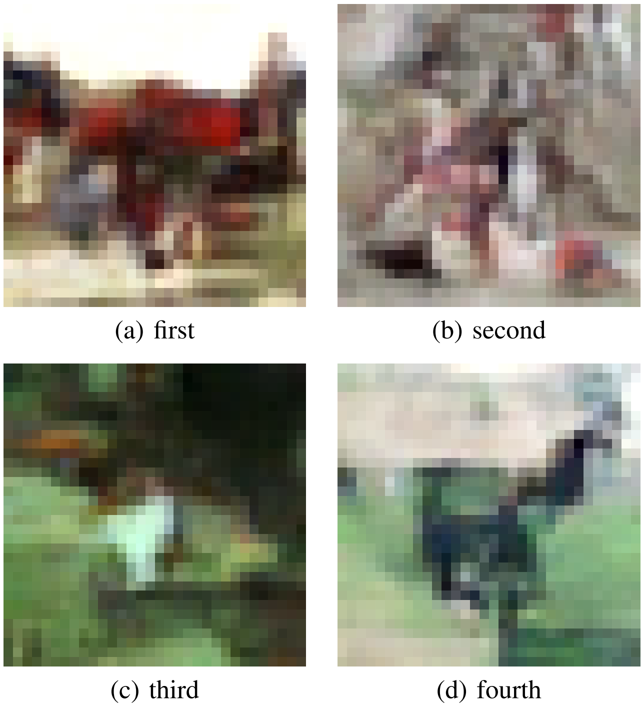
(a) first

(b) second

(c) third

(d) fourth

Fig. 7. Frog images, generated from the diffusion model



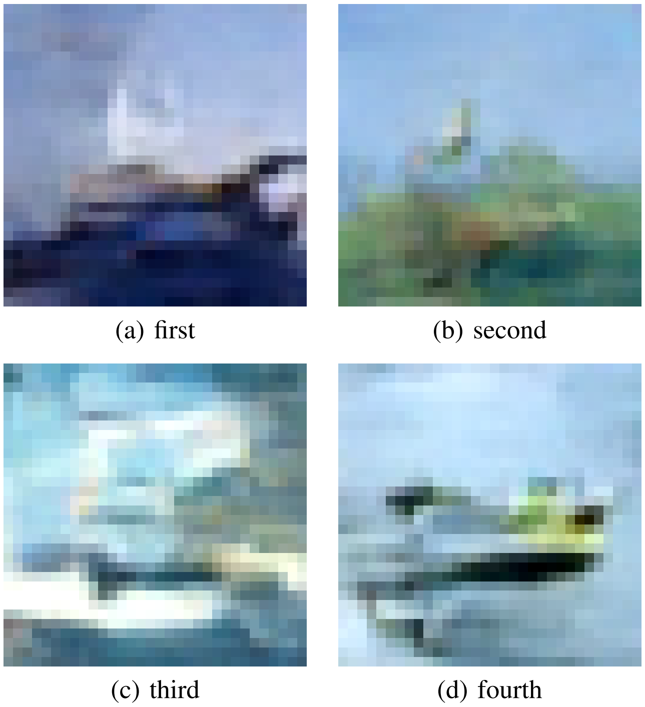
(a) first

(b) second

(c) third

(d) fourth

Fig. 8. Horse images, generated from the diffusion model



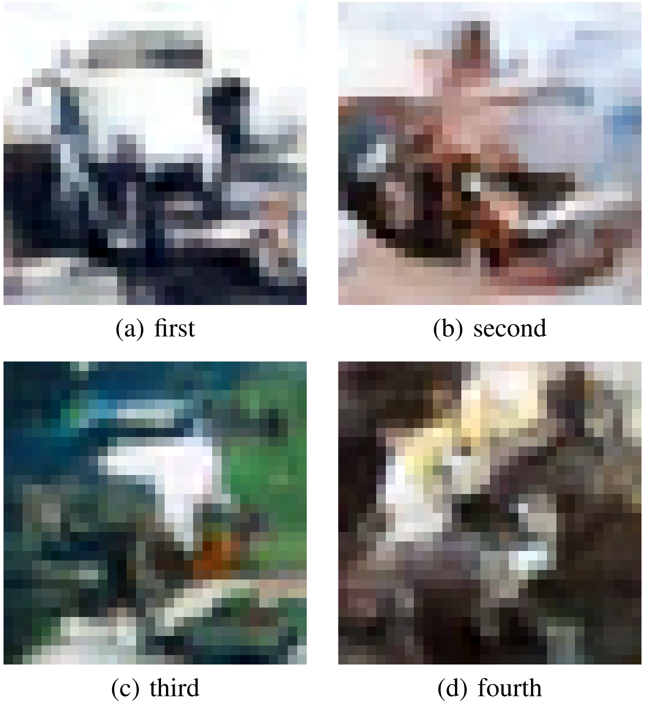
(a) first

(b) second

(c) third

(d) fourth

Fig. 9. Ship images, generated from the diffusion model



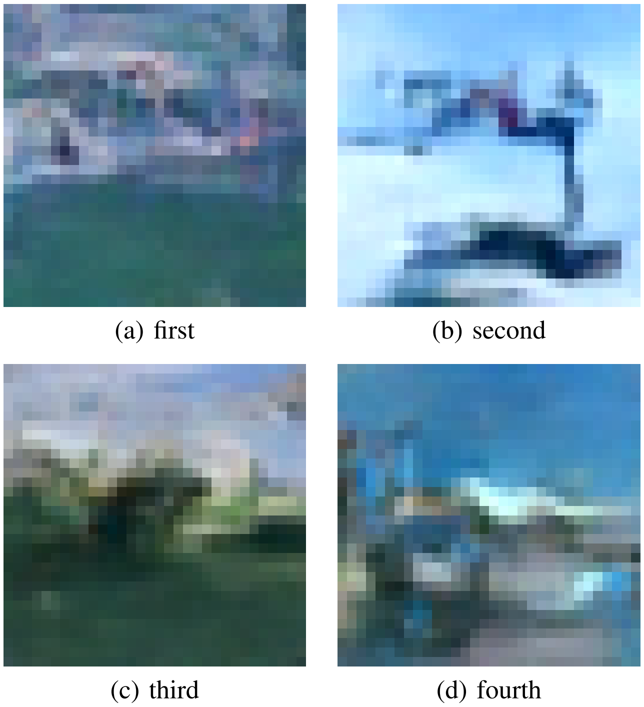
(a) first

(b) second

(c) third

(d) fourth

Fig. 10. Truck images, generated from the diffusion model


(a) first

(b) second

(c) third

(d) fourth

Fig. 11. Plane images, generated from the diffusion model

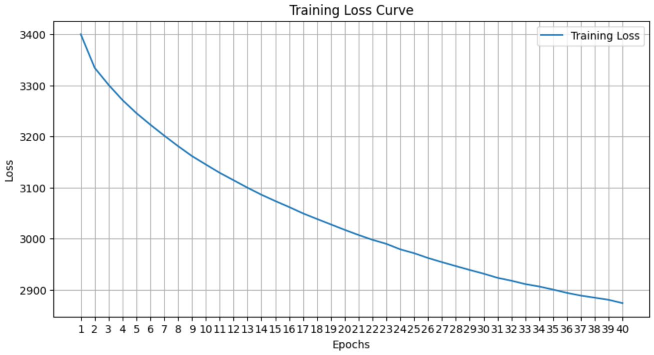
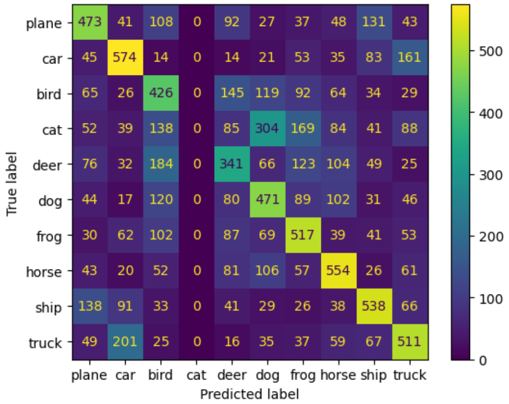


Fig. 12. Non-augmented data, loss plot



	plane	car	bird	cat	deer	dog	frog	horse	ship	truck
plane	473	41	108	0	92	27	37	48	131	43
car	45	574	14	0	14	21	53	35	83	161
bird	65	26	426	0	145	119	92	64	34	29
cat	52	39	138	0	85	304	169	84	41	88
deer	76	32	184	0	341	66	123	104	49	25
dog	44	17	120	0	80	471	89	102	31	46
frog	30	62	102	0	87	69	517	39	41	53
horse	43	20	52	0	81	106	57	554	26	61
ship	138	91	33	0	41	29	26	38	538	66
truck	49	201	25	0	16	35	37	59	67	511

Fig. 13. Non-augmented data, confusion matrix

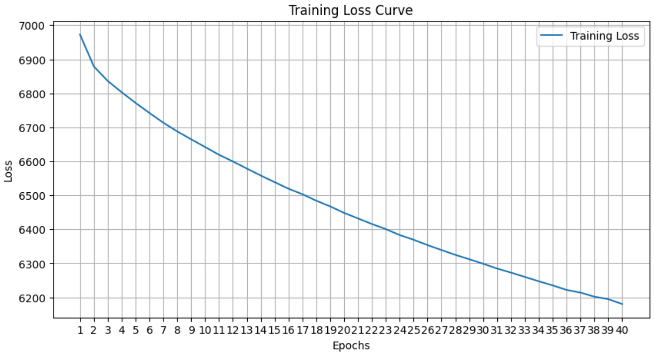
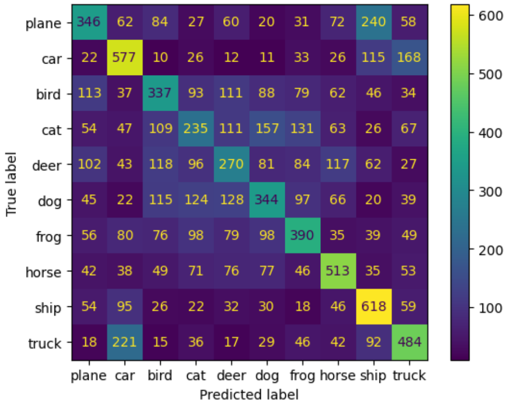


Fig. 14. Augmented data, loss plot



	plane	car	bird	cat	deer	dog	frog	horse	ship	truck
plane	346	62	84	27	60	20	31	72	240	58
car	22	577	10	26	12	11	33	26	115	168
bird	113	37	337	93	111	88	79	62	46	34
cat	54	47	109	235	111	157	131	63	26	67
deer	102	43	118	96	270	81	84	117	62	27
dog	45	22	115	124	128	344	97	66	20	39
frog	56	80	76	98	79	98	390	35	39	49
horse	42	38	49	71	76	77	46	513	35	53
ship	54	95	26	22	32	30	18	46	618	59
truck	18	221	15	36	17	29	46	42	92	484

Fig. 15. Augmented data, confusion matrix

random noise and real data, resulting in a training process that is less effective. The network takes longer to train, and the loss is significantly higher for the augmented data, almost double that of the non-augmented data.

This higher loss suggests that the model is not effectively learning from the augmented dataset and may even be forming incorrect patterns, which explains why the accuracy remains similar but doesn't improve with augmentation. In this case, the diffusion model's generated data does not contribute meaningful new information for the model to learn from, and may be decreasing performance due to the network learning to model the noise of the diffusion images.

The model essentially learns to classify the noise generated by the diffusion model, which causes overfitting and a decrease in performance. The model is not able to generalize well to the real data, as the noise generated by the diffusion model is not representative of the real data. This is why the accuracy is lower for the augmented data compared to the non-augmented data.

III. Part 3 - Cosine Scheduling Training

The same training as in Part 1 is done, but with cosine scheduling. Below are the hyperparameters used for training:

- Batch size: 80
- T: 500 (number of steps)

- Channel: 128
- Channel-multiplier: [1, 2, 2, 2]
- Learning rate: 1e-4
- Beta 1: 1e-4
- Scheduling: cosine
- Beta T: 0.028
- Loss Function: MSE loss

Figure 1 is the loss plot of the training:

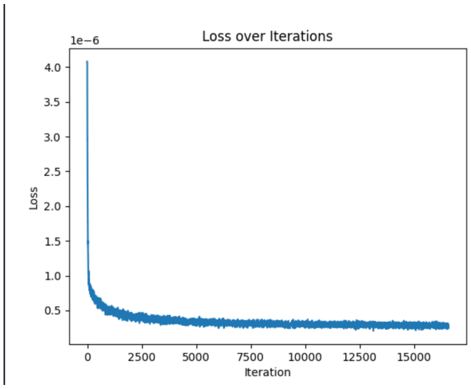


Fig. 16. Plot

Figure 2 to 11 show the images for every class generated by the diffusion model.

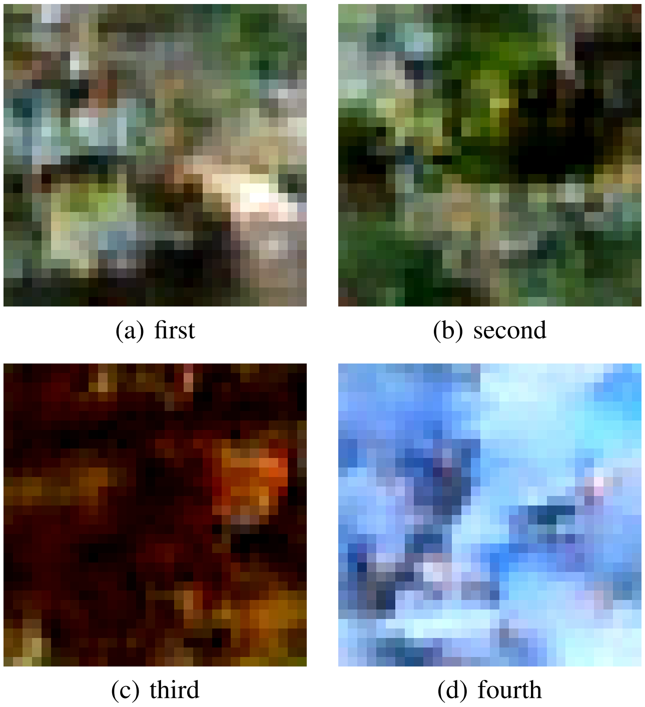
The difference between cosine and linear scheduling lies in how the learning rate decays over time. In linear scheduling, the learning rate decays at a constant rate throughout training, whereas in cosine scheduling, the learning rate decreases rapidly at first and then slows down, following a cosine curve. This allows the model to explore more during the early stages of training and then gradually refine its learning.

Loss and Performance Comparison The loss for cosine scheduling follows a similar trend as the linear schedule in Part 1, but with slight variations. The early stages of training using cosine scheduling see a sharper decline in loss, indicating that the model is adjusting more rapidly at the beginning. However, as training progresses, the rate of improvement in loss slows down, eventually reaching values comparable to those achieved with linear scheduling. This behavior is visible in the training loss plot (Figure 16).

Although the final loss values are similar, the training process with cosine scheduling produces smoother and potentially more stable results in the long run. The cosine decay helps the model avoid overly aggressive updates toward the end of training, which can prevent it from getting stuck in local minima or overfitting to noise.

A. Similarity in results

Despite these differences in how the learning rate decays, the overall performance in terms of accuracy and quality of the generated images remains quite similar to that observed with linear scheduling. This is expected because both linear and cosine approaches effectively balance exploration and refinement during training, though they do so at different paces.



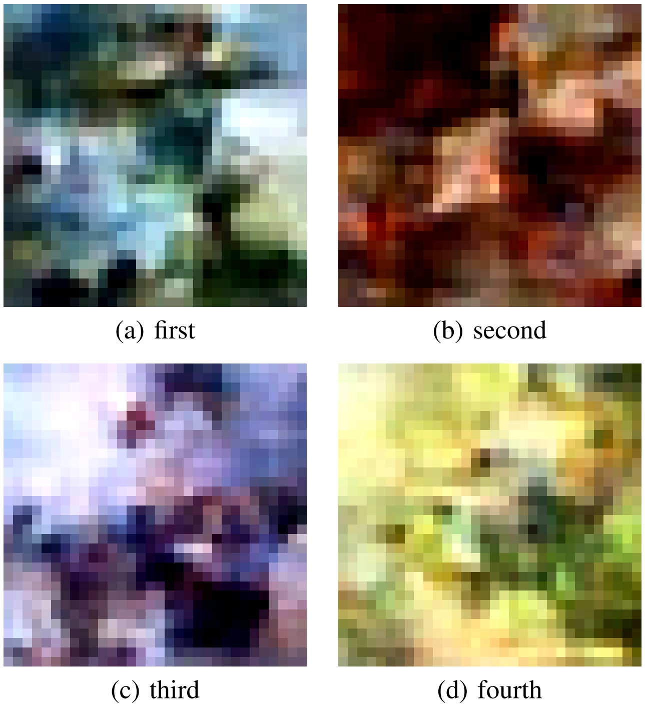
(a) first

(b) second

(c) third

(d) fourth

Fig. 17. Bird images, generated from the diffusion model



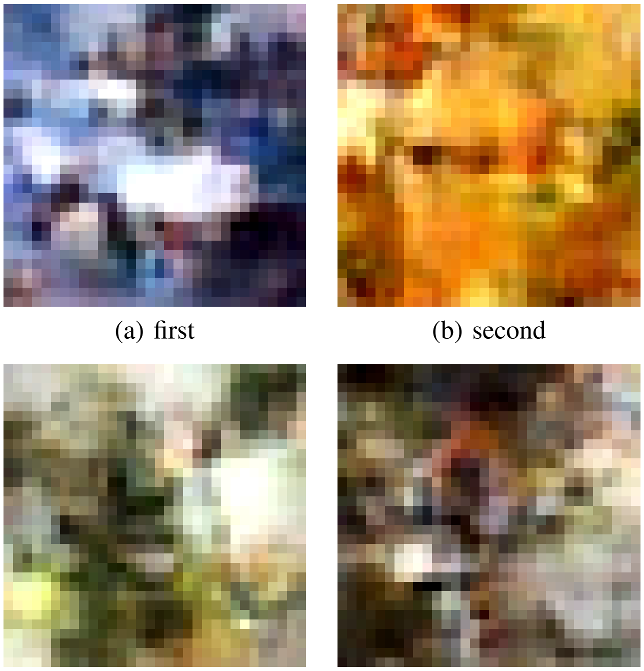
(a) first

(b) second

(c) third

(d) fourth

Fig. 18. Car images, generated from the diffusion model



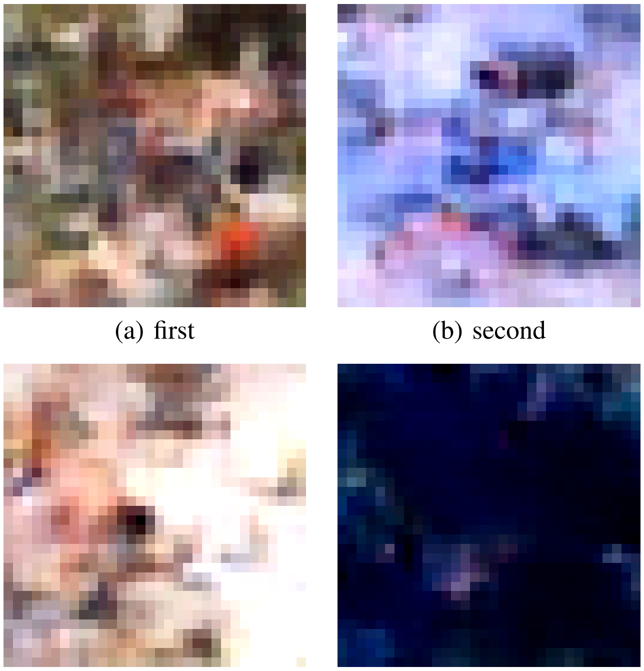
(a) first

(b) second

(c) third

(d) fourth

Fig. 19. Cat images, generated from the diffusion model



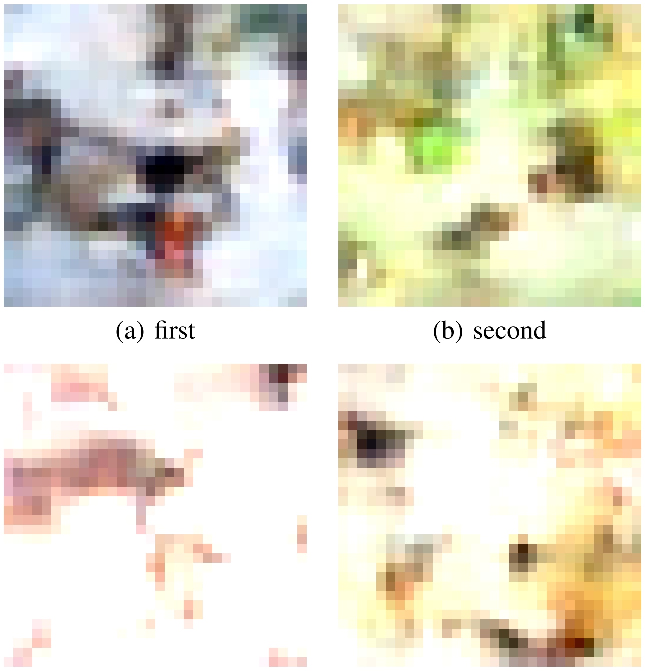
(a) first

(b) second

(c) third

(d) fourth

Fig. 20. Deer images, generated from the diffusion model



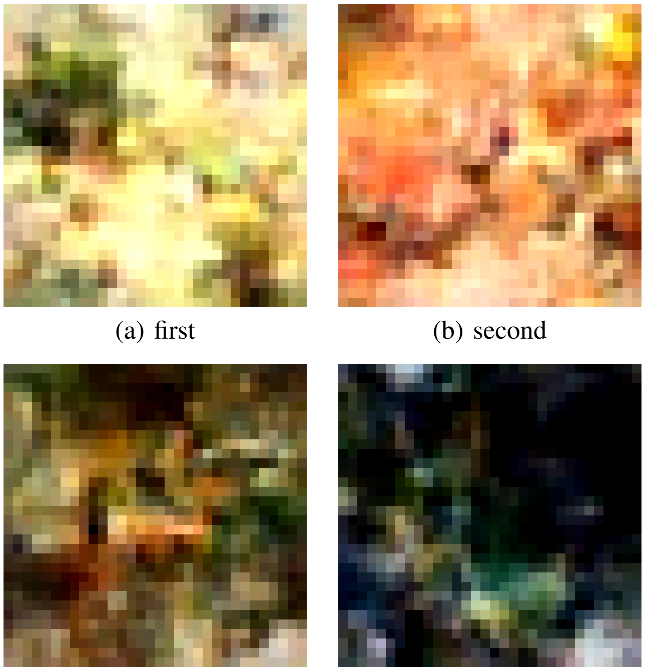
(a) first

(b) second

(c) third

(d) fourth

Fig. 21. Dog images, generated from the diffusion model



(a) first

(b) second

(c) third

(d) fourth

Fig. 22. Frog images, generated from the diffusion model

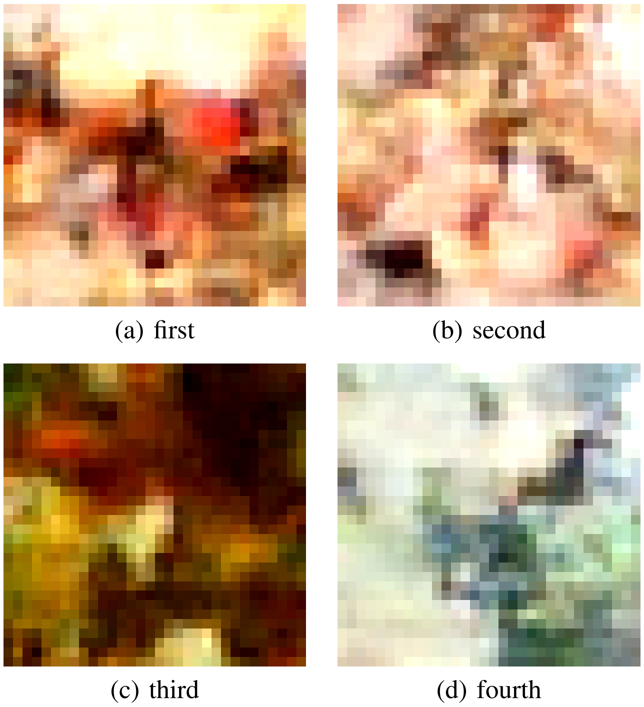

(a) first
(b) second
(c) third
(d) fourth

Fig. 23. Horse images, generated from the diffusion model

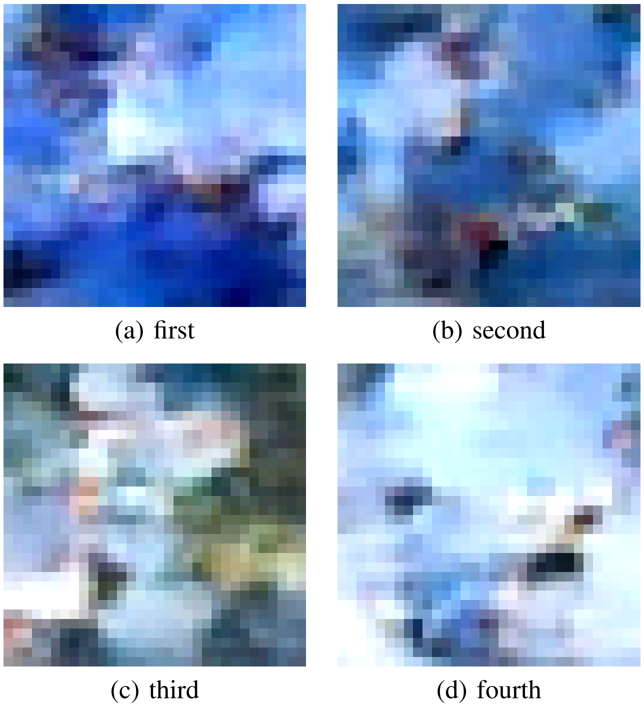

(a) first
(b) second
(c) third
(d) fourth

Fig. 24. Ship images, generated from the diffusion model

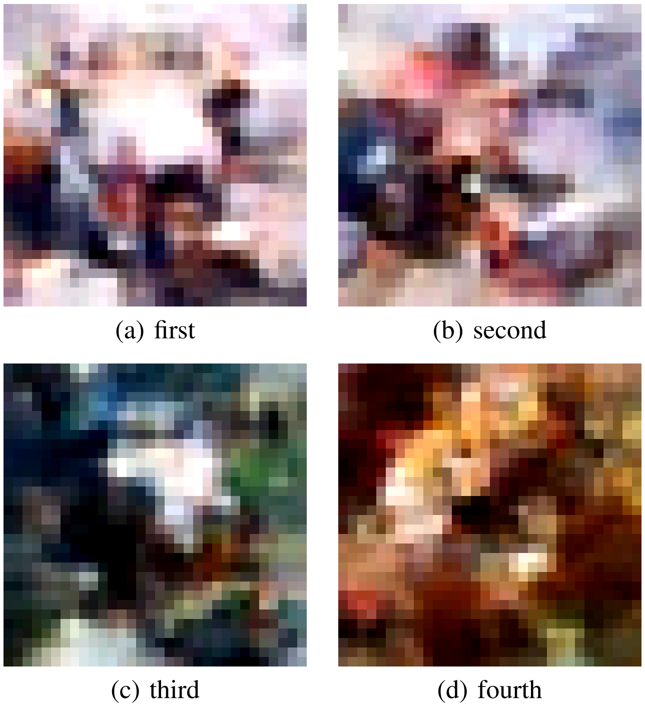

(a) first
(b) second
(c) third
(d) fourth

Fig. 25. Truck images, generated from the diffusion model

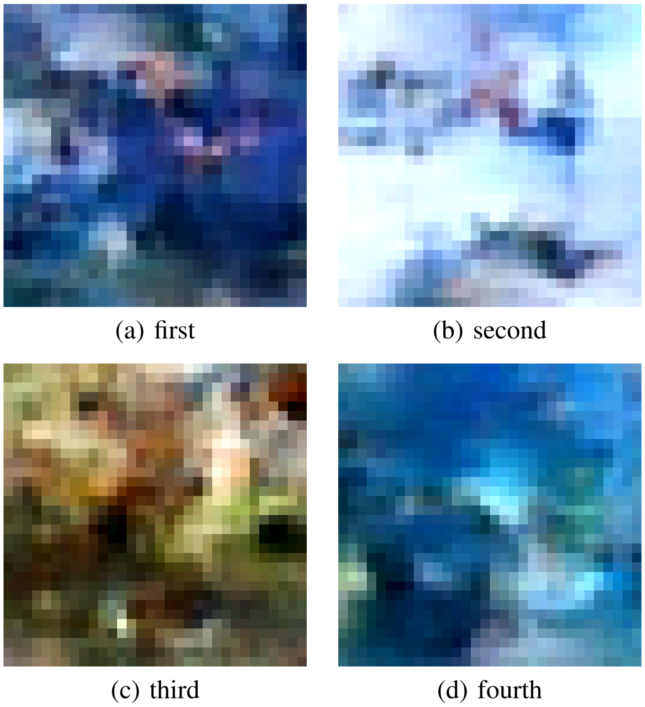
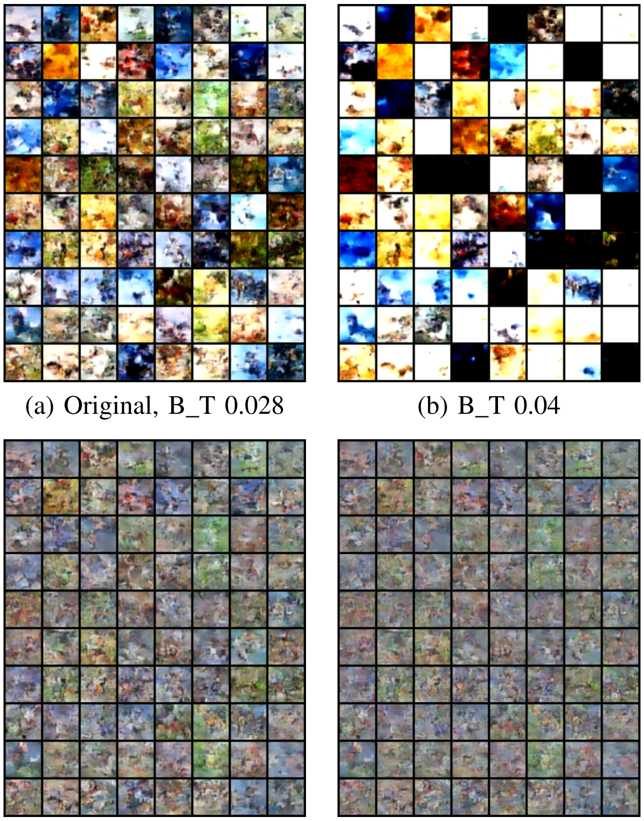

(a) first
(b) second
(c) third
(d) fourth

Fig. 26. Plane images, generated from the diffusion model



(a) Original, B_T 0.028

(b) B_T 0.04

(c) B_T 0.01

(d) B_T 0.005

Fig. 27. Diffusion outputs with different beta T values

The similar results suggest that for this particular dataset and model configuration, the choice between cosine and linear scheduling may not drastically affect the final outcome. However, cosine scheduling offers the advantage of more nuanced control over the learning process, especially during the later stages of training.

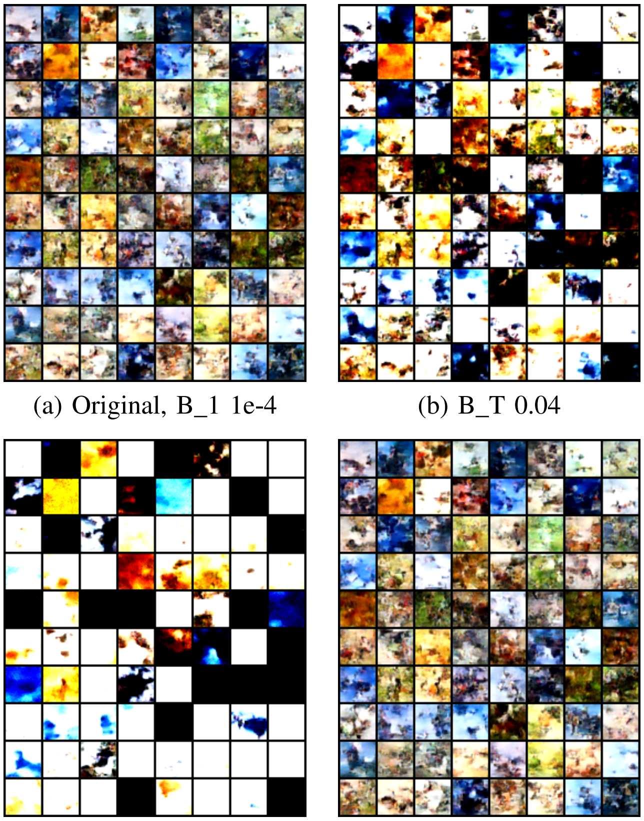
B. Parameter tuning

The most influencial hyperparameters for the diffusion model's evaluation are beta 1, beta T, and img size. Beta 1 and beta T are the parameters that control the noise level of the generated images. The img size parameter is the size of the images generated by the diffusion model.

The img size parameter is important because it determines the resolution of the generated images, and also effect the image generated to be much different than the generation of different resolutions.

If beta 1 is raised too high, or beta T is raised too high, the generated images will be washed out. Lower beta 1 values seem to not affect much in our testing.

If beta T is lowered to close to beta 1, the generated images will be too noisy.



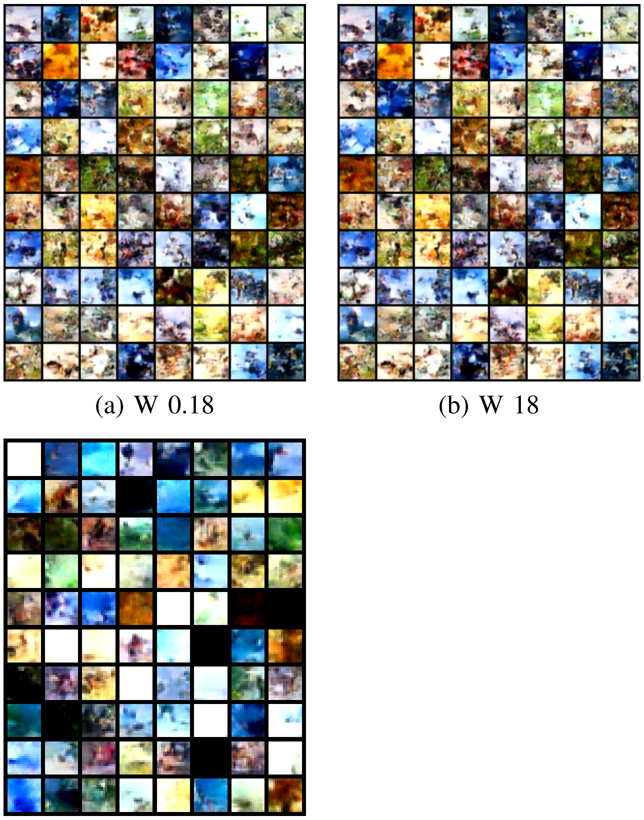
(a) Original, B_1 1e-4

(b) B_T 0.04

(c) B_1 1e-2, B_T 0.004

(d) B_1 1e-6

Fig. 28. Diffusion outputs with different beta 1 values



(a) W 0.18

(b) W 18

(c) Image size 16

Fig. 29. Diffusion outputs, other hyperparameters