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Université Paris-Saclay Machine Vision Project

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***Abstract*—**

***Index Terms*—**

I. Introduction

hello this is a test in the paper [2], in this text i am going to cite another paper exactly here [1].

II. Related Work

III. Methods

A. Conditional Generative adversarial network(GANs)

$$\min_G \max_D \mathcal{V}_{\text{GAN}}\left(D, G\right) = \tag{1}$$

$$\mathbb{E}_{x \sim p_{\text{data}(x)}}\left[\log\left\{D\left(x\right)\right\}\right] + \mathbb{E}_{z \sim p_z(z)}\left[\log\left\{1 - D\left(G\left(z\right)\right)\right\}\right].$$

where $G : R^{100} \longrightarrow R^{16,384}$

$$L_D = -\sum_{x \in \chi, z \in \zeta} \log(D(x)) + \log(1 - D(G(z))) \tag{6}$$

$$L_G = -\sum_{z \in \zeta} \log(D(G(z)) \tag{7}$$

B. Model Architecture

1) Generator:

$$h^{[i]} = LeakyRELU(W^{[i-1]}h^{[i-1]} + b[i-1]) \tag{2}$$

α, with h[i] $\epsilon R^{16\alpha 2^i}$ and we output the vector o $\epsilon R^{16,384}$ via

$$o = \tanh(W^{[L]}h^{[L]} + b[L]) \tag{3}$$

Where L is the final layer.

2) Discriminator: $h[0]$ denote the input image, $W[j]$ and $b[j]$ denoting the weight matrix and the bias vector in the L output layer, we have:

$$o = sigmoid(W^{[L]}h^{[L]} + b[L]) \tag{4}$$

3) Classifier:

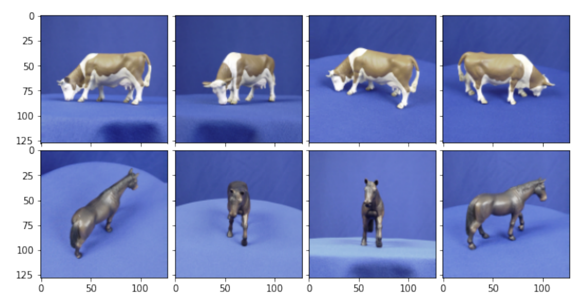

Fig. 1. Random Cows and Horses Images from Original Dataset

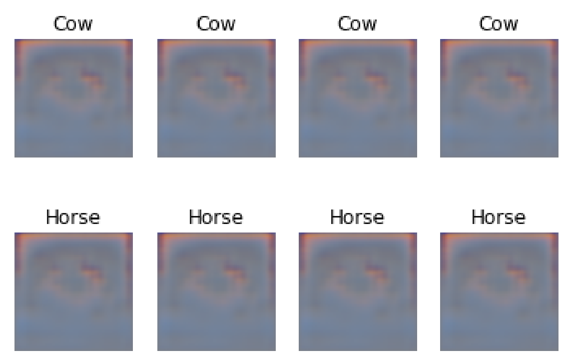

Fig. 2. Generated Output after 100 Steps

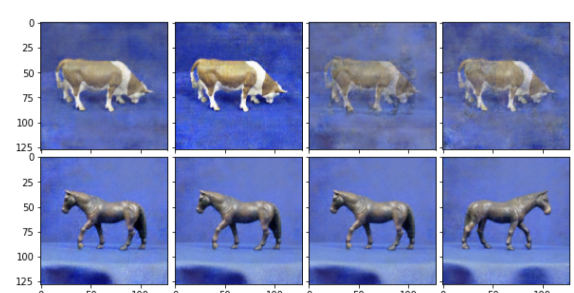

Fig. 3. Generated Output after 35000 Steps

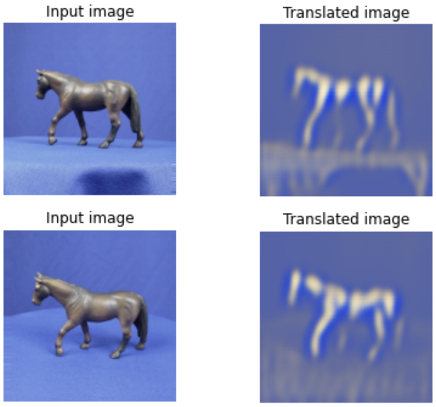

Fig. 4. Generated Translated Output after 1 Epoch

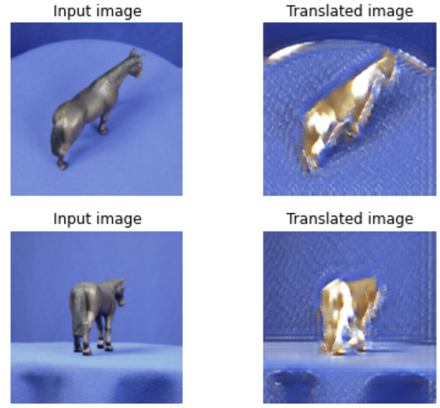

Fig. 5. Generated Output after 50 Epochs

IV. Experiments

A. Dataset

B. Evaluation Metrics

C. Experimentation Details

D. GAN Experimentation Results

E. CycleGAN Experimentation Results

- Pass real images through the generators and get the generated images
- Pass the generated images back to the generators to check if we can predict the original image from the generated image.
- Do an identity mapping of the real images using the generators.
- Pass the generated images in 1) to the corresponding discriminators.
- Calculate the generators total loss (adverserial + cycle + identity)
- Calculate the discriminators loss
- Update the weights of the generators
- Update the weights of the discriminators
- Return the losses in a dictionary.

F. Classifier Experimentation Results

Metric	Orig		Orig-250-GAN		Orig-500-GAN		Orig-1000-GAN	
-	**train**	**val**	**train**	**val**	**train**	**val**	**train**	**val**
BCE-Loss	0.01	5	0.01	0.7	0.01	0.7	8	0.7
Accuracy	1.0	0.5	1.0	0.6	1.0	0.5	0.5	0.5
Precision	1.0	0.1	1.0	0.5	1.0	0.5	0.5	0.5
Recall	1.0	0.5	1.0	0.4	1.0	1.0	1.0	1.0

TABLE I
COMPILED TABLE OF CLASSIFICATION METRICS

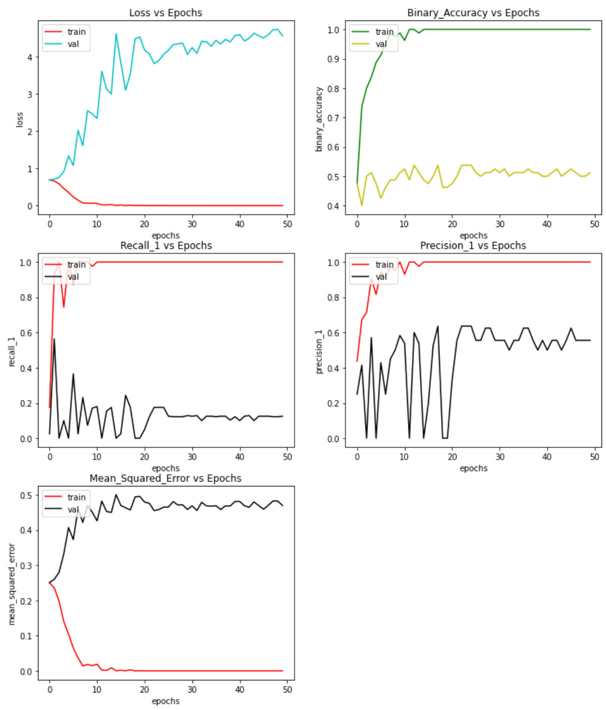

Fig. 6. Classification metrics for classifier trained on **original dataset**

V. Conclusion

References

[1] Mehdi Mirza and Simon Osindero. Conditional generative adversarial nets, 2014.

[2] Jun-Yan Zhu, Taesung Park, Phillip Isola, and Alexei A. Efros. Unpaired image-to-image translation using cycle-consistent adversarial networks. *CoRR*, abs/1703.10593, 2017.

Identify applicable funding agency here. If none, delete this.

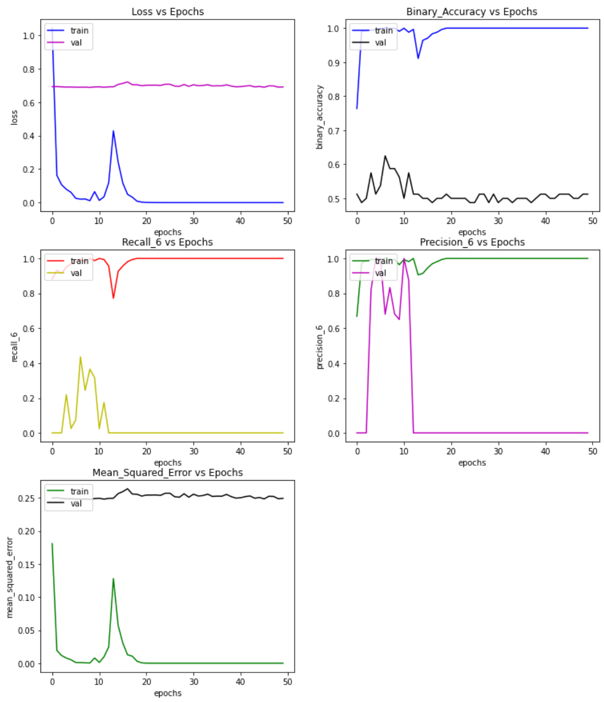

Fig. 7. Classification metrics for classifier trained on **original+250 GAN-based**

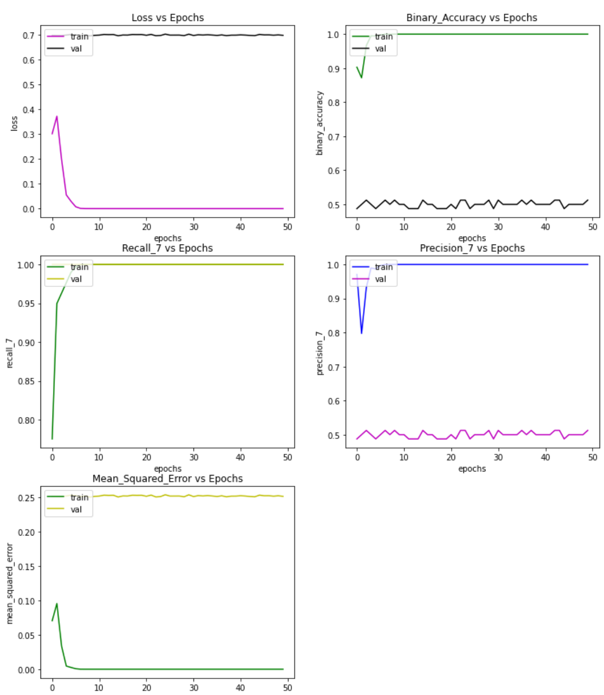

Fig. 8. Classification metrics for classifier trained on **original+250 GAN-based**

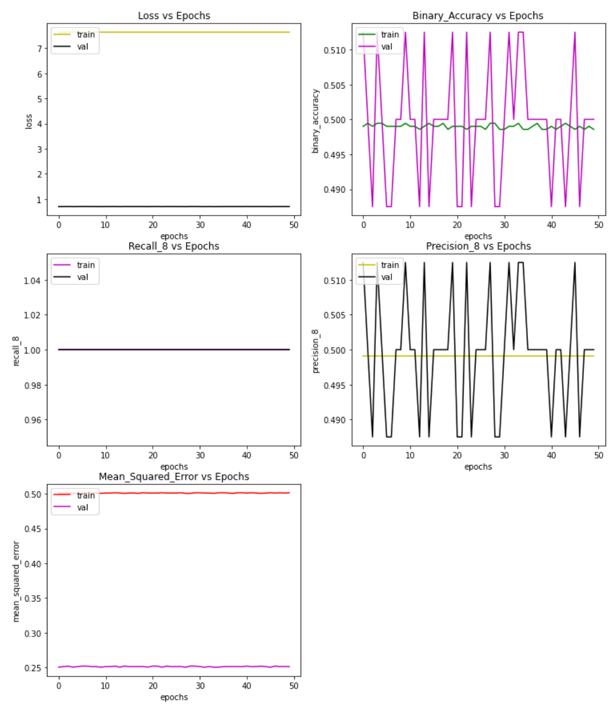

Fig. 9. Classification metrics for classifier trained on **original+250 GAN-based**