IDA-GAN: A Novel Imbalanced Data Augmentation GAN

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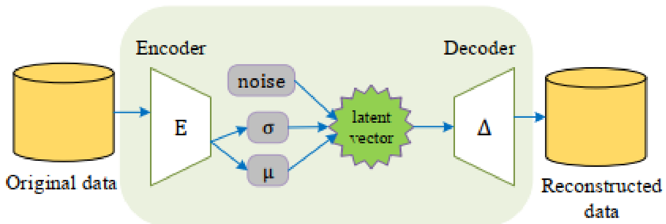
Contents

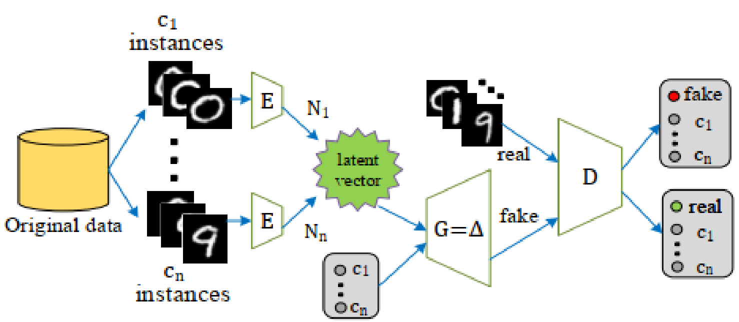
Introduction

- Imbalanced data problem
- Oversampling
- Undersampling
- Cost-sensitive learning

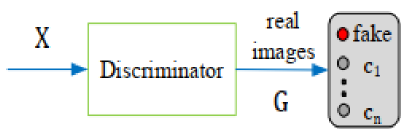
IDA-GAN



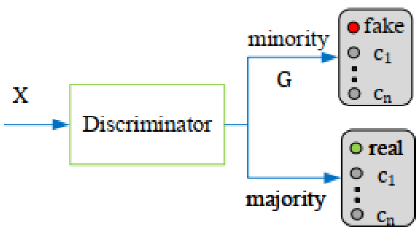
(a) VAE training.



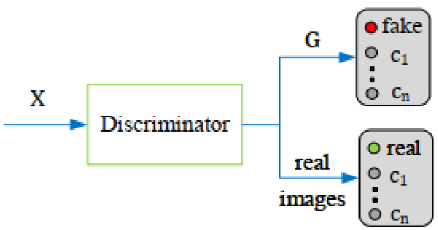
(b) GAN training.



(a) BAGAN discriminator



(b) ACGAN discriminator



(c) IDA-GAN discriminator

Fig. 1. Discriminator structures for BAGAN, ACGAN and IDA-GAN.

IDA-GAN

1.We use a continuous approach to train GANs to generate minority-class samples to solve the imbalanced data problem.

2.We propose an effective imbalanced classification framework by leveraging the strengths of variational autoencoder and GANs which enables us to identify the accurate boundary of classes.

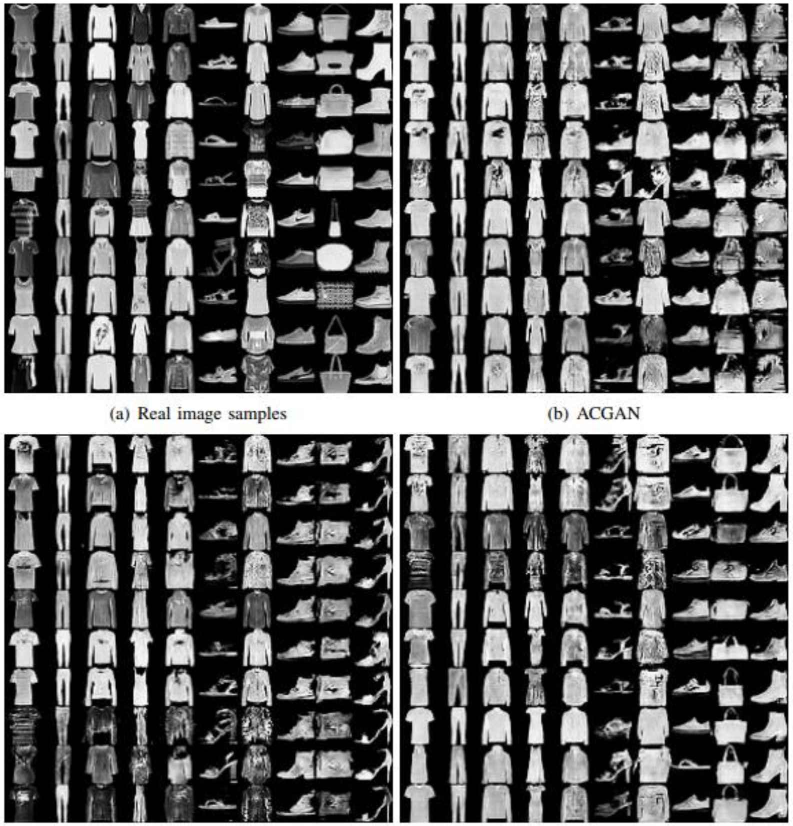
3.Extensive experiments on five widely-used benchmark datasets show that our IDA-GAN can generate highquality and diverse samples, while maintaining a reasonable overall accuracy.

Experiments

TABLE I
THE DETAILS OF THE EXPERIMENTAL DATASETS.

Dataset name	Shape	Classes	Training set	Testing set
MNIST	28 x 28 x 1	10	{4000,2000,1000,750, 500,350,200,100,60,40}	{980,1135,1032,1010,982 892,958,1028,974,1009}
Fashion-MNIST	28 x 28 x 1	10	{4000,2000,1000,750, 500,350,200,100,60,40}	{1000,1000,1000,1000,1000 1000,1000,1000,1000,1000}
SVHN	32 x 32 x 3	10	{4500,2000,1000,800, 600,500,400,250,150,80}	{1744,5099,4149,2882,2523 2384,1977,2019,1660,1595}
CIFAR-10	32 x 32 x 3	10	{4500,2000,1000,800, 600,500,400,250,100,80}	{1014,1012,1023,1012,991 1016,1005,1015,965,947}
GTSRB	32 x 32 x 3	43	{2250,2220,2160,2100, ...,240,240,210,210,210}	{750,720,720,690,690 ...,60,60,60,60}

Experiments



(a) Real image samples

(b) ACGAN

(c) BAGAN

(d) IDA-GAN

Fig. 4. The real examples and synthetic images generated by three models: (a) real images from Fashion-MNIST, (b) images generated by ACGAN, (c) images generated by BAGAN and (d) images generated by IDA-GAN.

Experiments

TABLE II
THE COMPARISION OF CLASSIFICATION PERFORMANCE IN TERMS OF PRECISION, RECALL AND F1 SCORE FOR SINGLE-CHANNEL DATASETS.

Method	MNIST			Fashion-MNIST		
	Precision(%)	**Recall**(%)	**F1**(%)	**Precision**(%)	**Recall**(%)	**F1**(%)
ACGAN	86.34	81.10	78.90	77.15	67.45	66.31
BAGAN	87.09	82.73	80.86	80.28	70.71	69.69
IDA-GAN	**88.45**	**83.25**	**82.56**	**83.33**	**79.72**	**78.85**

TABLE III
THE COMPARISION OF CLASSIFICATION PERFORMANCE IN TERMS OF PRECISION, RECALL AND F1 SCORE FOR THREE-CHANNEL DATASETS.

Method	SVHN			CIFAR-10			GTSRB		
	Precision (%)	**Recall**(%)	**F1**(%)	**Precision**(%)	**Recall**(%)	**F1**(%)	**Precision**(%)	**Recall**(%)	**F1**(%)
ACGAN	71.93	54.80	55.39	64.31	51.58	48.99	83.04	83.08	81.72
BAGAN	77.55	73.94	72.39	69.42	67.82	61.65	85.55	85.60	84.46
IDA-GAN	**79.32**	**75.59**	**74.44**	**73.77**	**66.01**	**64.36**	**87.20**	**87.53**	**86.41**

Conclusions

In this study, we present a novel imbalanced data augmentation GAN model named IDA-GAN. In the proposed IDA-GAN framework, variational autoencoder is used to stabilize the minority and the majority class data distribution. The GAN model combined with the variational autoencoder could generate more diverse and higher-quality images to restore dataset balance.

Thanks for your listening!