Data Augmentation Using Generative Adversarial Networks for Electrical Insulator Anomaly Detection

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ABSTRACT

Electrical insulators, which are widely used for electricity transmission, are prone to damage and need constant maintenance. Traditionally, the inspection job is time-consuming and dangerous as workers have to climb electrical towers to access insulators. However, deep learning, which offers a safe and quick way to automate inspections, requires large amounts of data. Generative adversarial networks (GANs) are introduced as a novel approach to augmenting data. However, traditional state-of-art GANs are either incapable of generating high quality images, or fail to generate minority class images when minority class examples are very infrequent. In order to mitigate drawbacks of existing GANs, a novel GAN model, Balancing and Progressive GANs (BPGANs), was proposed for effectively making use of all classes information and generating high quality images simultaneously. Results show that PGANs, StyleGANs, and BPGANs were able to generate high-resolution images and improve classification performance. PGANs achieved the better results than BPGANs. This may be because BPGANs only provides 2 additional latent codes since it is a binary classification, having little effect on generating desired images. BPGANs seemed to have difficulties generating class-specific images, which might be because that the classification loss is too little compared to the source loss and optimization was more focused to optimize the source loss. This indicates that learning representations of data progressively from low resolution to high resolution is an effective approach, however, embedding class label information in the fashion of AC-GANs and BGANs might not be appropriate for augmenting binary class data sets.

CCS Concepts

• **Computing methodologies** → **Artificial intelligence** → **Computer vision** → **Computer vision tasks** → **Scene anomaly detection**.

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Keywords

Data augmentation; generative adversarial networks; anomaly detection; insulators.

1. INTRODUCTION

There is a huge demand for electricity in the U.S. U.S. net electricity generation increased by 4% in 2018, reaching a record high of 4,178 million megawatt hours (MWh), surpassing once again the pre-recession peak of 4,157 million MWh set in 2007. Both the residential (about 1,500 MWh) and commercial sectors (about 1,400 MWh) reached all-time highs for retail sales of electricity in 2018 [25]. Power cut can cause large loss to all sectors of society. According to the report from the U.S. Energy Information Administration in 2013 [19], between 2003 and 2012, an estimated 679 widespread power outages occurred due to severe weather. Power outages close schools, shut down businesses and impede emergency services, costing the economy billions of dollars and disrupting the lives of millions of Americans. Therefore, regular inspections are required to prevent faults that cause power outage. Visual inspections on transmission lines is the common way to maintain electricity supply. They are usually carried out by skilled worker foot-patrolling or using helicopter-assisted methods [16], which is costly and risky.

Many efforts have been made to help inspect electrical transmission lines more efficiently. Drones and robots that are capable of patrolling are made to increase inspection safety and lower costs [11, 6, 23]. After images and videos are collected from robots, trained workers spend huge amount of time to look at them looking for any faults. This obviously is time-consuming and prone to human bias. To reduce the human bias and better classify insulators, new approaches should be explored.

Huge advances have been seen in the field of deep learning in recent years. Various types of deep neural networks (DNN) have achieved great success in various computer vision tasks, such as image classification [12, 24, 7] and object detection [2, 22, 21]. One of the drawbacks of deep learning methods is that they generally require huge amount of data in order to classify insulators. When training examples are not sufficient, there are several approaches to augmenting data, including image oversampling, random rotation, shifts, and etc. However, traditional data augmentation techniques do not improve the results significantly [1]. In addition to limited data sets, class imbalance also creates many problems for neural network classifiers [13]. Thus, it is necessary to propose new strategies to enrich data set and mitigate data imbalance issues.

In recent year, generative modeling, as a more promising approach to data augmentation, has risen, especially generative adversarial networks (GANs). GANs were first introduced in 2014 [5]. Since then, various GAN extensions were proposed, such as CycleGANs, DCGANs, and PGANs [29, 20, 9]. GANs have shown superior results compared to traditional data augmentation techniques as they are capable of imaging different alterations to images such that they have a better understanding of them [13]. However, these GANs might not work well when data set suffers severe class imbalance issue, because they are trained on the minority class examples for generating new examples and the GANs are not likely to learn well from a minority class, which has very few examples. In order to mediate the class imbalance issue, another branch of research has been focusing on developing the conditional version of GANs [18, 15, 14] aiming to include class label in GANs training. However, these conditional version of GANs generally works well with relatively low-resolution data set, such as images whose size are only 64×64 or 128×128.

To overcome the limitations of existing GANs, we need to assess the ability of various GANs on data augmentation and propose new approaches based on their existing limitations. Thus, the objectives of this study include:

- Train a DNN classifier on the original data set, which is not augmented and is imbalanced, to classify damaged insulators against good insulators. The classification results can serve as the baseline.
- Train various GANs models to augment and balance the data set. Then, train the same classifier on the augmented data set and compare the classification performance against the baseline.
- Propose and develop a new model that is able to make use of class label information and can generate high-resolution images.

2. RELATED WORK

In this section, we review on recently proposed GANs for generating high-resolution images and GANs for conditional image synthesis.

2.1 Generative Adversarial Networks

Generative models try to learn the statistical distribution of the training data, allowing synthesizing data from the learned distribution. The key incentive behind GANs is estimating the underlying probability density or probability mass function of the observed data. GANs learn the probability distribution implicitly by computing the similarity of the distribution between the real training examples and the fake data generated by the learned model. After the model is trained well, it naturally can be used to generate data that have similar distribution as the real data.

GANs typically consist of a generator and a discriminator. The two compete against one another: the generator tries to fool the discriminator by producing fake data and the discriminator aims to distinguish the fake data from the real data. The learning process is guided by a minimax game (See Equation 1) where the discriminator (D) desires to increase the log-probability when images (x) are sampled from the real distribution ($p_{data}(x)$) and wishes to decrease the log-likelihood when data is sampled from the generator. Meanwhile, the generator (G) wishes to increase the log-likelihood of fake images being classified as real when images are sample from the generator $p_z(z)$, where z is called the latent vector and is usually sampled from a normal distribution. As learning progresses the discriminator gets better at classifying the data being real or not and the generator becomes better at producing realistic data. Naturally, the generator can then be used to generate data when training examples are not sufficient.

$$\min_{G} \max_{D} V(D,G) = \underset{x \in p_{data}(x)}{E}[logD(x)] + \underset{z \in p_z(z)}{E}[\log(1 - D(G(z)))] \tag{1}$$

2.2 GANs for Generating High-resolution Images

GANs have difficulties in generating high-resolution images as they make it easier for the discriminator to distinguish the fake images among the real data. High-resolution data also prevents from using larger minibatches due to GPU memory limitations and thus compromising training stability [9, 18]. Based on the work of Wang et al., 2017 [26], Durugkar et al., 2016 [4], and Hierarchical GANs [3, 8, 27], Karras et al., 2018 [9] proposed PGANs, whose key idea is to grow both the generator and discriminator progressively, starting from easier low-resolution images, and add new layers that introduce higher-resolution details. This speeds up training and improves stability. Following the trace of PGANs and the idea of style transfer, Karras et al., 2019 [10] proposed a style-based generator for GANs. It features an automatically learned, unsupervised separation of high-level attributes and stochastic variation in the generated images, which enables intuitive, scale-specific control of the image synthesis.

2.3 GANs for Conditional Image Synthesis

Another branch of research focuses on GANs that can embed label information into GANs training process, aiming to generate class-dependent images [14, 15]. Conditional GANs [15] incorporate labels (y) into both generator and discriminator by modelling the conditional probability: $logD(x|y)$ and $\log(1 - D(G(z|y)))$. As a result, the objective function in Equation 1 is slightly modified into the conditional form (See Equation 2).

$$\min_{G} \max_{D} V(D,G) = \underset{x \in p_{data}(x)}{E}[logD(x|y)] + \underset{z \in p_z(z)}{E}[\log(1 - D(G(z|y)))] \tag{2}$$

Mariani et al., 2018 proposed Balancing GANs (BGANs) [14] as an augmentation tool to restore balance in imbalanced data sets. They argued that the few minority-class examples may not be enough to train a GAN, so they incorporated all available images of majority and minority classes. BGANs try to achieve class balance by applying class conditioning in the latent space to drive the generation process towards the target class. BGAN features an autoencoder that learns an accurate class-conditioning in the latent space and then initializes the generator with the encoder.

Based on conditional GANs, Odena et al., 2017 proposed Auxiliary Classifier GANs (AC-GANs) [17], which not only supplies both the generator and discriminator with class labels, but also includes a classifier to classify the image category. This model produces good results and appears to stabilize training compared to the standard GAN formulation. The objective function has two parts: the loglikelihood of the correct source, L_s, and the log-likelihood of the correct class, L_c.

$$L_s = E[\log P(S = real|X_{real})] + E[\log P(S = fake|X_{fake})] \quad (3)$$

$$L_c = E[\log P(C = c|X_{real})] + E[\log P(C = c|X_{fake})] \quad (4)$$

D is trained to maximize $L_s + L_c$ while G is trained to maximize $L_c - L_s$. C denotes class labels and S is the source of images fed into the discriminator.

3. METHOD

As mentioned in the previous section, existing GANs cannot produce high-resolution images and embed class label information at the same time. In order to address this limitation, a new GANs model, which is called Balancing and Progressive Growing GANs (BPGANs), is proposed.

The idea of BPGANs comes from BGANs, AC-GANs, and PGANs. In AC-GANs [17], the GANs embeds the class label information by having an extra classifier to predict which class images that are fed to discriminator belongs to. Instead of sampling from a standard normal distribution for initializing the latent vectors when training GANs, BGANs [14] uses a variational autoencoder that is trained to obtain a class-independent latent vector generator, which is then used to provide initialization for the random latent vectors for different class labels. Lastly, BPGANs also borrows idea from PGANs [9], which is able to generate high-resolution data by training the generator and the discriminator progressively from low resolution to high resolution. The proposed BPGANs model embeds class label information during training and is capable of generating high-resolution images. The architecture of BPGANs is shown in Figure 1, where both generator and discriminator are trained from low resolution of 4×4 to a high resolution of 512×512. The objectives of BPGANs are illustrated in Equation 3, 4 and the latent vectors (z) were sampled from a dense representation that was learned from a class label dependent variational autoencoder.

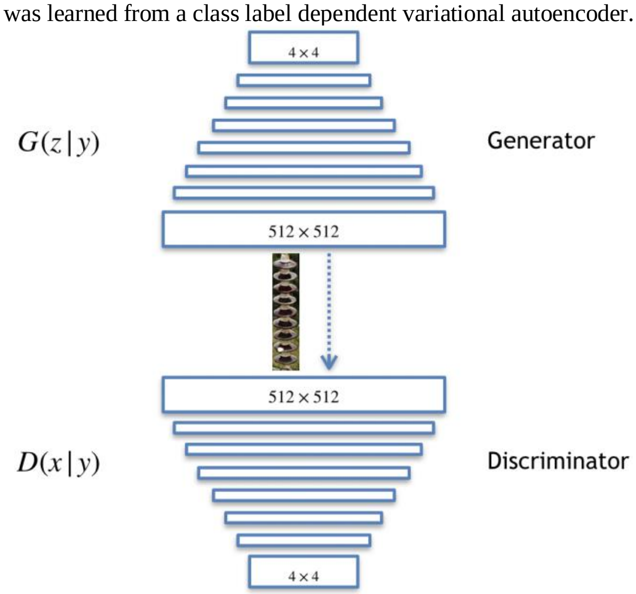

Figure 1. Architecture of BPGANs

4. DATA SET

Drones were used to take images of insulators. Raw insulator images were then annotated and labeled as damaged or undamaged. Next, images were cropped, and 3,861 individual insulators were obtained in total, among which 2,972 are good insulators and the rest of 989 insulators are damaged. 80% of images were used as training data set and the rest was equally split as validation and test data set. Some examples of insulators are shown in Figure 2. (a) is a raw image of insulator image taken by a drone. (b) and (c) are examples of good and damaged insulator, respectively.

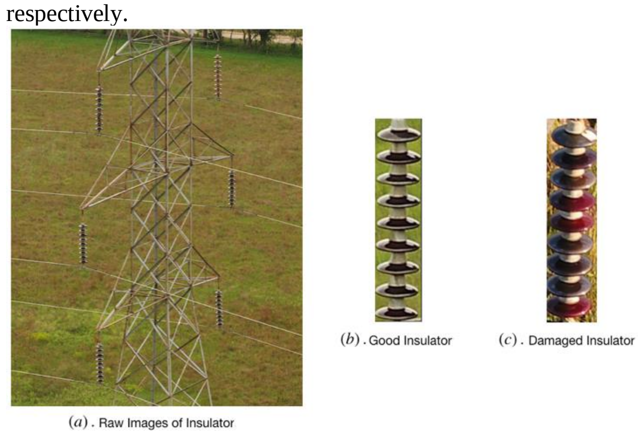

Figure 2. Examples of Insulators

5. RESULTS

In this section, results of various GANs models from the previous section, are discussed. GANs were trained with the purpose of augmenting the unbalanced data set, so different GANs were then used to generate minority-class images. Therefore, a DNN classifier trained with data set with and without augmentation was used to evaluate the quality of generated images by different GANs. In order to assess the diversity of images generated by GANs, structural similarity indices (SSIM) [27] were calculated and compared among different GANs.

5.1 Image Quality Assessment

Several examples of generated damaged insulators by BGANs are shown in Figure 3. BGANs is designed to work with images whose size is 64×64, and since the final output image resolution is 512×512, so the generated images from BGANs are blurry.

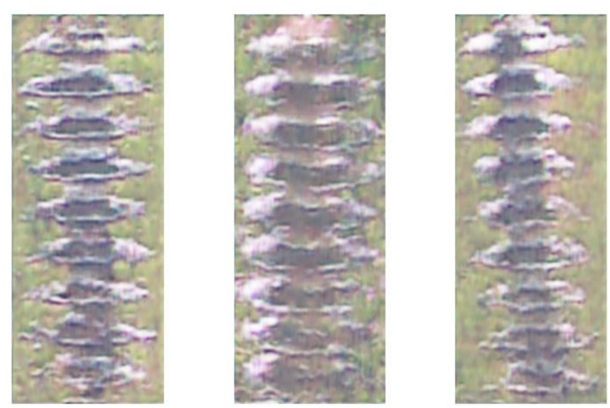

Figure 3. Damaged Insulator Examples Imagined by BGANs

Three examples of damaged insulators produced by AC-GANs are shown in Figure 4. AC-GANs produced images that have better quality than that of BGANs, but they are still blurry and difficult to distinguish damaged versus good insulators. This might be owing to that the classification loss was dominated by the source loss and much optimization was done to decrease the source loss.

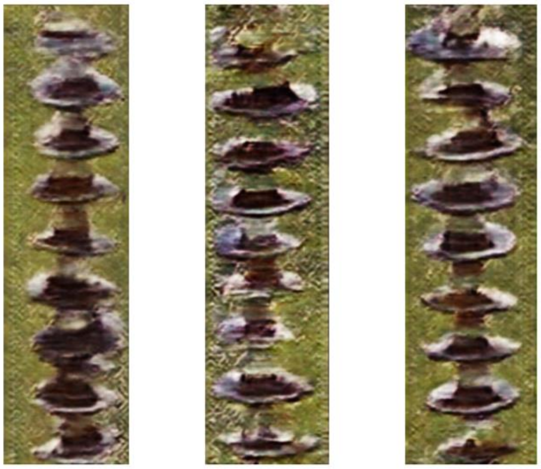

Figure 4. Damaged Insulator Examples Imagined by AC-GANs

Compared to images generated by BGANs and AC-GANs, StyleGANs was able to produce images with much higher quality. Four examples are shown in Figure 5, where the first three images are of better quality and the last one is one of the poorly produced image examples.

Figure 5. Damaged Insulator Images Imagined by StyleGANs

PGANs was able to produce images with similar quality as StyleGANs. Four examples are shown in Figure 6, where the first three images have better quality and the last one is a little blurry. Compare to images generated by StyleGANs, PGANs seems to be able to produce images with better image quality, where flashovers (white dots on insulators) are clearer to spot.

Figure 6. Damaged Insulator Examples Imagined by PGANs

BPGANs produced mixed results. Some damaged insulators are shown in Figure 7. (a) and (b) look like damaged insulators. (c) seems to be a good insulator and (d) and (e) are blurry. The reason that some damaged insulators imagined by BPGANs look like undamaged insulators might be because that the classification loss is too little compared to the source loss and more optimization was done to reduce the source loss.

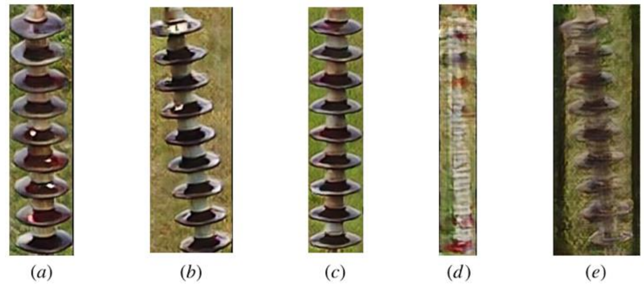

Figure 7. Damaged Insulator Examples Imagined by BPGANs

In order to assess the quality of generated images from GANs, the images were evaluated by a trained classifier. The rationale behind this assessment strategy is that more examples can be recognized as damaged by the trained classifier, the better the image quality. The results from different GANs are summarized in Figure 8. As it shows, the trained classifier only recognized nearly 30% of damaged insulators produced by BGANs as damaged, which makes sense as the image quality of the generated images is poor. AC-GANs achieved better results than BGANs. StyleGANs and PGANs produce images with much higher quality, and as a result more images are recognized as damaged. Since BPGANs generated images with mixed quality, it did not achieve highest result among all GANs. The results showed that PGANs, StyleGANs, and BPGANs produced images with high recognition rate.

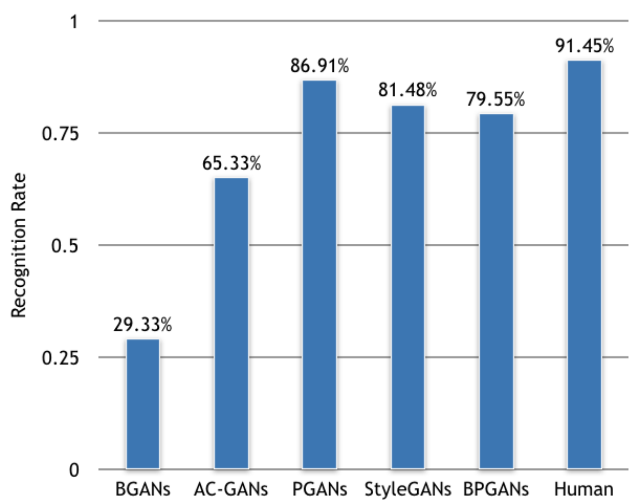

Figure 8. Recognition Rate of Damaged Insulators by Different GANs

5.2 Image Diversity Assessment

In order to assess how diverse the generated images are, SSIM values were calculated for images from different GANs. For each groups of images produce by GANs, 100 images were randomly selected and SSIM values were calculated. Figure 9 shows the maximum SSIM values and standard deviations for different GANs. Low similarity results from all of GANs indicated that images do not look like one another within each group.

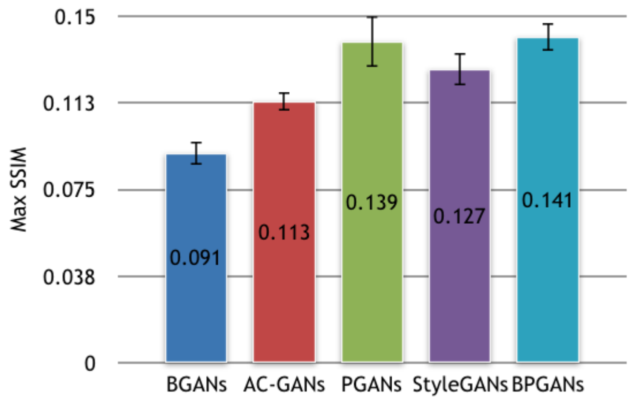

Figure 9. Similarity Comparison on Images Produced using GANs

To verify how similar imagined examples by GANs to the training examples, in other words whether the training overfitted, SSIM values were compared against the closest images in the training data set. Similarly, 100 images were randomly selected from each GANs-produced result, to which 100 closest images from the training set were chosen. Then, 100 closest images of the selected real images from the training set were chosen. Eventually, the two sets of SSIM values were calculated and compared.

Figure 10 shows the maximum SSIM values and standard deviations for different GANs. Bars labelled as fake are similarity results from the generated images by GANs and bars labelled as real are SSIM values for the training data set. Except for StyleGANs, all other GANs models produced images with low similarity values than the training data set, which indicates that the images produced by GANs are not similar to the training images and models did not overfit.

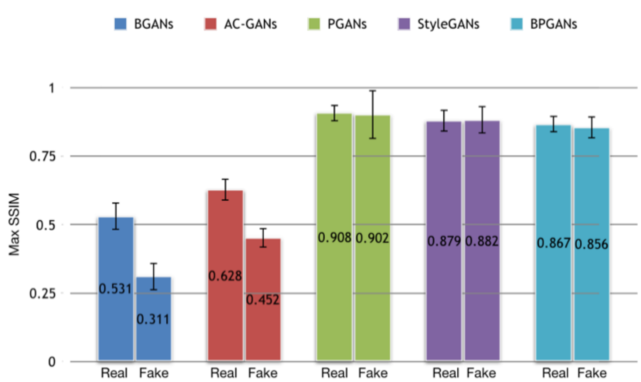

Figure 10. Similarity Comparison between Imagined Examples and Training Examples

5.3 Classification Results

The ultimate goal of this study is to utilize GANs to augment and balance the data set in hope that a better classifier can be obtained to distinguish damaged insulators and good insulators. Therefore, the final assessment is to train the same classifier on the augmented data set, observing if the classification performance would increase or not.

Figure 11 shows that the F1-scores and classification accuracy improved for all GANs, expect for the BGANs and AC-GANs, compared to the classifier trained on the original classifier. Results indicated that classifier trained on data set augmented by PGANs achieved highest F1-score and accuracy.

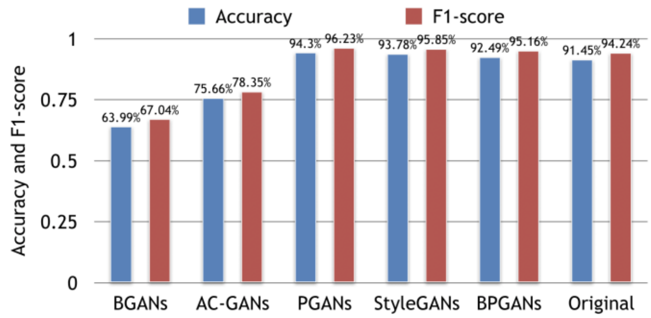

Figure 11. F1-score and Accuracy of Classifier Trained on Data set Augmented using GANs

6. CONCLUSION

Electricity is of great importance to ensure functionalities of all aspects of society, and thus regular electrical inspections are needed. Recent advances in deep learning has offered viable approaches to automate inspection jobs. However, data availability can restrict how deep learning can be successfully applied. Generative adversarial networks are capable of learning good representations of images and generate imagined ones based on learned representations. Therefore, in this study, extensive experiments have been conducted on generating images, especially damage insulators, based on GANs.

Results show that BGANs and AC-GANs are able to combine class label during training, and thus provide more information guiding the generation of damaged insulators. However, they are designed to produce relative low-resolution images, and thus images generated are blurry and even sabotage the classifier when augmenting the data set with images produced by them. StyleGANs and PGANs are capable to generate images of much higher quality because of the hierarchical architecture in both generator and discriminator. However, they are both trained only on the damaged insulators, and therefore does not make any use of information from the good insulators. Motivated by the advantages and drawbacks of existing GANs models, BPGANs is proposed. BPGANs is able to make full use of label information to generate images with good quality.

StyleGANs, PGANs, and BPGANs are able to produce damaged insulators examples with high quality. PGANs produced the best quality images with recognition rate about 87%, followed by StyleGANs (81%) and BPGANs (80%). The rest of GANs models failed to produce good quality images, having low recognition rate less than 70%. Low SSIM values by all the GANs models indicated that generated images are of great mode and are not similar to training data set. The classification accuracy and F1-score trained on the unaugmented data set is 91.45% and 0.9424. After augmenting the original data set, the classifier achieved higher F1-scores and classification accuracy. Highest improvement was seen on results from PGANs, with classification accuracy increased by about 3% and F1-score by 2%. StyleGANs and BPGANs also improved classification performance. The former achieved accuracy of 93.78% and F1-score of 0.9585, and the latter had accuracy of 92.49%, F1-score of 0.9516. BGANs and AC-GANs degraded the classification performance compared to the baseline as images generated by the two were of low quality.

The reason why BPGANs had difficulties distinguishing good versus damaged insulators might be because the classification loss is too little in magnitude compared to the source loss, which tried to tell if the images shown to the discriminator are from real or fake images. As a result, the optimizer focused more on optimizing the parameters to reduce the source loss. Another reason might be because there are only two class labels, which only provide 2 additional latent codes compared to original 512 latent codes, having limited effect on the model. Results indicated that learning representations of data progressively from low resolution to high resolution is an effective approach, however, embedding class label information in the fashion of AC-GANs and BGANs might not be appropriate for augmenting binary class data sets.

7. ACKNOWLEDGMENTS

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8. REFERENCES

[1] Arsenovic, M., Karanovic, M., Sladojevic, S., Anderla, A., and Stefanovic, D. 2019. Solving current limitations of deep learning based approaches for plant disease detection. *Symmetry, 11*(7), 939.

[2] Chen, K., Pang, J., Wang, J., Xiong, Y., Li, X., Sun, S., and Loy, C. C. 2019. Hybrid task cascade for instance segmentation. In *Proceedings of the IEEE conference on computer vision and pattern recognition* (pp. 4974-4983).

[3] Denton, E. L., Chintala, S., and Fergus, R. 2015. Deep generative image models using a laplacian pyramid of adversarial networks. In *Advances in neural information processing systems* (pp. 1486-1494).

[4] Durugkar, I., Gemp, I., and Mahadevan, S. 2016. Generative multi-adversarial networks. *arXiv preprint arXiv:1611.01673*.

[5] Goodfellow, I., Pouget-Abadie, J., Mirza, M., Xu, B., Warde-Farley, D., Ozair, S., ... and Bengio, Y. 2014. Generative adversarial nets. In *Advances in neural information processing systems* (pp. 2672-2680).

[6] Gulzar, M. A., Kumar, K., Javed, M. A., and Sharif, M. 2018, February. High-voltage transmission line inspection robot. In *2018 International Conference on Engineering and Emerging Technologies (ICEET)* (pp. 1-7). IEEE.

[7] He, K., Zhang, X., Ren, S., and Sun, J. 2016. Deep residual learning for image recognition. In *Proceedings of the IEEE conference on computer vision and pattern recognition* (pp. 770-778).

[8] Huang, X., Li, Y., Poursaeed, O., Hopcroft, J., and Belongie, S. 2017. Stacked generative adversarial networks. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition* (pp. 5077-5086).

[9] Karras, T., Aila, T., Laine, S., and Lehtinen, J. 2017. Progressive growing of gans for improved quality, stability, and variation. *arXiv preprint arXiv:1710.10196*.

[10] Karras, T., Laine, S., and Aila, T. 2019. A style-based generator architecture for generative adversarial networks. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition* (pp. 4401-4410).

[11] Katrasnik, J., Pernus, F., and Likar, B. 2009. A survey of mobile robots for distribution power line inspection. *IEEE Transactions on power delivery*, *25*(1), 485-493.

[12] Krizhevsky, A., Sutskever, I., and Hinton, G. E. 2012. Imagenet classification with deep convolutional neural networks. In *Advances in neural information processing systems* (pp. 1097-1105).

[13] Leevy, J. L., Khoshgoftaar, T. M., Bauder, R. A., and Seliya, N. 2018. A survey on addressing high-class imbalance in big data. *Journal of Big Data*, *5*(1), 42.

[14] Mariani, G., Scheidegger, F., Istrate, R., Bekas, C., and Malossi, C. 2018. Bagan: Data augmentation with balancing gan. *arXiv preprint arXiv:1803.09655*.

[15] Mirza, M., and Osindero, S. 2014. Conditional generative adversarial nets. *arXiv preprint arXiv:1411.1784*.

[16] Nguyen, V. N., Jenssen, R., and Roverso, D. 2018. Automatic autonomous vision-based power line inspection: A review of current status and the potential role of deep learning. *International Journal of Electrical Power & Energy Systems*, *99*, 107-120.

[17] Odena, A., Olah, C., and Shlens, J. 2017, August. Conditional image synthesis with auxiliary classifier gans. In *Proceedings of the 34th International Conference on Machine Learning-Volume 70* (pp. 2642-2651). JMLR. org.

[18] House, W. 2013. Economic benefits of increasing electric grid resilience to weather outages. *Washington, DC: Executive Office of the President*.

[19] Radford, A., Metz, L., and Chintala, S. 2015. Unsupervised representation learning with deep convolutional generative adversarial networks. *arXiv preprint arXiv:1511.06434*.

[20] Redmon, J., Divvala, S., Girshick, R., and Farhadi, A. 2016. You only look once: Unified, real-time object detection. In *Proceedings of the IEEE conference on computer vision and pattern recognition* (pp. 779-788).

[21] Ren, S., He, K., Girshick, R., and Sun, J. 2015. Faster r-cnn: Towards real-time object detection with region proposal networks. In *Advances in neural information processing systems* (pp. 91-99).

[22] Shruthi, C. M., Sudheer, A. P., and Joy, M. L. 2019. Dual arm electrical transmission line robot: motion through straight and jumper cable. *Automatika*, *60*(2), 207-226.

[23] Szegedy, C., Liu, W., Jia, Y., Sermanet, P., Reed, S., Anguelov, D., and Rabinovich, A. 2015. Going deeper with convolutions. In *Proceedings of the IEEE conference on computer vision and pattern recognition* (pp. 1-9).

[24] Woodward, M. 2019. *Record U.S. Electricity Generation in 2018 Driven by Record Residential, Commercial Sales*. U.S. Energy Information Administration.

[25] Yang, J., Kannan, A., Batra, D., and Parikh, D. 2017. Lr-gan: Layered recursive generative adversarial networks for image generation. *arXiv preprint arXiv:1703.01560*.

[26] Zhang, H., Xu, T., Li, H., Zhang, S., Wang, X., Huang, X., and Metaxas, D. N. 2017. Stackgan: Text to photo-realistic image synthesis with stacked generative adversarial networks. In *Proceedings of the IEEE International Conference on Computer Vision* (pp. 5907-5915).

[27] Wang, Z., Bovik, A. C., Sheikh, H. R., and Simoncelli, E. P. 2004. Image quality assessment: from error visibility to structural similarity. *IEEE transactions on image processing*, *13*(4), 600-612.

[28] Zhu, J. Y., Park, T., Isola, P., and Efros, A. A. 2017. Unpaired image-to-image translation using cycle-consistent adversarial networks. In *Proceedings of the IEEE international conference on computer vision* (pp. 2223-2232).

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