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A SURVEY ON IMAGE SUPER-RESOLUTION USING ESRGAN

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***Abstract*— Conversion of a low-resolution image to a high-resolution image, the process is known as Super Resolution (SR), and it has important applications in a variety of sectors, including object recognition, medical imaging, satellite remote sensing, and more. To create the model and comprehend image super-resolution in this paper, Enhanced Super-Resolution Generative Adversarial Networks (ESRGAN) [8] was used. Additional expanded data is kept by adding residual blocks between neighbouring convolutional layers of the GAN generator. At the same time, the coaching outcome is improved and image super-resolution is attained by using the Wasserstein distance as a loss operation.**

Keywords*—*Image Super Resolution, ESRGAN, SRGAN, Residual-in-Residual Block

I. INTRODUCTION

Researchers and AI companies are increasingly interested in single image super-resolution (SISR)[8]. SISR converts a low-resolution (HR) image to a single high-resolution (LR) image. The peak signal-to-noise ratio (PSNR) number in particular has seen constant improvements in SR performance thanks to various network architectural designs and training approaches. But the PSNR metric contradicts human observers' subjective judgement, these PSNR-oriented approaches usually produce too smoothed results with insufficient high-frequency information.

The addition of Xintao Wang's *et al* [8] . Generative Adversarial Network (GAN) to SR pushes the network to select solutions that resemble nearly natural images. SRGAN is a key development in locating aesthetically appealing outcomes. The basic model in a GAN framework is constructed using residual blocks and improved using perceptual loss. Super-Resolution GAN(SRGAN) significantly outperforms PSNR-focused methods in terms of overall visual quality of reconstruction using all these techniques.

The difference between SRGAN results and ground-truth (GT) photos is still visible, though. The key SRGAN components are revisited and three features of the model are improved in the study of Xintao Wang et al. [8]. First, the Residual-in-Residual Dense Block (RDDB), is added to improve the network structure. In order to make training a very deep network easier,

batch normalisation (BN) layers are also eliminated. Second, Relativistic average GAN (RaGAN) is utilised to enhance the discriminator. RaGAN learns to judge "whether one image is more realistic than the other" rather than "if one image is real or fake." This enhancement aids the generator in recovering more realistic texture information. Thirdly, it is suggested that a better perceptual loss be achieved by utilising VGG features prior to activation rather than later as in SRGAN. They discover empirically that the modified perceptual loss produces results with edges that are sharp and more aesthetically acceptable outcomes. The extended SRGAN, also known as ESRGAN, routinely beats the best techniques in terms of sharpness & detail, according to extensive testing.

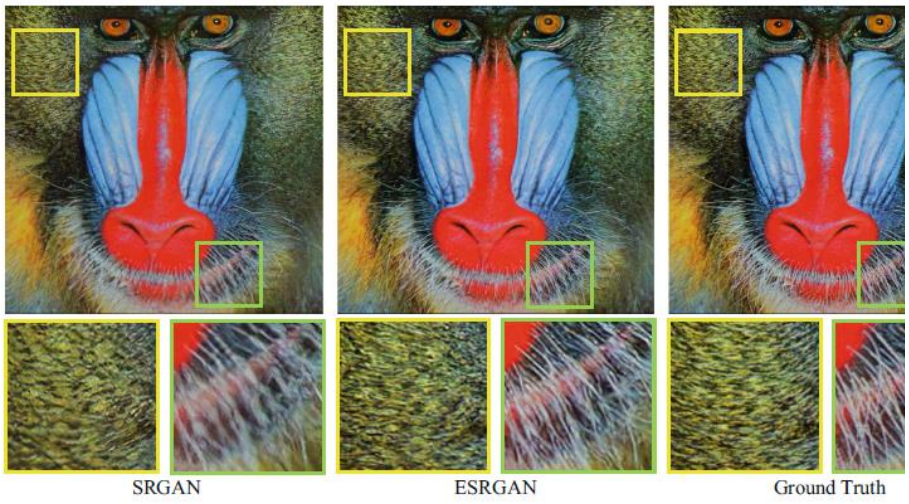

Fig. 1 The super-resolution results of x4, the suggested ESRGAN and the ground truth. The crispness and details of ESRGAN surpass those of SRGAN. [8]

II. LITERATURE REVIEW

In this section, we go over a few ESRGAN algorithm approaches and applications.

Xintao Wang, *et al.* have proposed "Image Resolution by Enhanced Super-Resolution Generative Adversarial Networks" to further enhance the image resolution produced by SRGAN model. To enhance the SRGAN model, Batch Normalization (BN) layers [18] were removed, and Residual-in-Residual Block (RRDB) was added. Comparing this strategy to the SRGAN model, the quality was higher. [8]

The authors of "Deep Learning for Remote Sensing Image Super-Resolution" Md Reshad Ul Hoque *et al.* sought to boost image resolution while maintaining the quality of the original image. This study suggests deep learning-based image super-resolution approaches combined with Convolutional Neural Network(CNN) and GAN in order to quadratically boost the resolution of remote sensing data. The experiment's findings show that GAN models perform admirably visually but poorly in terms of image quality. [5]

"AIM 2019 Challenge on Real-World Image Super-Resolution: Methods and Results" by K. Purohit *et al.* focused on the collaborating ways and final results. They utilized a fine-tuned ESRGAN network in an exceedingly and very absolutely supervised manner, by applying the artificial degradation operation. SR model enabled by ESRGAN is then trained using the generated knowledge, which enhances the model's performance on real-world data. [3]

"3D Brain MRI Reconstruction based on 2D Super-Resolution Technology" by Zhang Hongtao *et al.* states that ESRGAN was used to gather frequent details in the SR reconstruction of 2-D MRI slices, which was based on super-resolution GAN. They rebuilt reconstructed 2-D images into a 3-D form using the 2-D SR approach on slices from three entirely distinct latitudes. Following that, the null value of each slice was interpolated based on the linear interpolation concept to create the three-dimensional reconstruction of the brain MRI scan. [1]

Jie Song *et al.* have proposed "Dual Perceptual Loss for Single Image Super-Resolution Using

ESRGAN" which fixes the issue of the reconstructed image being too smooth due to per pixel difference loss. Additionally, the super-resolution field is used to apply GANs, which significantly enhances the visual quality of the rebuilt image. In order to address the issue of single-image super-resolution reconstruction, this article suggests a method known as Dual Perceptual Loss, which is used to replace the original perceptual loss. [6]

"A Lightweight Image Super-Resolution Network Based on ESRGAN for Rapid Tomato Leaf Disease Classification" by Lei Zha, *et al.* illustrates losses due to crop diseases can be reduced by studying crop image super-resolution reconstruction using ESRGAN. In this paper, Shuffle Blocks were introduced in place of RRDBs in the ESRGAN. The classification is done by using the VGG16 CNN.[9]

"Artificial Intelligence (Enhanced Super-Resolution Generative Adversarial Network) for Calcium Deblooming in Coronary Computed Tomography Angiography: A Feasibility Study" paper published by Curtise K. C. Ng and Zhonghua Sun used ESRGAN approach to bring down the blooming artefact in Coronary Computed Tomography Angiography (CCTA) and resolve its result on rising the diagnostic performance of CCTA in calcified plaques. This demonstrates the potential benefit of images that have undergone ESRGAN processing in upgrading the diagnostic value of CCTA for patients with calcified plaques.[4]

"Enhanced Super Resolution for Remote Sensing Imageries" by S. Kakuta *et al.* explored the efficiency of the ESRGAN models for remote sensing images by conducting two experiments for two different levels of resolution. The first experiment was designed to evaluate the model performance of the resolution of satellite images from degraded images. The second experiment trained a model to resolve S2(Sentinal-2 mission of the European Space Agency) four-fold.[7]

Lihui Sun and Yiyou Zhao in their paper "Research on Infrared Image Super-Resolution Based on Enhanced Generative Adversarial Network" presents a way to revamp the nature of IR (infrared) images in an enhanced model. This was accomplished by enhancing the first ESRGAN model with a residual module and an attention mechanism. An improvement in image texture and sharper fine features were discovered when comparing the improved version to the original ESRGAN model.[11]

Chengkun Song *et al.* in the paper "Low-Resolution Face Recognition System Based on ESRGAN" present a method to improve the accuracy of Low-Resolution Face Recognition (LRFR). They have compared the two methods of SRGAN and ESRGAN, concluding with the latter having higher accuracy than the former method. [10]

III. SUMMARY ON LITERATURE SURVEY

Author Name	Method Used	Dataset	Findings
Wenlong Zhang *et al.* [13]	Use Ranker SRGAN to optimise the generator for perceptual metrics (RankSRGAN).	Adopted to use Rank Dataset	The best NIQE and PI performance was achieved for RankSRGAN.
Shunta Maeda [19]	GAN-based unpaired SR technique that works without paired or aligned training data.	Diverse datasets like DOTA validation set, LR test set provided by Bulat *et al.* [2]	The proposed approach to the unpaired SR problem is superior to the ones now in use.
Xintao Wang *et al.* [14]	Models that have been trained using simulated	Adopted DIV2K, Flickr2K and Outdoor Scene Training datasets for training.	Extended the powerful ESRGAN to a practical restoration application,

	data for the standard deterioration model		
Yunxuan Wei, *et al.* [20]	DASR - Domain-Distance aware super-resolution approach.	Synthetic and real datasets	Results on real-world and synthetic datasets demonstrated the technique's applicability for real-world SR.
Yuwu Wang, *et al.* [18]	ESRGAN is utilised by the Target Detection on Super-Resolution Reconstruction (TdoSR) approach.	The DOTA-v1.5 remote sensing picture dataset.	Comparing the TdoSR method's recognition rate to low-resolution foggy remote sensing photos revealed a 20% increase.
Étienne Clabaut *et al.* [12]	Single image super-resolution (SISR) Haralick	Datasets–DIV2K Airborne WorldView HiRISE imagery	Specialised ESRGAN model for a particular task as opposed to attempting to increase example variability.
Yu-Zhang Chen, *et al.* [17]	Edge Enhanced Network (EEN), Ultra-Dense Subnet (UDSN), and (EEN).	Kaggle open experimental dataset	Images with enhanced visual quality can be produced using the super-resolution technique. The suggested approach outperforms the SR approaches that use satellite imagery currently.
Qiang Wang, *et al.* [15]	ESRGAN-based SR method.	The generative loss function is composed of three components: energy-based regularisation, adversarial loss, and content loss.	EGAN-based super-resolution algorithm. Convolutional skip-convolution and the Laplacian pyramid have both gained acceptance.
Habeeb Salaudeen and Erbu ˘g Çelebi [21]	ESRGAN and a detection network.	Using the EfficientDet and You Only Look Once (YOLOv5) networks.	Results produced by models that were trained on LR images had substantially lower mAP values than the methods that were suggested.
Yunhe Li, *et al.* [16]	Model TS-SRGAN (Two-Step Super-Resolution Generative Adversarial Network)	Sentinel-2 satellites' photos with a 10 m resolution	A typical NIQE as low as 2.54 outperformed cutting-edge models.

IV. METHODOLOGY

We can apply the methodology proposed by Xintao Wang et al. [8] in their study, in which they go through the key features of SRGAN and upgrade the model. Firstly, the introduction of the Residual-in RDDB, in the network structure and removal of BN layers. Secondly, the discriminator is enhanced using RaGAN, which judges "whether an image is more realistic than the other" rather than "whether an image is real or fake“. The generator recover additional realistic texture details with the help of RaGAN. Thirdly, an improving perceptual loss is by exploiting the VGG features before activation rather than after activation as in SRGAN.

ESRGAN model is develops more realistic high-resolution images through the following strategies:

1. Generator: Adding residual-in-residual dense block layers and removing batch normalization layers from the SRGAN.
2. Discriminator: Implementation of the relativistic average discriminator to determine whether or not a picture is more realistic rather than "real" or "fake".
3. Loss function: For better control of the brightness and texture of the image, perceptual loss should be assessed using the VGG features prior to the activation employed in the SRGAN.

V. CONCLUSION

In this essay, we've covered a number of techniques for enhancing low-resolution photos to a higher resolution utilising the ESRGAN and its uses in a variety of domains, including object recognition and infrared imaging. This model has been determined to be superior to a few other ones that have been put forth.

The accuracy and processing speed of picture improvement, as well as the use of datasets from other domains, will be improved in next work.

VI. REFERENCES

[1] Yoshida, S., Shinomiya, Y. and Hongtao, Z., 2020, October. 3D brain MRI reconstruction based on 2D super-resolution technology. In *2020 IEEE international conference on systems, man, and cybernetics (SMC)* (pp. 18-23). IEEE.

[2] Yang, J. ,Tzimiropoulos, G.and Bulat, A., 2018. To learn image super-resolution, use a gan to learn how to do image degradation first. In *Proceedings of the European conference on computer vision (ECCV)* (pp. 185-200).

[3] Purohit, K., Lugmayr, A., Joon, N.H., Danelljan, M., Timofte, R., Gu, S., Kandula, P., Suin, M., Rajagoapalan, A.N. and Won, Y.S., 2019, October. Aim 2019 challenge on real-world image super-resolution: Methods and results. In *2019 IEEE/CVF International Conference on Computer Vision Workshop (ICCVW)* (pp. 3575-3583). IEEE.

[4] Ng, C.K. and Sun, Z., 2022. Artificial Intelligence (Enhanced Super-Resolution Generative Adversarial Network) for Calcium Deblooming in Coronary Computed Tomography Angiography: A Feasibility Study. *Diagnostics*, *12*(4), p.991.

[5] Burks, R., Li, J., Hoque, M.R.U. and Kwan, C., 2019, October. Deep learning for remote sensing image super-resolution. In *2019 IEEE 10th Annual Ubiquitous Computing, Electronics & Mobile Communication Conference (UEMCON)* (pp. 0286-0292). IEEE.

[6] H., Xu, Song, J., Li, B., Yi, W., Li, X. and Liu, Y., 2022. Dual Perceptual Loss for Single Image Super-Resolution Using ESRGAN. *arXiv preprint arXiv:2201.06383*.

[7] Kakuta, S., Kapilaratne, R.G.C.J. and Kaneta, S., 2022. ENHANCED SUPER RESOLUTION FOR REMOTE SENSING IMAGERIES. *ISPRS Annals of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, *3*, pp.53-60.

[8] Wu, S., Wang, X., Yu, K., Liu, Y., Dong, C., Qiao, Y., Gu, J. and Change Loy, C., 2018. Esrgan: Enhanced super-resolution generative adversarial networks. In *Proceedings of the European conference on computer vision (ECCV) workshops* (pp. 0-0).

[9] Zha, L., Shi, Y. and Wen, J., 2022. A Lightweight Image Super-Resolution Network Based on ESRGAN for Rapid Tomato Leaf Disease Classification. In *The International Conference on Image, Vision and Intelligent Systems (ICIVIS 2021)* (pp. 97-110). Springer, Singapore.

[10] Song, C., He, Z., Yu, Y. and Zhang, Z., 2021, July. Low Resolution Face Recognition System Based on ESRGAN. In *2021 3rd International Conference on Applied Machine Learning (ICAML)* (pp. 76-79). IEEE.

[11] Sun, L. and Zhao, Y., 2022, July. Research on Infrared Image Super-Resolution Based on Enhanced Generative Adversarial Network. In *2022 International Conference on Computer Engineering and Artificial Intelligence (ICCEAI)* (pp. 334-338). IEEE.

[12] Lemelin, M., Clabaut, É., Germain, M., St-Pierre and T. Bouroubi, Y., 2021. Model Specialization for the Use of ESRGAN on

Satellite and Airborne Imagery. *Remote Sensing*, *13*(20), p.4044.

[13] Liu, Y., Zhang, W., Qiao, Y. and Dong, C., 2019. Ranksrgan: Generative adversarial networks with ranker for image super-resolution. In *Proceedings of the IEEE/CVF International Conference on Computer Vision* (pp. 3096-3105).

[14] Dong, C., Xie, L., Wang, X. and Shan, Y., 2021. Real-esrgan: Training real-world blind super-resolution with pure synthetic data. In *Proceedings of the IEEE/CVF International Conference on Computer Vision* (pp. 1905-1914).

[15] Li, G., Zhou, H., Wang, Q. and Guo, J., 2022. Single Image Super-Resolution Method Based on an Improved Adversarial Generation Network. *Applied Sciences*, *12*(12), p.6067.

[16] Wu, S., Wang, Y., Li, Y. and Li, B., 2022. Super-Resolution of Remote Sensing Images for× 4 Resolution without Reference Images. *Electronics*, *11*(21), p.3474.

[17] Chen, Y.Z., Liu, K.H. and Liu, T.J., 2022, January. Super-Resolution of Satellite Images Based on Two-Dimensional RRDB and Edge-Enhanced Generative Adversarial Network. In *2022 IEEE International Conference on Consumer Electronics (ICCE)* (pp. 1-4). IEEE.

[18] Sun, G., Wang, Y. and Guo, S., 2021, October. Target Detection Method for Low-Resolution Remote Sensing Image Based on ESRGAN and ReDet. In *Photonics* (Vol. 8, No. 10, p. 431). MDPI.

[19] Maeda, S., 2020. Unpaired image super-resolution using pseudo-supervision. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition* (pp. 291-300).

[20] Gu, S., Wei, Y., Li, Y., Jin, L., Timofte, R. and Song, H., 2021. Unsupervised real-world image super resolution via domain-distance aware training. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition* (pp. 13385-13394).

[21] Çelebi, E. and Salaudeen, H., 2022. Pothole Detection Using Image Enhancement GAN and Object Detection Network. *Electronics*, *11*(12), p.1882.