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Preface

This volume contains the papers presented at ITED 2022: Information Technology for Education and Development held on 1-3rd December 2022 in ABUJA, Nigeria.

On behalf of the organizing committee, it is my honor to welcome you to ITED22. After previous editions with the IEEE consultants' network and Computer society, we are finally able to provide an on-site edition hosted by AITP at Nile University Abuja, Nigeria. There were 177 submissions. Each submission was reviewed by at least 1, and on average 2.0, program committee members. The committee decided to accept 143 papers. The program also includes 7 invited talks.

On top of the disruptive research in technology evolution, we have presented technical tracks, and have also gathered panel sessions, keynotes, and workshops. These are all valued by our experts and knowledge leaders. As is known, the ITED 2022 Conference considered evolving trends in both academic and industry research domains. We believe that ITED 2022 provides the needed opportunity to gain new understanding and record significant progress across multi-disciplinary fields. I will be looking forward to meeting you in Abuja Nigeria.

Putting together a good conference is feasible with only a winning team. I thank the leadership of the IEEE Nigeria Section and I give special appreciation to the publication Chair, Prof Faruk Nasir, and other members of the Technical Program Committee as well as the members of the organizing committee. Without you, this conference would not have been possible. The efforts of the reviewers working at Universities and Institutions from around the world are appreciated. They devoted their resources to ensure a high-quality review process. Many thanks!

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Finally, I would like to express my gratitude to all authors whose research results have been published in ITED 2022 Proceedings and IEEE Xplore digital library for their in-depth evaluations.

We hope that ITED 2022 inspires and entices you to submit your contributions to the upcoming IEEE Nigeria Section Conference in 2023.

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Thank you for sharing your wisdom.

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Kennedy Chinedu Okafor, *PhD, FASI*, *Senior Member, IEEE*
General Conference Co-Chair & Chair, Technical Program Committee.
ITED 2022.

December 30, 2022

Kennedy Okafor
Afolayan Obiniyi
Faruk Nasir
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2022 5th Information Technology for Education and Development (ITED)

A Concept-Based Review on Generative Adversarial Network for Generating Super Resolution Medical Image Using SWOT Analysis

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***Abstract*—Several alarming health challenges are urging medical experts and practitioners to research and develop new approaches to diagnose, detect and control the early spread of deadly diseases. One of the most challenging is Coronavirus Infection (Covid-19). Models have been proposed to detect and diagnose early infection of the virus to attain proper precautions against the Covid-19 virus. However, some researchers adopt parameter optimization to attain better accuracy on the Chest X-ray images of covid-19 and other related diseases. Hence, this research work adopts a hybridized cascaded feature extraction technique (Local Binary Pattern LBP and Histogram of Oriented Gradients HOG) and Convolutional Neural Network CNN for the deep learning classification model. The merging of LBP and HOG feature extraction significantly improved the performance level of the deep-learning CNN classifier. As a result, 95% accuracy, 92% precision, and 93% recall are attained by the proposed model.**

***Keywords*— GAN, medical image, swot analysis, super-resolution, concept based**

I. INTRODUCTION

In recent years Generative Adversarial Networks (GAN) are now popularly used in processing, diagnosing, and generating high-resolution images [1][2]. Super-resolution (SR) denotes the approach used for improving spatial resolution in digital imaging. Several algorithms have been developed to achieve higher resolutions on natural images, satellite images, and medical images [3]. In medical image analysis, medical experts frequently use medical imaging systems such as Nuclear Magneti Resonance Imaging (MRI), Positron Emission Computed Topography (PET-CT), and Ultrasound (US) for performing image analysis. This traditional technique used by medical experts generates low-resolution images with noise and structurally low data due to technology limitations and hardware devices. Single-image super-resolution is frequently used in the Artificial Intelligent community to generate a high-resolution image from a low-resolution image [4].

However, single image super-resolution (SISR) technology is majorly divided into three groups, this includes [5] Edge-based, Image-based statistics, and Sample-based methods. Furthermore, the GAN model is currently state-of-art in computer vision and it can be utilized in constructing augmented data (new sample data) and learning adversarial samples. The Generative adversarial model can also be used in generating medical super-resolution images from Radiography MR1 [6].

A Generative Adversarial Network (GAN) is a special deep neural network architecture used in computer vision and image processing, the architectural model consists of two networks that are trained simultaneously [7]. The first network is majorly based on image generation and the other is centered on image discrimination. The GAN model is currently the top-notch model for generating augmented images, super-resolution imaging, and image-to-image translations [8].

SWOT analysis is one of the most widely used methods in gathering facts about a system or concept using four main components thus, strengths, weaknesses, opportunities, and threats. The utilization and adoption of SWOT analysis are common in management, engineering, agriculture, medical care, and medical sectors. The approach considers strengths (positive aspects of the system), weaknesses (Limitations or negative aspects associated with the system), opportunities (opportunities in the future), and threats (which can negatively affect the system adversely). The use of SWOT analysis is widely adopted in the domain of medicine for medical approach analysis, medical equipment evaluation, and other areas in the domain [10] [11]

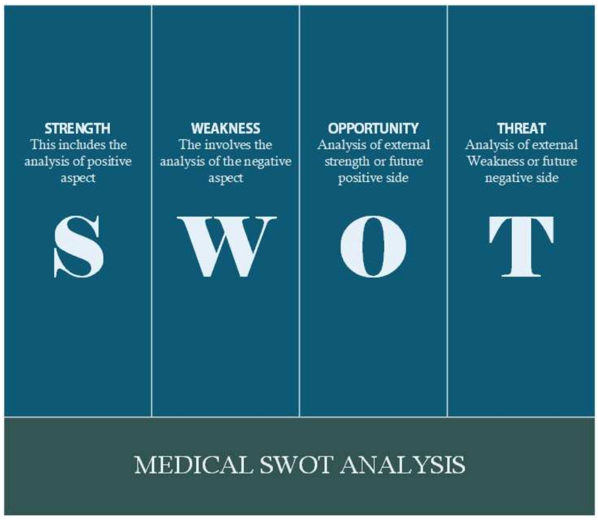

Fig. 1 The SWOT Analysis Approach

The Super Resolution for medical imagining using Generative adversarial Network is still under development, and various diversity of GAN has been designed for generating high-resolution images in the medical domain [3]. Hence, it's essential to present and organize the current strength, weaknesses, and futuristic opportunities of the existing GAN's Architecture for generating medical super-resolution images.

This study aims to adopt a conceptual-based and SWOT analysis approach to identify Strengths (Usability /Advantages), Weaknesses (Limitations), Opportunities (Probability of futuristic usability), and Threats (Future limitations) of existing GAN variants for generating Medical Super-Resolution Images.

II. LITERATURE REVIEW

A. CONCEPTUAL APPROACH

A conceptual approach is considered in this sturdy for proper review of the characteristics or properties that affect the efficiency and performance of various Generative adversarial Networks used for generating super-resolution medical images.

Gupta et al [6] Generate a Super-resolution image of Lungs Radiology MRI medical scan for tuberculosis using GAN's approach. The paperwork adopts a transfer learning approach on the generative neural network and trains their discriminator network from scratch using perceptual loss. The image datasets are all sampled in other too minimize the similarities between data. This ensures that data are not overfitting. The researcher uses the Neuroimaging Informatics Technology Initiative (NIFTI-1) to achieve this, and this leads to further filtering and cleaning of the inconsistent and biased image dataset. This preprocessing improved the efficiency of the network.

Zhu [12] and other researchers (2020) Proposed CSRGAN for generating super-resolution images for medical use, the generative adversarial network hybridized CGAN, and SRGAN for achieving the proposed novel super-resolution. The sturdy uses the Jacobian Determinant (JD) and the Curl Vector (CV) geometric information for the conditional input of both the generator and the discriminator SRGAN. However, for the content loss, the CV feature is used instead of the VGG loss in the SRGAN. The architecture is trained on the Celeb-Faces large-scale dataset and evaluated on 1000 low-resolution images of a clinical ultrasound image.

The MIASSR approach for generating super-resolution medical images is proposed by Zhu and others in 2021 [11]. The researcher identifies that existing work is limited only to scale specific Single Resolution tasks, and there are no generalized over-magnification scales. Hence, the sturdy proposes a Medical Image Arbitrary Scaled Super-Resolution Image (MIASSR). The MIASSR is integrated with some metadata learning using generative adversarial networks (GANs) to generate super-resolution images of any magnification scale. The network is trained on T1-weighted brain MR Images and MR scan multi-modal images. Furthermore, the researchers also adopt a transfer learning mechanism to ensure that the MIASSR is capable of tackling new medical modalities, such as COVID-CT tomography-computed images and Cardiac MR images. It's clearly shown that the MIASSR approach can potentially become the baseline technique for pre/post-processing steps in analyzing clinical images such as image quality enhancement, image segmentation, and image reconstruction.

[13] In this study illumination and structure constrain GAN for the enhancement of medical image was adopted. This study aims to resolve the issue of global appearance, without enforcing limitations on illumination. The researcher proposed a StillGAN (Structural and illuminated constrained GAN), which contains important features for interpreting medical images. The approach is used for enhancing medical image quality, by differentiating or classifying high-quality and low-quality images. The strength of the proposed method is how it adopts illumination constraints and local structure in overall attribute and local details learning.

[4] This study proposed an Enhanced SRGAN called the ESRGAN architecture, to improve on the existing architecture. The researcher had to study the basic building block of the SRGAN network. This includes perceptual loss and adversarial loss. The residual-in-residual dense block (RRDB) is utilized without the normalization batch for building the network basic block. In addition, an improvement was made in the perceptual loss by considering the feature before the activation. The proposed approach achieved an efficient image quality with a more realistic attribute than SRGAN.

The resulting blurry image and noise features which come as a result of the auto-encoder network bottleneck and insufficient constraints were identified and addressed using the Cycle-GAN [14]. In other to improve on these limitations the researcher proposes a more accurate synthesized and meaningful approach to generating a medical image. A weight-based feature transfer for a Generative adversarial network is proposed (WFT-GAN) to improve image quality. A weight feature transfer is adopted instead of the traditional skill connection, this is done to minimize the encoding information inference on image decoding. The generated image is more realistic and meaningful due to the combination of local perceptual adversarial loss with a feature map of VGG and adversarial mode.

[15] Kudo along with other researchers in the year 2019 proposed a Conditional Generative Adversarial Network for generating a high-resolution image of major body parts, which includes; the abdomen, leg, chest, and head. The traditional GAN suffers from a situation called mode collapse. Hence, this sturdy address this issue by proposing a conditional discriminator on the various body part. In addition, the generator network is expanded to a fully connected 3-Dimensional Convolutional Neural Network,

this result in the generation of a high-resolution image from diverse fields. It expects this approach to contribute significantly to the existing large amount of thick CT images that are stored in the hospitals.

The lack of image data in the domain of skin cancer for training supervised Convolution Neural Networks has limited the CNN performance in solving various tasks [16]. Hence, the researcher proposed a Generative adversarial network to produce synthetic Skin cancer images. This generated image is merged with existing data for training. Using the hybridized dataset (synthetic and existing data) for CNN training an accuracy of 71% is achieved, while an accuracy of 53% is attained using only the existing dataset.

The CP-GAN was developed by Zeng [17] and is based on attention mechanism and content preservation loss for improving medical image quality. The architectural design is developed in three stages, in which each stage creates a feature map in which various scales combined with attention features serve as input for the next stage. The adopted content preservation loss can dramatically increase the similarity between the generated image and the real image. This approach can effectively save the hospital storage resources and enhance the accuracy and speed of the doctor's diagnosis.

The use of a Generative Adversarial Network for generating synthetic gastrointestinal images was proposed by Adjei in 2020 [18]. The training of the proposed network is highly dependent on segmented maps prepared by clinicians' experts. This is done to generate a synthetic image of gastrointestinal images from a segmentation map. The sturdy helps in addressing the challenges of data scarcity.

[19] The generation of high-resolution images synthetically can be highly useful for data classification.

III. FINDINGS

Augmentation, detection of outlier distribution, and specifically Full Field Digital Mammograms (FFDM). The researchers adopted the MammoGAN model to generate mammograms at the highest report resolution reported so far thus, 1280x1024 pixels. Learning diverse features from low-resolution images is highly difficult to achieve using a deep learning algorithm. The infrared images that are produced by optical equipment are of low-resolution images and it's difficult to obtain such equipment. [20] As a result, Haung with other researchers proposes a Heterogenous Kernel-based super-resolution Wasserstein GAN (HetSRW-GAN). The algorithm is described as a lightweight GAN architecture that utilizes plug-and-play heterogenous kernel-based residual block.

L. In clinical practice improving pathological diagnosis require various staining information, but due to limited sample tissue being examined diagnosis are difficult to carry out by pathologist.[7] hence, this study tries to understand the reliability and usability of generative architecture in the domain of pathology. The researchers generate a large set of sample data by hybridizing DCGAN model and ESRGAN model. The developed model was able to generate an artificial effect of staining without tempering with histopathological slide physically. It is suggested by the researcher to feed the GAN models with prior information such as the capillary wall, urinary pole, and nuclei placement, to produce paraffin and constant embedded tissue image quality. It has been concluded by the researchers that adopting deep learning models for pathology diagnosis requires a high level of expertise.

Table 1. Showing various approach strengths, opportunities, weaknesses, and threat

S/N	Approach	Strength(s)	Weakness(es)	Opportunity (ies)	Threat(s)
1	[6] GAN approach	Transfer learning based on the Generative Neural Network, adoption of Neuroimaging Informatics Technology Initiative (NIFTI-1)	Dataset and hardware limitation, the model required modification for generating other body parts scan	generating high resolution lungs image from Radiology MRI medical images with an increase in computation power as time goes on	Generating fake medical data will prevail as time goes on
2	CSRGAN [12]	Hybridization of CGAN and SRGAN with CV feature for computing loss instead of VGG loss in SRGAN, which adopt Jacobian Determinant (JD) and Curl Vector (CV) for conditional input	High computational cost associated with computing the Jacobian Determinant (JD) and the Curl Vector (CV)	The proposed method will be later adopted to enhance the performance of Single Resolution of medical generation for clinical diagnosis	Highly dependent on ultrasound low-resolution medical images for generating medical sample
3	MIASSR [11]	Integration of meta-learning schemes, and capability of generating cardiac image based on fine-tuning the transfer learning model	Alternative forgone between the parameters and meta learning	Can be used for both generating high resolution the image on both the MR brain scan and Cardiac MR scan in the hospitals for clinical decision making	Computational cost, and power consumption
4	[13] Still-GAN	The approach introduces illumination and local structure constrain for learning local details and overall characteristics	The incorrect translation may occur due to limited or heterogeneous disease or condition during training	Further adaptation of Still-GAN to various medical imaging modalities and used the enhanced image in for clinical scenarios in real-world disease diagnosis	Lack of High voluminous data from different diseases, limited storage capacity, and lack of computational power
5	[4] ESRGAN	The introduction of Residual-in-Residual Dense Block (RRDB) without the batch normalization and there is an improvement in perceptual loss by adopting features before activation	Computational cost associated with training of generator and discriminator	Adopted in health to generate a more realistic medical image and naturally good texture image	Dataset constraints
6	[14]WFT-GAN	The strength lies in the adoption of the Weight feature transfer (WFT), and combining local perceptual adversarial (LPA) loss with VGG feature map	The model depends on transfer-weighted knowledge	Used in the future for medical auxiliary diagnosis, surgical guardians, and other intelligent medical data	Computational power or limited access to external transfer learning affects image quality
7	[15] Conditional-GAN	The use of conditional discriminator and fully connected threedimensional convolutional neural networks.	The approach is limited to image analysis and diagnosis support such as the labeling of bones, segmentation of lung section	. It expects this approach to contribute significantly to the efficient adoption of an existing large amount of thick CT images that are stored in the hospitals	The future utilization depends on Accessing vast amounts of thick CT images
8	[16] CNN-GAN	Generating of Synthetic Skin Cancer image using GAN	Lack of sufficient Skin Cancer Image	This approach will improve Skin Cancer diagnosis in the health domain	Limited data from the International Skin Imaging Collaboration (ISIC)

9	[17] CP-GAN	The use of content preservation loss to improve image similarity, and attention mechanism	Complexity in architecture due to the adoption of content preservation loss consisting of MSE loss, VGG loss and TV loss	Can be used in a hospital to preserve hospital storage resources and improve on doctor diagnosis speed and accuracy	Cost of training
10	[18] GAN-BASED Approach	The use of a segmentation map prepare by expert clinicians	Highly depends on the clinician's expertise level	Used in the future to generate augmented gastrointestinal image for medical analysis	Generating fake gastrointestinal medical data will be difficult to distinguish from a real image of humans
11	[20] HetSRW-GAN	the adoption of plug plays heterogenous kernel-based residual block	It requires heterogenous convolution and adversarial training	Can be integrated with infrared optical devices in the future to generate a high-resolution image	Low-resolution images (source data) are gotten from high-cost infrared devices.
12	[19] MammoGAN	The use of high-resolution textural heterogeneity, specific tissue, and fine structural detail properties	The challenge of producing a precise pattern of pathology images remains	Mammograms images of the highest resolution can be easily achieved	Counterfeit images are even difficult to distinguish from what an expert can produce.

IV. CONCLUSION

This study considered 13 Varieties of Generative Adversarial Networks thus, GAN's Architecture for Generating high-resolution Medical Images. The Conceptual base approach and SWOT analysis are used to carry out the comprehensive survey. The first stage of this sturdy includes identifying the properties or attributes adopted by various researchers to improve or modify the traditional GAN network. While the second stage uses the SWOT analysis to identify the Strength (capability, usability, and merit), weaknesses (limitations), opportunities (future merit, or external usability), and finally the threat (external limitations) that is associated with each reviewed GAN Architecture. however, based on the

Strengths identify that in generating good quality medical images, the Proposed GAN approaches require a vast amount of data to train the generator and discriminator network from a general point of view. However, the reviewed GAN models that adopt transfer learning thus, pre-trained models achieved good quality images in comparison to models that are trained from scratch. Generally, it can be concluded that the Weaknesses associated with most of the reviewed GAN

The architecture includes; the cost of computation due to architecture complexity and insufficient medical images. Furthermore, Opportunities identifies includes; generating a high-resolution image (X-ray, CT scan) for medical analysis in hospital, and medical image augmentation for accurate diagnosis and treatment prediction in AI application. Finally, the Threats that are generally associated with all the proposed approaches including generating fake medical images will soon prevail with the advancement of technology, and it would be difficult to differentiate fake images from realistic images. Currently, Storage resources, Processing Speed, and Power Consumption are challenges identified in most GAN Architecture.

V. FUTURE WORK

Quantitative comparison (survey) could be made on GAN based approach for generating high-resolution medical images for various body part

REFERENCES

[1] Kazeminia, S., Baur, C., Kuijper, A., van Ginneken, B., Navab, N., Albarqouni, S., & Mukhopadhyay, A. (2020). GANs for medical image analysis. Artificial Intelligence in Medicine, 109, 101938, arXiv:1809.06222v3.

[2] Frid-Adar, M., Diamant, I., Klang, E., Amitai, M., Goldberger, J., & Greenspan, H. (2018). GANbased synthetic medical image augmentation for increased CNN performance in liver lesion classification. Neurocomputing, 321, 321-331 arXiv:1803.01229v1.

[3] Li, Y., Sixou, B., & Peyrin, F. (2021). A review of the deep learning methods for medical images super resolution problems. Irbm, 42(2), 120-133: 2020 published by Elsevier, https://www.sciencedirect.com/science/article/pii/S1959031820301408.

[4] Coudron, I., Puttemans, S., & Goedemé, T. (2018).

Polygonal reconstruction of building interiors from cluttered pointclouds. In Proceedings of the European Conference on Computer Vision (ECCV) Workshops (pp. 0-0). https://openaccess.thecvf.com/content_ECCVW_2018/papers/11129/Coudron_Polygonal_reconstruction_of_building_interiors_from_cluttered_pointclouds_ECCVW_2018_paper.pdf.

[5] S. Zhang, G. Liang, S. Pan, and L. Zheng, "A Fast

Medical Image Super Resolution Method Based on Deep Learning Network," IEEE Access, vol. 7, no. c, pp. 12319–12327, 2019, doi:

10.1109/ACCESS.2018.2871626.

[6] Gupta, R., Sharma, A., & Kumar, A. (2020), "Super-Resolution using GANs for Medical

Imaging," Procedia Comput. Sci., vol. 173, no.

2019, pp. 28–35, 2020, doi: 10.1016/j.procs.2020.06.005.

[7] Murali, L. K., Lutnick, B., Ginley, B., Tomaszewski, J. E., & Sarder, P. (2020, March).

Generative modeling for renal microanatomy.

In Medical Imaging 2020: Digital Pathology (Vol. 11320, pp. 99-108). SPI doi: 10.1117/12.2549891.

[8] Yi, X., Walia, E., & Babyn, P. (1809), "Generative adversarial network in medical imaging: A review," Med. Image Anal., vol. 58, 2019, doi:

10.1016/j.media.2019.101552.

[9] Benzaghta, M. A., Elwalda, A., Mousa, M. M., Erkan, I., & Rahman, M. (2021). SWOT analysis applications: An integrative literature review. Journal of Global Business Insights, 6(1),

55-73, https://www.doi.org/ 10.5038/2640-

6489.6.1.1148"

[10] Turankar, A., Motghare, V., Kinage, P., Deshpande, R., & Sinha Sh, T. S. (2014). SWOT analysis in medical sciences. J Rational Pharmacother Res, 2(2), 39-43 https://v2.vcliniq.com/isrpt/wpcontent/uploads/21/2020/09/Rational_Pharmacother apeutics.pdf.

[11] Q. Aini, U. Rahardja, M. R. Tangkaw, N. Puji, and L. Santoso, "Embedding a Blockchain Technology Pattern Into the QR Code for an Authentication Certificate," vol. 5, no. 2, pp. 239–244, 2020, doi:

10.15575/join.v5i2.583.

[12] Zhu, Y., Zhou, Z., Liao, G., & Yuan, K. (2020, April). Csrgan: Medical Image Super-Resolution

Using A Generative Adversarial Network. In 2020

IEEE 17th International Symposium on Biomedical Imaging Workshops (ISBI Workshops) (pp. 1-4).

IEEE.

doi: 10.1109/isbiworkshops50223.2020.9153436.

[13] Ma, Y., Liu, Y., Cheng, J., Zheng, Y., Ghahremani, M., Chen, H., ... & Zhao, Y. (2020, October). Cycle structure and illumination constrained GAN for medical image enhancement. In International conference on medical image computing and computer-assisted intervention (pp. 667-677).

Springer, Cham.

https://livrepository.liverpool.ac.uk/3106288/1/micc ai-myh-sub-2.pdf.

[14] Yao, S., Tan, J., Chen, Y., & Gu, Y. (2021). A weighted feature transfer gan for medical image synthesis. Machine Vision and Applications, 32(1), 1-11." Mach. Vis. Appl., vol..32, no. 1, 2021, doi:

10.1007/s00138-020-01152-8.

[15] Kudo, A., Kitamura, Y., Li, Y., Iizuka, S., & SimoSerra, E. (2019, October). Virtual thin slice: 3D conditional GAN-based super-resolution for CT slice interval. In International Workshop on Machine Learning for Medical Image

Reconstruction (pp. 91-100). Springer, Cham., vol. 11905 LNCS, pp. 91–100, 2019, doi: 10.1007/9783-030-33843-5_9.

[16] Sedigh, P., Sadeghian, R., & Masouleh, M. T. (2019, November). Generating synthetic medical images by using GAN to improve CNN performance in skin cancer classification. In 2019 7th International Conference on Robotics and Mechatronics (ICRoM) (pp. 497-502). doi: 10.1109/ICRoM48714.2019.9071823.

[17] Zeng, X., Huang, Z., Xu, L., & Xie, Y. (2022). CPGAN: Meet the high requirements of diagnose report to medical image by content preservation. IET Image Processing, 16(1), 29-38. doi: 10.1049/ipr2.12145.

[18] Adjei, P. E., Lonseko, Z. M., & Rao, N. (2020, December). GAN-Based Synthetic Gastrointestinal

Image Generation. In 2020 17th International