5th International Conference on Electronics and Sustainable Communication Systems (ICESC 2024)
IEEE XPlore Part Number: CFP24V66-ART; ISBN: 979-8-3503-7994-5

2024 5th International Conference on Electronics and Sustainable Communication Systems (ICESC) | 979-8-3503-7994-5/24/$31.00 ©2024 IEEE | DOI: 10.1109/ICESC60852.2024.10690154

Advancements in Medical Imaging based on Image Denoising, Data Augmentation, and Classification with Computational Techniques

V.Muthulakshmi
Alliance College *of Engineering and Design*
Alliance University
Karnataka,India
vmuthulakshmiPHD721@ced.alliance.edu.in

K.Ramalakshmi
Alliance College *of Engineering and Design*
Alliance University
Karnataka,India
ramalakshmi.k@alliance.edu.in

***Abstract*— Nowadays, medical imaging techniques are often not directly suitable for disease classification due to various noise factors and limited image availability. Innovative approaches to image denoising, data augmentation, and classification have been made possible by the fast development of computer technologies, which have had a significant influence on medical imaging. The use of Generative Adversarial Networks (GANs) for image denoising and the creation of synthetic data to supplement training datasets are the primary focus of this review, which analyzes the development and incorporation of state-of-the-art computational methods. This survey also highlights the critical function of GANs in separating important anatomical features from background noise, greatly improving the accuracy of medical picture analysis. Exploring data augmentation by synthetic picture synthesis also reveals how it helps overcome dataset restrictions to train deep learning models. In addition, the developments in classification approaches, this survey highlights how Convolutional Neural Networks (CNNs) and ensemble learning have revolutionized diagnostic capacities and detection accuracies in security applications. This survey lays out the complex effects of these technology developments on the accuracy and trustworthiness of medical imaging procedures by synthesizing all the latest research findings.**

Keywords*— *Medical Imaging, Image Denoising, Data Augmentation, Classification Techniques, Generative Adversarial Networks (GANs), Convolutional Neural Networks (CNNs)

I. INTRODUCTION

The rapid progress in medical imaging technology has greatly improved the ability to diagnose and treat a wide range of disorders. However, these images are affected by the presence of noise, which can be caused by ambient conditions or the intrinsic limitations of imaging systems. Throughout the years, a variety of techniques have been used to reduce noise in these images, including methods based on spatial and transform domains, as well as adaptive and non-adaptive filtering approaches. These approaches are successful, but their success depends on the quality of the photos and often involves a compromise between reducing noise and other factors. Generative Adversarial Network (GAN) have significantly transformed the method of medical image denoising. The Wasserstein-GAN loss function is used to provide training stability, with the Wasserstein distance between real and generated images acting as a metric of image quality [1]. The Conditional Generative Adversarial Network (CGAN) technique is employed for denoising medical images, efficiently mitigating various forms of unidentifiable noise while preserving the image structure. The combined objective loss function, which integrates both the reconstruction loss and WGAN loss, effectively generated denoising outcomes with elevated PSNR (Peak Signal-to-Noise Ratio) and SSIM (Structural Similarity Index) on the JSRT and LIDC datasets. CGAN outperforms the most sophisticated methods in the domain of medical image denoising[2]. The study in [3] examines the application of the DudeNet model for chest X-ray image denoising in the field of medical imaging. The DudeNet model has four sections: feature extraction, augmentation, compression, and reconstruction. GAN is employed to enhance the quality of low-dose CT scans by specifically targeting the removal of artifacts and enhancing the level of detail. Individualized loss functions, specifically the sub-channel requires its own design [4]. The denoising of MRI images is accomplished by utilizing conditional GAN, with CNN serving as the discriminator to distinguish between genuine and fabricated image pairs. A generator based on convolutional encoder-decoder networks is utilized to eliminate noise. The adversarial learning strategy shown improved performance in terms of denoising level and preservation of structures compared to conventional approaches [5]. GAN is used to denoise x-ray images in digital radiography, effectively eliminating statistical noise while maintaining crisp edges and clear structure. The proposed method produces a more refined image in comparison to the conventional CNN-based approach [6].

Optical coherence tomography (OCT) is a noninvasive imaging method used in ophthalmology. DN-GAN use GAN to reduce speckle noise in OCT images. The discriminator guides the denoising generator to preserve the integrity of edges and delicate features. The generator is trained to efficiently eliminate noise from the original OCT pictures and improve their quality[7]. A technique for reducing noise in CT images utilizing transfer learning of GAN. The dataset underwent training using U-WGAN with pairs of high-dose and low-dose CT images of the human chest. A network that was adjusted to optimize performance using dental CT image pairs of human skull phantoms obtained denoising results comparable to those of WGAN, while also reducing computation time [8]. A deep learning technique using a CGAN is used to decrease noise in low-dose chest pictures. The model was trained using the lung-CT-challenge and Lung-Image-Database-Consortium datasets. The quantitative analysis revealed the superiority of the CGAN technique over conventional approaches [9]. A multi-resolution parallel residual convolutional neural network (CNN) is developed for the purpose of denoising chest X-ray (CXR) pictures, with a specific focus on COVID-19 situations. The AMFF approach utilizes attention mechanisms to enhance the network's capacity to effectively represent and preserve intricate image features. The categorization with MPR-CNN demonstrates enhanced preservation of texture structure intricacies in CXR images [10]. DL denoising framework called edge-enhancement densenet (EEDN) that is used to maintain details in denoised X-ray fluoroscopy images. Developed an attention-awareness edge-enhancement module as part of the EEDN architecture to enhance the sharpness of edges. It was shown that EEDN can effectively eliminate visual noise and improve the signal-to-noise ratio (SNR) while maintaining accurate catheter detection [11].

Data augmentation is an essential approach used in the preprocessing of medical pictures to artificially enhance the variety of datasets utilized in machine learning models. Data augmentation increases the amount and variety of data utilized for training can be implemented by various transformations such as rotation, flipping, scaling, and elastic deformations. A methodology that incorporates both noisy and denoised data to improve the performance of deep convolutional neural networks (CNN) in detecting COVID-19 in X-ray images. To strengthen the resilience and generalization of the model, they employed Bayesian optimization to discover the ideal noise type and parameters for data augmentation, hence improving the noise parameters and creating new variations of images. An autoencoder model is employed to produce supplementary data by leveraging denoised images, hence improving the augmentation process [12]. Computer-Aided Diagnosis (CAD) systems employing Deep Learning (DL) techniques were utilized to enhance the identification of lung illnesses. A Genetic Fine-Tuning technique was devised to maximize the hyperparameters for the Deep Learning models. The reworded CNN architectures, ResNet50 and VGG16, undergo fine-tuning utilizing the optimal hyperparameters [13]. Conventional methods of enhancing images, which involve applying several transformations, are employed to address these difficulties and avoid overfitting. The potential application of GAN in medical picture synthesis, particularly in augmenting chest X-ray (CXR), has not been thoroughly investigated. To assess the impact of traditional augmentation (TA) and GAN-based augmentation (GA) on the performance of a CXR abnormality classifier, a progressive-growing GAN (PG-GAN) model was employed to generate authentic CXR images for GA. The classifier's performance was then evaluated utilizing different augmentation strategies [14]. The introduction of imaging technologies such as MRI and CT have significantly transformed medical diagnosis by offering intricate observations of the inside components of the human body. Historically, image classification in medical imaging depended on the process of feature extraction and machine learning techniques. This involved manually defining and extracting characteristics from the images before they could be classified. However, the emergence of deep learning, particularly CNN, has profoundly transformed the discipline. CNN has exhibited outstanding proficiency in precisely and dependably categorizing MRI and CT images, surpassing traditional methods. In [15] DL approach was specifically designed to diagnose pneumonia through the analysis of chest X-ray pictures. An evaluation is conducted on popular deep learning models like Alex Net, VGG16, VGG19, and ResNet50, and it is determined that VGG19 exhibits the highest level of accuracy. The suggested model is a modified version of the VGG19 network that combines manually crafted features and deep features to improve accuracy. The system utilizes an ensemble Feature Scheme (EFS) that combines features derived from Complex Wavelet Transform (CWT), Discrete Wavelet Transform (DWT), and Gray-Level Co-Occurrence Matrix (GLCM).

II. Related works

Current literature emphasizes the significance of overcoming obstacles in order to fully utilize the potential of medical imaging in clinical environments. Efficient denoising methods are vital to enhance image quality while retaining essential features needed for precise interpretation and diagnosis. To tackle this issue, it is necessary to create advanced algorithms that can effectively differentiate between irrelevant signals and crucial anatomical characteristics. The GAN is employed to compare the noisy image, the denoised image, and the ground truth image. The model was trained on AWS p2.xlarge GPU using the TensorFlow framework. The training technique had a batch size of 7 and underwent 10,000 iterations [16]. The U-Swin-transformer network is used for the denoising process in medical picture synthesis using diffusion fusion. Statistical model based on probability theory [17]. Additionally, an ablation study was undertaken to assess the influence of various settings on model performance [18].

Image denoising framework based on the Wasserstein Generative Adversarial Networks (WGAN) [19], Trilateral weighted sparse coding (TWSC) [20] , Style GAN2 [21], Improved WGAN [22], Noise learning GAN [23], GAN with Wasserstein distance [24], GAN with DnCNN [25], Fidelity-embedded GAN [26], Adversarial Gaussian denoiser network (AGDN) [27], Hybrid algorithm with edge detection, image enhancement, and collaborative filtering [28] and Adaptive two-stage weighted median with hybrid genetic algorithm [29]. GAN utilizes CNN for both the generator and discriminator components to generate new images. The assessment of the visual fidelity of the produced images is conducted by employing the Frechet Inception Distance (FID) metric. The generated images are incorporated into the training database and utilized to train a basic CNN model, with the objective of enhancing the network's accuracy in classifying data [30]. Using GANs to enhance data by generating synthetic chest X-ray images for the specific task of classifying pneumonia. Progressive Generative Adversarial Networks (ProGAN) are employed to generate high-resolution images that are essential for accurate analysis of X-ray images. This approach enhances the precision of a DCNN classifier by instructing it using a dataset that comprises both authentic and artificially generated images [31]. In [32] devised a weight allocation technique for the base CNN models by considering four assessment metrics: precision, recall, f1-score, and AUC. This method demonstrates the superior performance on two publicly available pneumonia X-ray datasets using a five-fold cross-validation scheme. Weighted average ensemble technique was utilized in order to improve the performance of the base CNN learners in pneumonia classification. Employed statistical tests like McNemar's and ANOVA to establish the robustness of the proposed ensemble framework. Effective denoising techniques are required to improve image quality without losing crucial details necessary for accurate interpretation and diagnosis. Addressing this problem involves developing sophisticated algorithms that can distinguish between noise and important anatomical features, enhancing the reliability of medical imaging as a diagnostic tool. Table 1 presents a comprehensive summary of various algorithms and their performance in the field of medical image analysis, specifically focusing on tasks like segmentation, classification, and enhancement of medical images, such as CXR, CT scans, and Digitally Reconstructed Radiographs (DRRs).

TABLE I. COMPREHENSIVE SUMMARY OF VARIOUS ALGORITHMS AND THEIR PERFORMANCES

Ref. no	Algorithm	Results	Dataset Used
[33]	Deep Image-to-Image network (DI2I) for multi-organ segmentation TD-GAN	Average dice score: 86% for proposed model, 89% for supervised training.	Labeled 3D CT scans, Digitally Reconstructed Radiographs (DRRs) Topogram dataset JSRT chest X-ray dataset
[34]	GAN for lung segmentation	Dice-score achieved: 0.9740, IOU score: 0.943.	CXR datasets
[35]	Total Variation-based Active Contour (TVAC) GAN Self-Attention DNN	Recall of 92.03%	4999 CXR images from the NIH dataset
[36]	SVM, RF, and LR	88.51% accuracy	Crowdsourced dataset
[37]	LR, CNN, PCA and GAN	97.6% Accuracy	COVID-19 X-ray images dataset with 198 images. Augmented dataset with 500 images (250 COVID-19, 250 normal)
[38]	CNN and SGD	92.4 Specificity	Dataset consists of 909 lung X-ray images.
[39]	GAN-based data augmentation for chest X-ray classification	0.03 AUC Gain, 0.07 AUC Gain	Stanford CheXpert dataset
[40]	DCGAN	FID score of 1.289 for DCGAN augmented chest X-ray images	Chest X-ray dataset augmented with DCGAN for data generation
[15]	Conventional DLS algorithms used: AlexNet, VGG16, VGG19, ResNet50	VGG19 classification accuracy: 86.97% Customized VGG19 with RF classifier accuracy: 97.94%	The dataset used in the research consists of chest radiograph images.
[31]	IAGAN, DCGAN	AUC for Dataset I: IAGAN outperforms no augmentation, DCGAN, traditional methods	Datasets used in the study are publicly available.
[41]	SVM, k-NN	CNN1 DADLM Sensitivity: 99.7, Specificity: 98.7, F1-Score: 99.0	CT images dataset X-ray images dataset
[42]	Deep Convolutional Neural Network , VGG19 network, AlexNet, VGG16Net, InceptionNet, DCGAN	Proposed Deep CNN model achieved 99.34%	Pneumonia Chest X-ray Dataset containing 12,000 images
[43]	Customized CNN model in DL-CRC framework.	COVID-19 detection accuracy: 93.94%	Combined dataset from GitHub, Stanford ML group, and CheXpert
[44]	DC-GAN	AUC achieved: 95%	Covid 19 Dataset
[45]	VGG19	VGG19 achieved 89.3% accuracy with F1 score of 0.90.	860 images used in the study 260 COVID-19 cases 300 healthy cases 300 pneumonia cases
[46]	Bounding box algorithm used to cover LV myocardium and cavity. CNN trained to predict transformation of proposed bounding box.	Mean DSC for myocardium: 0.84, scar: 0.72	EMIDEC challenge dataset
[47]	RANDGAN: Randomized generative adversarial network for COVID-19 detection	-	COVIDx dataset used for detection of COVID-19 in chest X-ray.

III. METHODOLOGY

The introduction of deep learning and GAN has led to major advancements in upgrading image quality, producing synthetic data, and improving classification accuracy. This research consolidates findings from multiple investigations, emphasizing the advancement and use of advanced algorithms that enhance the visual quality of medical images and preserve crucial anatomical information required for accurate diagnosis. Medical imaging is an essential tool in clinical settings, providing non-invasive information about the human body that helps with diagnosing and planning treatments. The presence of image noise, data imbalance, and the requirement for precise classification of medical diseases make it imperative to use sophisticated computational methods.

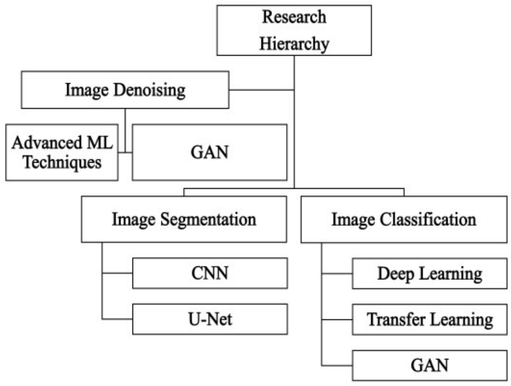

Fig. 1. Research Hirerrachy diagram

Figure 1 depicts a range of image processing algorithms employed in computer vision. Methods such as denoising, segmentation, and classification aid in extracting significant data from photos. Advanced techniques such as CNN and transfer learning significantly improve these capabilities.

A. Image Denoising Techniques

GAN have proven to be very successful in the field of picture denoising, especially when utilizing the WGAN and its following enhancements. The WGAN algorithm utilizes the Wasserstein distance to achieve a more robust training process and an improved capability to differentiate between irrelevant noise and important image characteristics. Preserving anatomical details is of utmost importance in medical imaging, as it is essential for precise diagnosis. Enhanced versions of WGAN and Fidelity-embedded GAN created to enhance the process of generating denoised images. These modifications aim to capture the distribution of noise-free images more accurately, resulting in denoised images that preserve important details without the distortion commonly caused by traditional denoising methods. The U-Swin-transformer network combines the ability of the transformer design to simulate long-range dependencies with the efficient local feature extraction of U-Net, resulting in a notable improvement. This combination is highly efficient in the process of removing noise from medical images, as it ensures the preservation of both overall structure and specific details. The use of advanced denoising techniques in synthesizing high-quality pictures for COVID-19 classification showcases the potential to get better diagnoses from medical images, highlighting the revolutionary significance of these approaches in healthcare.

1) Advanced Algorithms for Noise Reduction

Researchers have devised a variety of sophisticated algorithms to tackle the problem of reducing noise in medical images, surpassing conventional denoising procedures. Hybrid algorithms are notable for their ability to integrate different methods, such as edge recognition, picture enhancement, and collaborative filtering, to obtain a more thorough noise reduction. The ability to adapt enables the retention of vital information and boundaries, which are critical for the analysis and diagnosis in medical imaging. These improved noise reduction algorithms are a major advancement that have the potential to greatly increase image quality while also maintaining or boosting the visibility of important anatomical features.

B. Image Augumentation Techniques

The application of GAN (Generative Adversarial Network) in generating synthetic X-ray pictures is a major advancement in medical imaging, especially for illnesses such as pneumonia where the availability and diversity of data can hinder the accuracy of classification models. Researchers have successfully used Progressive GANs (ProGAN) to create synthetic chest X-ray pictures that are of such good quality that they cannot be distinguished from genuine images. This technological progress is needed for training deep convolutional neural networks (DCNN) since it enables the addition of a wide range of artificially generated pictures to existing datasets. This helps to overcome the challenges caused by having limited datasets in terms of both diversity and quantity. This incorporation greatly enhances the training of more resilient and precise DCNN classifiers. By exposing the models to a broader range of situations throughout the learning phase, they become more proficient in accurately categorizing real-life images. The integration of augumented data into training datasets has a significant influence on the efficacy of machine learning models, specifically in the field of medical picture categorization. When classifying pneumonia, assigning weights strategically to basic CNN models based on these variables helps optimize the performance of the model. In addition, the utilization of a weighted average ensemble technique harnesses the advantages of several base models to enhance classification accuracy, successfully overcoming the constraints of individual models. This method, supported by the increased variety and accuracy of artificially generated training data, represents substantial progress in the area, highlighting the potential of synthetic data to greatly expand the capabilities of diagnostic models.

C. Classification Techniques in Medical Imaging

CNNs have transformed the area of medical imaging, expanding their usefulness beyond clinical diagnostics to tasks such as identifying prohibited goods in X-ray security systems. CNNs, due to their capacity to extract information automatically and hierarchically from images, have played a crucial role in the development of efficient systems that can identify potentially hazardous objects in baggage or cargo. This application has distinctive problems, such as the requirement for exceptional precision and the capability to differentiate between items that have like looks but distinct characteristics. Previous approaches have employed the development of specific CNN structures and training techniques that prioritize the distinction of features and the reduction of both cases false positives and false negatives. The CNNs' success in this field highlights their versatility and efficacy, demonstrating how deep learning can adjust to unique and crucial tasks in security operations. This adaption not only increases the effectiveness of screening operations but also greatly decreases the need for manual inspection, hence boosting the overall speed and dependability of security measures.

Ensemble approaches and stringent statistical tests, such as McNemar's and ANOVA, have improved the sophistication of categorization frameworks in medical imaging. Ensemble approaches integrate predictions from numerous models to enhance the overall accuracy and resilience of the classification system. Ensemble approaches can achieve better performance, especially in complicated tasks like classifying medical images or detecting restricted goods, by utilizing the strengths and minimizing the flaws of individual models. McNemar's test examines the statistical significance of the disparity between two classifiers, whereas ANOVA can analyze the variation across numerous models to ascertain the presence of any noteworthy differences in performance. These statistical methods are necessary for verifying the efficacy of ensemble approaches, guaranteeing that improvements in classification algorithms are both meaningful and advantageous for practical applications.

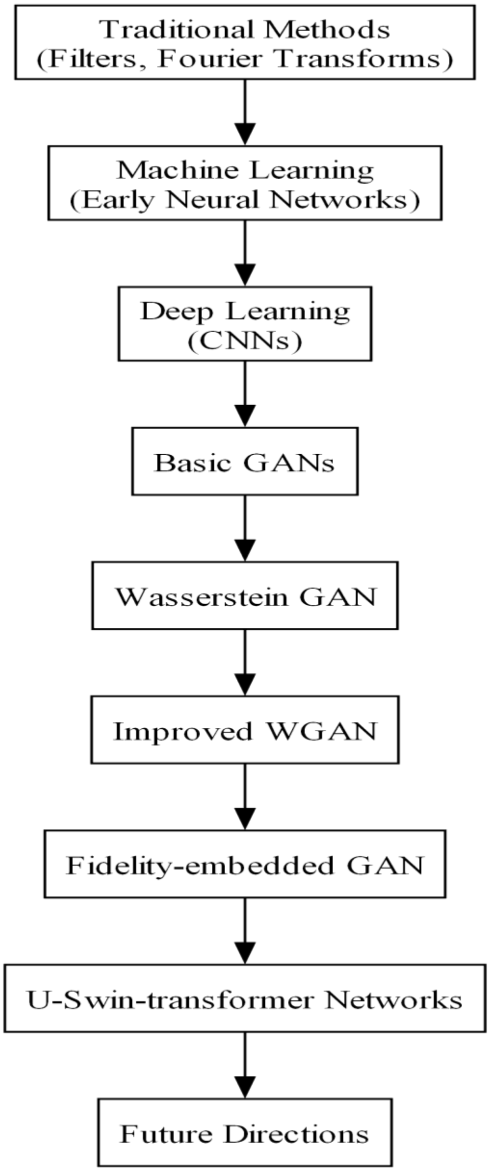

Fig.2. State of Art using advanced deep learning techniques

Figure 2 presents a state of art of advanced deep learning technique architectures. The flowchart originates with foundational techniques like traditional methods (filters, Fourier transforms) and early neural networks. These methods pave the way for the creation of more sophisticated techniques used in GANs.

IV. Discussion

This literature analysis focuses on a crucial period in medical imaging technology, characterized by notable progress in image denoising, data augmentation, and classification approaches. The field of medical imaging has experienced noteworthy advancements in the quality, detail, and precision of pictures by utilizing a combination of GAN and CNN approaches, combined with unique ensemble learning methods. The skillful differentiation between irrelevant noise and important information using advanced denoising techniques, together with the enhancement of training datasets through the creation of synthetic data, has significantly reduced the long-standing problems of limited dataset availability and image quality. These developments not only enhance the accuracy and dependability of diagnoses, but also simplify operational processes in the healthcare and security sectors. Table 2 and 3 provides a detailed description of the approaches used, as well as the outcomes and a summary of the classification metrics.

TABLE II. Summary of Methodologies and Outcomes

Methodology	Key Features	Applications	Performance Metrics
Basic Filtering	Removes simple noise patterns	Preliminary image cleaning	Low improvement in Signal-to-Noise Ratio (SNR)
CNNs	Learns complex features for noise reduction	General medical imaging enhancement	Moderate improvement in SNR and image clarity
Basic GANs	Learns to generate noise-free images	General image denoising	Significant improvement in SNR
WGAN & Improvements	Stabilizes GAN training, better noise/artifact differentiation	Enhanced medical image denoising	High-quality denoising, better detail preservation
U-Swin-transformer Networks	Integrates transformer models for detailed feature extraction	COVID-19 classification, detailed denoising	Superior classification accuracy, excellent denoising with detail preservation

TABLE III. Summary of Classification Metrics

Ref. No	Model Used	Accuracy	Dataset
[48]	AlexNet, GoogleNet, SqueezeNet	90%	3 public chest X-ray databases
[36]	Pretrained CNNs including VGG-19, MobileNet-v2, etc.	99.34%	COVID-19, bacterial pneumonia, viral pneumonia, healthy conditions
[37]	LR, CNN, PCA and GAN	97.6%	Multiple including COVID-19 Radiography Database

V. Conclusion

This research study has highlighted the most recent progress in technology and medical imaging, offering prospects for future research to explore and improve the mutually advantageous relationship between these two domains. The integration of cutting-edge computational approaches, such as GANs for image denoising and synthetic data generation, together with advanced classification methods like CNNs and ensemble learning, greatly enhances the possibility for more precise and dependable medical diagnostics. Subsequent investigations should prioritize the improvement of these techniques, tackling existing constraints, and investigating novel uses to enhance the quality of medical imaging and patient results.

REFERENCES

[1] Y. Zhong, L. Liu, D. Zhao, and H. Li, "A generative adversarial network for image denoising," *Multimedia Tools and Applications*, vol. 79, no. 23–24, pp. 16517–16529, 2020, doi: 10.1007/s11042-019-7556-x.

[2] V. Göreke, "A novel method based on Wiener filter for denoising Poisson noise from medical X-Ray images," *Biomedical Signal Processing and Control*, vol. 79, 2022, doi: 10.1016/j.bspc.2022.104031.

[3] A. Sahu, K. P. S. Rana, and V. Kumar, "An application of deep dual convolutional neural network for enhanced medical image denoising," *Medical and Biological Engineering and Computing*, vol. 61, no. 5, pp. 991–1004, 2023, doi: 10.1007/s11517-022-02731-9.

[4] X. Zhang, Z. Han, H. Shangguan, X. Han, X. Cui, and A. Wang, "Artifact and Detail Attention Generative Adversarial Networks for Low-Dose CT Denoising," *IEEE Transactions on Medical Imaging*, vol. 40, no. 12, pp. 3901–3918, 2021, doi: 10.1109/TMI.2021.3101616.

[5] M. Tian and K. Song, "Boosting Magnetic Resonance Image Denoising with Generative Adversarial Networks," *IEEE Access*, vol. 9, pp. 62266–62275, 2021, doi: 10.1109/ACCESS.2021.3073944.

[6] Y. Sun, X. Liu, P. Cong, L. Li, and Z. Zhao, "Digital radiography image denoising using a generative adversarial network," *Journal of X-Ray Science and Technology*, vol. 26, no. 4, pp. 523–534, 2018, doi: 10.3233/XST-17356.

[7] Z. Chen, Z. Zeng, H. Shen, X. Zheng, P. Dai, and P. Ouyang, "DN-GAN: Denoising generative adversarial networks for speckle noise reduction in optical coherence tomography images," *Biomedical Signal Processing and Control*, vol. 55, p. 101632, 2020, doi: 10.1016/j.bspc.2019.101632.

[8] M. A. A. Hegazy, M. H. Cho, and S. Y. Lee, "Image denoising by transfer learning of generative adversarial network for dental CT," *Biomedical Physics and Engineering Express*, vol. 6, no. 5, 2020, doi: 10.1088/2057-1976/abb068.

[9] H. J. Kim and D. Lee, "Image denoising with conditional generative adversarial networks (CGAN) in low dose chest images," *Nuclear Instruments and Methods in Physics Research, Section A: Accelerators, Spectrometers, Detectors and Associated Equipment*, vol. 954, no. July 2018, 2020, doi: 10.1016/j.nima.2019.02.041.

[10] X. Jiang, Y. Zhu, B. Zheng, and D. Yang, "Images denoising for COVID-19 chest X-ray based on multi-resolution parallel residual CNN," *Machine Vision and Applications*, vol. 32, no. 4, pp. 1–15, 2021, doi: 10.1007/s00138-021-01224-3.

[11] Yimin Luo1 Yingliang Ma2 Hugh O' Brien1 Kui Jiang3 Vikram Kohli1, S. Maidelin1, M. S. E. D. K. Pushparajah1, K. S. Rhode1, and 1, "Medical Physics - 2022 - Luo - Edge-enhancement densenet for X-ray fluoroscopy image denoising in cardiac electrophysiology.pdf." p. 15, 2021.

[12] M. Momeny *et al.*, "Learning-to-augment strategy using noisy and denoised data: Improving generalizability of deep CNN for the detection of COVID-19 in X-ray images," *Computers in Biology and Medicine*, vol. 136, no. May, p. 104704, 2021, doi: 10.1016/j.compbiomed.2021.104704.

[13] P. A. Vieira, D. M. V. Magalhães, A. O. Carvalho-Filho, R. M. S. Veras, R. A. L. Rabêlo, and R. R. V. Silva, "Classification of COVID-19 in X-ray images with Genetic Fine-tuning," *Computers and Electrical Engineering*, vol. 96, no. August, 2021, doi: 10.1016/j.compeleceng.2021.107467.

[14] P. Ganesan, S. Rajaraman, R. Long, B. Ghoraani, and S. Antani, "Assessment of Data Augmentation Strategies Toward Performance Improvement of Abnormality Classification in Chest Radiographs," *Proceedings of the Annual International Conference of the IEEE Engineering in Medicine and Biology Society, EMBS*, pp. 841–844, 2019, doi: 10.1109/EMBC.2019.8857516.

[15] N. Dey, Y. D. Zhang, V. Rajinikanth, R. Pugalenthi, and N. S. M. Raja, "Customized VGG19 Architecture for Pneumonia Detection in Chest X-Rays," *Pattern Recognition Letters*, vol. 143, pp. 67–74, 2021, doi: 10.1016/j.patrec.2020.12.010.

[16] A. Alsaiari, R. Rustagi, A. Alhakamy, M. M. Thomas, and A. G. Forbes, "Image Denoising Using A Generative Adversarial Network," in *2019 IEEE 2nd International Conference on Information and Computer Technologies (ICICT)*, Kahului, HI, USA: IEEE, Mar. 2019, pp. 126–132. doi: 10.1109/INFOCT.2019.8710893.

[17] S. Pan *et al.*, "2D medical image synthesis using transformer-based denoising diffusion probabilistic model," *Physics in Medicine and Biology*, vol. 68, no. 10, 2023, doi: 10.1088/1361-6560/acca5c.

[18] M. Jamjoom, A. M. Mahmoud, S. Abbas, and R. Hodhod, "Gaussian Mixture with Max Expectation Guide for Stacked Architecture of Denoising Autoencoder and DRBM for Medical Chest Scans and Disease Identification," *Electronics (Switzerland)*, vol. 12, no. 1, 2023, doi: 10.3390/electronics12010105.

[19] S. Chen, D. Shi, M. Sadiq, and X. Cheng, "Image denoising with generative adversarial networks and its application to cell image enhancement," *IEEE Access*, vol. 8, pp. 82819–82831, 2020, doi: 10.1109/ACCESS.2020.2988284.

[20] R. Agrawal, D. D. Patil, and P. Subramanium, "Image Noise Removal System," *International Research Journal of Engineering and Technology*, no. May, pp. 1632–1634, 2020.

[21] F. Jiao, Z. Yang, S. Shi, and W. Cao, "Low-dose CT I mage D enoising M ethod B ased on Generative Adversarial Network," In Review, preprint, Jun. 2022. doi: 10.21203/rs.3.rs-1672475/v1.

[22] Z. Li *et al.*, "Low-Dose CT Image Denoising with Improving WGAN and Hybrid Loss Function," *Computational and Mathematical Methods in Medicine*, vol. 2021, 2021, doi: 10.1155/2021/2973108.

[23] Y. Ma, B. Wei, P. Feng, P. He, X. Guo, and G. Wang, "Low-Dose CT Image Denoising Using a Generative Adversarial Network with a Hybrid Loss Function for Noise Learning," *IEEE Access*, vol. 8, pp. 67519–67529, 2020, doi: 10.1109/ACCESS.2020.2986388.

[24] Q. Yang *et al.*, "Low-Dose CT Image Denoising Using a Generative Adversarial Network With Wasserstein Distance and Perceptual Loss," *IEEE Transactions on Medical Imaging*, vol. 37, no. 6, pp. 1348–1357, 2018, doi: 10.1109/TMI.2018.2827462.

[25] L. D. Tran, S. M. Nguyen, and M. Arai, "GAN-Based Noise Model for Denoising Real Images," *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, vol. 12625 LNCS, pp. 560–572, 2021, doi: 10.1007/978-3-030-69538-5_34.

[26] H. S. Park, J. Baek, S. K. You, J. K. Choi, and J. K. Seo, "Unpaired image denoising using a generative adversarial network in x-ray CT," *IEEE Access*, vol. 7, pp. 110414–110425, 2019, doi: 10.1109/ACCESS.2019.2934178.

[27] A. Khan, W. Jin, A. Haider, M. Rahman, and D. Wang, "Adversarial gaussian denoiser for multiple-level image denoising," *Sensors*, vol. 21, no. 9, 2021, doi: 10.3390/s21092998.

[28] A. Annavarapu, S. Borra, V. B. R. Dinnepu, and M. P. Mishra, "A Hybrid Medical Image Denoising Based on Block Matching 3D Collaborative Filtering," *SN Computer Science*, vol. 5, no. 1, pp. 0–38, 2023, doi: 10.1007/s42979-023-02359-y.

[29] S. Guo, G. Wang, L. Han, X. Song, and W. Yang, "COVID-19 CT image denoising algorithm based on adaptive threshold and optimized weighted median filter," *Biomedical Signal Processing and Control*, vol. 75, no. October 2021, p. 103552, 2022, doi: 10.1016/j.bspc.2022.103552.

[30] J. Yang, Z. Zhao, H. Zhang, and Y. Shi, "Data augmentation for X-ray prohibited item images using generative adversarial networks," *IEEE Access*, vol. 7, pp. 28894–28902, 2019, doi: 10.1109/ACCESS.2019.2902121.

[31] V. Bhagat and S. Bhaumik, "Data Augmentation using Generative Adversarial Networks for Pneumonia classification in chest Xrays," *Proceedings of the IEEE International Conference Image Information Processing*, vol. 2019-November, pp. 574–579, 2019, doi: 10.1109/ICIIP47207.2019.8985892.

[32] R. Kundu, R. Das, Z. W. Geem, G. T. Han, and R. Sarkar, "Pneumonia detection in chest X-ray images using an ensemble of deep learning models," *PLoS ONE*, vol. 16, no. 9 September, 2021, doi: 10.1371/journal.pone.0256630.

[33] Y. Zhang, S. Miao, T. Mansi, and R. Liao, "Unsupervised X-ray image segmentation with task driven generative adversarial

networks," *Medical Image Analysis*, vol. 62, p. 101664, 2020, doi: 10.1016/j.media.2020.101664.

[34] F. Munawar, S. Azmat, T. Iqbal, C. Gronlund, and H. Ali, "Segmentation of Lungs in Chest X-Ray Image Using Generative Adversarial Networks," *IEEE Access*, vol. 8, pp. 153535–153545, 2020, doi: 10.1109/ACCESS.2020.3017915.

[35] A. Victor Ikechukwu, S. Murali, R. Deepu, and R. C. Shivamurthy, "ResNet-50 vs VGG-19 vs training from scratch: A comparative analysis of the segmentation and classification of Pneumonia from chest X-ray images," *Global Transitions Proceedings*, vol. 2, no. 2, pp. 375–381, 2021, doi: 10.1016/j.gltp.2021.08.027.

[36] D. Y. Song, S. Y. Kim, G. Bong, J. M. Kim, and H. J. Yoo, "The Use of Artificial Intelligence in Screening and Diagnosis of Autism Spectrum Disorder: A Literature Review," *Journal of the Korean Academy of Child and Adolescent Psychiatry*, vol. 30, no. 4, pp. 145–152, 2019, doi: 10.5765/jkacap.190027.

[37] J. Rasheed, A. A. Hameed, C. Djeddi, A. Jamil, and F. Al-Turjman, "A machine learning-based framework for diagnosis of COVID-19 from chest X-ray images," *Interdisciplinary Sciences – Computational Life Sciences*, vol. 13, no. 1. pp. 103–117, 2021. doi: 10.1007/s12539-020-00403-6.

[38] J. Rama, C. Nalini, and A. Kumaravel, "Image pre-processing: enhance the performance of medical image classification using various data augmentation technique," *ACCENTS Transactions on Image Processing and Computer Vision*, vol. 5, no. 14, pp. 7–14, 2019, doi: 10.19101/tipcv.413001.

[39] S. Sundaram and N. Hulkund, *GAN-based Data Augmentation for Chest X-ray Classification*, vol. 1. Association for Computing Machinery, 2021. [Online]. Available: http://arxiv.org/abs/2107.02970

[40] S. K. Venu and S. Ravula, "Evaluation of deep convolutional generative adversarial networks for data augmentation of chest x-ray images," *Future Internet*, vol. 13, no. 1, pp. 1–13, 2021, doi: 10.3390/fi13010008.

[41] A. Sedik *et al.*, "Deploying machine and deep learning models for efficient data-augmented detection of COVID-19 infections," *Viruses*, vol. 12, no. 7, 2020, doi: 10.3390/v12070769.

[42] T. Rajasenbagam, S. Jeyanthi, and J. A. Pandian, "Detection of pneumonia infection in lungs from chest X-ray images using deep convolutional neural network and content-based image retrieval techniques," *Journal of Ambient Intelligence and Humanized Computing*, no. 2016, 2021, doi: 10.1007/s12652-021-03075-2.

[43] S. Sakib, T. Tazrin, M. M. Fouda, Z. M. Fadlullah, and M. Guizani, "DL-CRC: Deep learning-based chest radiograph classification for covid-19 detection: A novel approach," *IEEE Access*, vol. 8, no. July, pp. 171575–171589, 2020, doi: 10.1109/ACCESS.2020.3025010.

[44] P. M. Shah *et al.*, "\textlessscp\textgreaterDC-GAN\textless/scp\textgreater -based synthetic X-ray images augmentation for increasing the performance of \textlessscp\textgreaterEfficientNet\textless/scp\textgreater for \textlessscp\textgreaterCOVID\textless/scp\textgreater -19 detection," *Expert Systems*, vol. 39, no. 3, Mar. 2022, doi: 10.1111/exsy.12823.

[45] M. M. Rahaman *et al.*, "Identification of COVID-19 samples from chest X-Ray images using deep learning: A comparison of transfer learning approaches," *Journal of X-Ray Science and Technology*, vol. 28, no. 5, pp. 821–839, 2020, doi: 10.3233/XST-200715.

[46] D. R. P. R. M. Lustermans, S. Amirrajab, M. Veta, M. Breeuwer, and C. M. Scannell, "Optimized automated cardiac MR scar quantification with GAN-based data augmentation," *Computer Methods and Programs in Biomedicine*, vol. 226, p. 107116, 2022, doi: 10.1016/j.cmpb.2022.107116.

[47] S. Motamed, P. Rogalla, and F. Khalvati, "RANDGAN: Randomized generative adversarial network for detection of COVID-19 in chest X-ray," *Scientific Reports*, vol. 11, no. 1. 2021. doi: 10.1038/s41598-021-87994-2.

[48] T. D. Pham, "Classification of COVID-19 chest X-rays with deep learning: new models or fine tuning?," *Health Information Science and Systems*, vol. 9, no. 1, pp. 1–11, 2021, doi: 10.1007/s13755-020-00135-3.