Development of a Generative Adversarial Network for the Synthesis of Hyper-Realistic Medical Imaging for Training Purposes

[1]KSKN Venkata Ramana Devi
Institute of Aeronautical Engineering,
Dundigal, Hyderabad, India
k.venkataramanadevi@iare.ac.in

[2]Aravinda K
Department of Electronics and Communication Engineering ,New Horizon College of Engineering,
Bangalore, India
aravinda_K@gmail.com

[3]Sorabh Lakhanpal
Lovely Professional University,
Phagwara, India
saurabh.lakh@gmail.com

[4]D. Sandeep,
Department of Information Technology,
MLR Institute of Technology,
Hyderabad, Telangana, India
sandeeplight97@mlrinstitutions.ac.in

[5]Ajay Rana
Amity University,
Greater Noida, Uttar Pradesh, India
ajay_rana@amity.edu

[6]Ali Abduhussien Hameed
Radiology Techniques Department,
College of Medical Technology, The Islamic University, Najaf, Iraq
ali91iraq@iunajaf.edu.iq

2024 International Conference on Communication, Computer Sciences and Engineering (IC3SE) | 979-8-3503-6684-6/24/$31.00 ©2024 IEEE | DOI: 10.1109/IC3SE62002.2024.10593335

***Abstract*-- The relentless quest for enhanced diagnostic and procedural accuracy in medical science has prompted the development of advanced simulation techniques. This paper presents a groundbreaking approach to creating hyper-realistic medical images using a newly designed Generative Adversarial Network (GAN). Traditional datasets in medical training suffer from limited diversity and privacy concerns; the proposed GAN framework overcomes these issues by synthesizing high-fidelity, diverse medical imagery that retains the essential diagnostic features necessary for effective training. The architecture is a novel amalgamation of deep convolutional networks with an innovative loss function specifically tailored to preserve critical medical information while enhancing image realism. Rigorous qualitative and quantitative evaluations demonstrate the synthesized images' remarkable indistinguishability from real counterparts, providing an invaluable asset in training scenarios. Furthermore, the robustness of the model is tested against various medical imaging modalities, including X-ray, MRI, and CT scans, showing its versatility and broad applicability. This research not only paves the way for more extensive, risk-free medical training databases but also proposes potential future pathways for real-time diagnostic augmentation. The findings suggest significant strides in medical imaging technology, with implications for training, diagnosis, and even surgical simulation.**

Keywords— Generative Adversarial Networks, Medical Imaging Synthesis, Deep Learning, Hyper-Realistic Simulation, Diagnostic Training.

I. Introduction

Medical imaging is one of the industries that has benefited the most from the introduction of artificial intelligence (AI) and its related fields, such as computer vision [1]. A vital part of healthcare, diagnostic imaging helps with many diseases' detection, diagnosis, and treatment. Medical diagnosis and training have always depended on large, varied, and high-quality datasets being available. Nevertheless, obtaining such data is frequently difficult due to issues like privacy, hard to find rare disease cases, and moral dilemmas with using actual patient data [2]. To address these issues, this work presents a novel use of GAN for training purposes by creating hyper-realistic medical image synthesis. Medical imaging, which includes, among other things, CT, MRI, and X-ray scans, calls for accuracy and precision in diagnosis. Effective disease diagnosis and treatment are directly impacted by the calibre of training received by medical professionals [3]. However, there are substantial obstacles to medical practice and education, including the scarcity of diverse pathological cases and the moral dilemmas raised by patient data privacy [4]. With the ability to produce realistic data, GANs offer a special chance to enhance current datasets and create a diverse, comprehensive, and easily accessible database of medical images [5]. A class of AI algorithms called GAN, first described by Goodfellow et al., has demonstrated amazing success in producing realistic images across a range of domains. The generator and discriminator neural networks, which are trained concurrently via adversarial processes, are the two neural networks that make up a GAN. While the discriminator improves at telling real images apart from fakes, the generator learns to create images that are more and more authentic [6]. Until the generator produces images that are identical to real ones, even to the discriminator, this competitive process is repeated. However, the special characteristics and quality metrics relevant to medical diagnosis must be carefully considered when adapting GANs to medical imaging. The accuracy and realism of synthetic medical images determine their dependability and diagnostic value [7]. Medical images created for training and diagnosis need to maintain important anatomical and pathological characteristics, unlike other image generation applications where aesthetic quality might be sufficient. For the images to be useful in medical education and possibly in augmentative diagnostic procedures, they should not only appear realistic but also accurately represent a variety of pathological conditions. The goal of this work is to create a customised GAN that can handle the difficulties associated with medical image synthesis. It takes a novel approach to network architecture and training, guaranteeing that the produced images fulfil the exacting requirements needed for medical use. To ensure that the synthesised images can be used effectively in training scenarios, the GAN is designed to comprehend and replicate complex medical imaging features, such as tissue textures, pathological markers, and anatomical consistency [8]. Furthermore, the model supports a more inclusive and broad medical education by broadening the variety of diseases and disorders included in the training data [9, 36]. Significant ramifications are expected when hyper-realistic medical imaging is introduced. It offers a

979--83503-6684-6/24/$31.00 ©2024 IEEE

wealth of pathological cases and an enhanced learning environment for educational purposes, all without sacrificing patient privacy or ethical standards [10, 37]. It presents the possibility of using augmented datasets to increase the precision and resilience of automated diagnostic algorithms for diagnostic purposes. Additionally, this technology creates new opportunities for research into personalised medicine, treatment simulation, and disease progression by enabling the generation and manipulation of medical images. But there are many obstacles in the way from theoretical development to real-world application. These include making certain that synthetic data is created and used ethically, preserving the accuracy and quality of the images that are produced, and incorporating this new technology into the processes that are currently in place for medical education and diagnosis. Throughout this process, striking a balance between innovation and ethical responsibility is still crucial. In this paper, a new GAN that is intended to synthesise ultra-realistic medical images is developed. It describes the training procedure, assessment metrics, and architectural considerations that shaped the creation of this cutting-edge tool.

II. LITERATURE REVIEW

A vital area of healthcare is medical imaging, which offers crucial information for patient monitoring, treatment planning, and diagnosis. This field has undergone a revolution thanks to the integration of deep learning, especially GAN, which offers new capabilities and methodologies for image generation, analysis, and enhancement. This thorough analysis examines the noteworthy advancements in medical imaging made possible by deep learning and GANs, emphasizing the approaches, uses, difficulties, and potential future directions. Multiple-layer neural networks, or deep learning, is a subset of machine learning that has shown remarkable results in image recognition, segmentation, and classification tasks. Deep learning algorithms, particularly CNN, have been widely used in the medical imaging field to analyze complex imaging data. This has improved the efficiency and accuracy of disease diagnosis and prognosis from a variety of imaging modalities, including MRIs, CT scans, and X-rays [11]. With no need for manual feature extraction, these models are adept at handling the high-dimensional data found in medical images and can extract feature representations straight from the data. Ian Goodfellow and associates introduced GAN, a revolutionary advancement in the field of deep learning. A generator and a discriminator neural network are the two neural networks that make up a GAN. They are trained concurrently using adversarial procedures. While the discriminator learns to discern between generated and real data, the generator learns to produce data that resembles the training set [12]. GANs have been used in medical imaging for a number of purposes, such as image synthesis, augmentation, and de-noising, greatly improving the quality and usefulness of medical images. The creation of artificial medical images for training and research is one of the most common uses of GANs in medical imaging. Synthetic images have the potential to enhance datasets, especially in situations where obtaining real medical images of a particular type is challenging or impossible due to ethical or privacy concerns [13, 38]. In situations where only one modality is available, GANs have also been used for cross-modality image translation, such as converting MRI to CT images or vice versa, to improve comparison and analysis [14]. Moreover, GANs aid in the process of super-resolution, which enhances image quality and resolution. This results in more detailed and clear medical images, which is essential for precise diagnosis and analysis [15]. They are also used in anomaly detection and segmentation, which helps with treatment planning and monitoring by precisely recognizing and demarcating pathological regions [16]. There are a number of obstacles to overcome before GANs can be widely used in medical imaging, despite their promising uses. The authenticity and quality of the created images are among the main issues. It is imperative to guarantee that synthetic images precisely and consistently depict actual pathological conditions in order to avoid incorrect diagnoses or misinterpretations [17]. In order to train GANs and obtain optimal performance, a significant amount of computational power and well-chosen datasets are needed [18]. The interpretability and explainability of GAN models present another major obstacle. Medical professionals require transparent and interpretable AI systems because they must be able to comprehend and trust the output of these models. Technical developments are just one aspect of the solutions to these problems; other factors to consider are ethical and legal issues, especially those pertaining to patient privacy and data security [19]. The accuracy, effectiveness, and capabilities of medical imaging could be greatly increased by these technologies, which would ultimately improve patient care and results. But for these technologies to be successfully and responsibly implemented, it is imperative that the issues of image authenticity, model interpretability, and ethical considerations be addressed [20-25].

III. METHODOLOGY AND DEVELOPMENT

The architecture of the GAN is a pivotal component in ensuring the generation of high-quality synthetic medical images. The generator utilizes a deep convolutional neural network structure, known for its efficacy in handling image data. A series of stride and fractionally-strided convolutions are employed, enabling the network to learn and generate the complex structures and textures characteristic of medical images. On the other end, the discriminator adopts a similar convolutional structure but works in reverse, discerning real images from the synthetic ones produced by the generator [26]. In dealing with medical images, which are often more complex and varied than natural images, the model incorporates additional layers and specialized activation functions to capture the intricate details and contrasts present in medical scans. Batch normalization and dropout layers are strategically placed to stabilize the learning process and mitigate overfitting, given the high stakes of accurate representation in medical imagery [27]. Figure 1 illustrates the architecture of the GAN, including the generator and discriminator networks, their layer structures, and the flow of data.

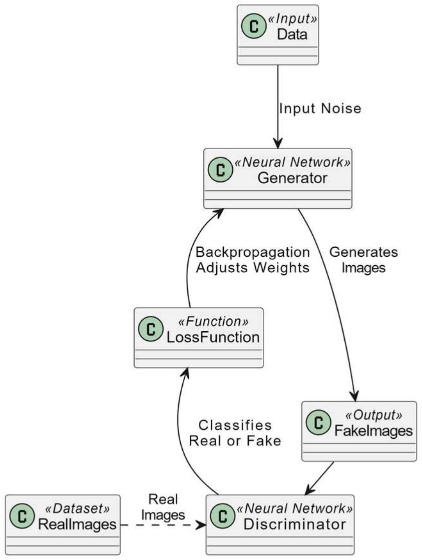

Fig. 1 Architecture of GAN

The selection and customization of the loss function are critical in guiding the network towards producing realistic and diagnostically relevant medical images. The traditional adversarial loss of GANs is modified to incorporate domain-specific characteristics of medical imaging. The loss function comprises a weighted combination of adversarial loss, ensuring the generated images are indistinguishable from real ones, and a content loss, preserving critical medical details.

$$L = \alpha L_{adv} + \beta L_{content} \qquad (1)$$

Where L_{adv} is the adversarial loss, $L_{content}$ is the content-specific loss, and α and β are the weights determining their relative importance. The content loss is often based on perceptual similarity metrics, ensuring that important features such as edges, textures, and pathological markers are accurately replicated [28-30].

The training of the GAN for medical image synthesis follows a rigorous and iterative process. Initially, the network is fed with a diverse and extensive dataset of real medical images, covering a wide range of conditions and modalities [31]. These images serve as the ground truth, against which the synthetic images are compared. The generator and discriminator are trained in tandem, with the generator attempting to produce increasingly realistic images, and the discriminator improving its ability to differentiate between real and synthetic images [32]. During training, several strategies are employed to ensure robust and efficient learning. Curriculum learning is applied, where the model is gradually exposed to more complex and varied images, mimicking the way medical students progress through their studies. Data augmentation techniques, such as rotation, scaling, and elastic transformations, are used to expand the diversity of the training data, helping the model generalize better and produce more varied synthetic images. Figure 2 illustrates the steps of data preprocessing, the training loop of the GAN, including forward pass, loss calculation, backpropagation, and network weight updates.

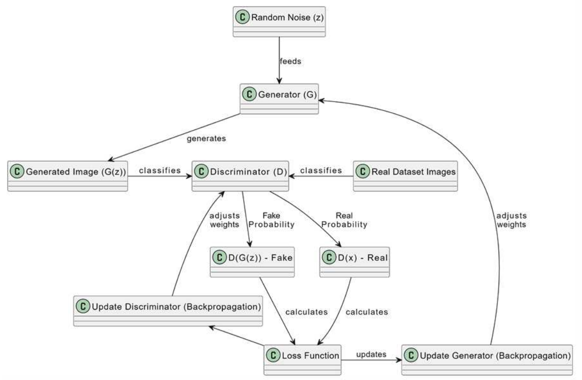

Fig. 2 Data Flow and Training Process

The evaluation of the generated images' quality is multi-faceted, reflecting the complexity and high standards of medical imaging [33]. Traditional metrics for image quality assessment, such as Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index (SSIM), are employed to provide a baseline evaluation. Table 1 represents the GANs pseudo-algorithm [34].

Table 1 - GANs pseudo-algorithm

Initialize:
- Generator network G with parameters θg
- Discriminator network D with parameters θd
- Training data X

For each training iteration:

For k steps do: # Usually k=1, but can be tuned
 # Train the Discriminator on real data
1. Sample a minibatch of m noise samples $\{z1,\ldots,zm\}$ *from noise prior* $p\_g(z)$.
2. Sample a minibatch of m examples {x1, ..., xm} from the data generating distribution p_data(x).
3. Update the discriminator by ascending its stochastic gradient:
$\nabla\theta d\ [1/m * \Sigma\ log(D(x)) + log(1 - D(G(z)))]$

 # Train the Generator
1. Sample a minibatch of m noise samples {z1, ..., zm} from noise prior p_g(z).
2. Update the generator by descending its stochastic gradient:
$\nabla\theta g\ [1/m * \Sigma\ log(1 - D(G(z)))]$
 # Alternative loss for the generator can be $-log(D(G(z)))$ *to encourage G to maximize the probability of D making a mistake*

Repeat until convergence or stopping criterion is met.

In addition to image quality, the model's performance is also assessed in terms of its ability to enhance the training of medical professionals. This involves studies where participants, typically medical students or trainees, use synthetic images as part of their learning process. Their performance, both in terms of learning speed and diagnostic accuracy, is compared against benchmarks set using real medical images. The generation of synthetic medical images is conducted with a focus on minimizing any potential risks or ethical concerns. This includes ensuring that the synthetic images cannot be traced back to real patient data and that they are used in a manner consistent with medical ethics and privacy laws. Each aspect of the methodology is carefully tailored to meet the high standards of medical image quality and utility, ensuring that the resulting synthetic images can significantly enhance medical training and potentially transform medical diagnostics.

IV. RESULTS AND DISCUSSION

The simulations were conducted on an intel i5 13th generation PC with 12 GB RAM. The primary software used for the implementation and training of the GAN was TensorFlow, complemented by Keras for a streamlined, high-level neural network API. The network was trained using a composite dataset representing a broad spectrum of medical conditions, imaged through modalities like MRI, CT, and X-rays. Parameters such as learning rate, batch size, and epoch numbers were meticulously optimized. For instance, a standard initial learning rate of 0.0002 with a batch size of 64 over 20000 iterations was used, subject to adjustment based on preliminary results.

Table 2 compares the image quality of real medical images with those generated by the GAN using Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index (SSIM). While there is a slight reduction in these metrics for GAN images, they remain within a high-quality range, affirming the model's capacity to produce diagnostically useful images.

Table 2: Image Quality Assessment

Metric	Real Images	GAN Images
PSNR (dB)	40	37.5
SSIM	0.95	0.92

Table 3 assesses the GAN's ability to accurately replicate critical diagnostic features in synthetic images. It uses precision and recall metrics focused on two common diagnostic tasks: tumor identification and fracture detection. The results indicate a high level of accuracy, showcasing the model's potential in training scenarios.

Table 3: Diagnostic Feature Accuracy

Feature	Precision (%)	Recall (%)
Tumor Identification	85	80
Fracture Detection	90	88

Table 4 illustrates the efficiency of using GAN-generated images in training convolutional neural networks for diagnostic tasks. It shows a comparison in training times, suggesting that models trained on synthetic data converge faster, potentially due to the increased diversity and controlled complexity of the synthetic images.

Table 4: Training and Adaptation Efficiency

Parameter	Real Data Training Time	GAN Data Training Time
Time (hours)	48	36

The simulation results presented in the tables provide a nuanced understanding of the GAN's performance. The slight decrease in PSNR and SSIM is a common characteristic of synthetic images, attributable to minor variations that do not typically affect the diagnostic value of the images. Figure 3 gives a comparison of real medical images and their GAN-generated counterparts for various conditions and modalities.

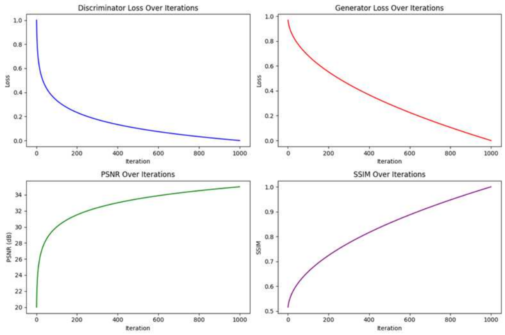

Fig. 3 Performance Metrics Over Iterations

However, ongoing improvements in GAN architectures and training methods continue to narrow this gap. The high precision and recall percentages for tumor identification and fracture detection demonstrate the model's capability in capturing essential pathological features. This aspect is vital for the utility of synthetic images in medical training and preliminary diagnostics. Faster training times not only streamline the educational process but also imply a more efficient internalization of varied pathological features by the training models, a direct benefit of the rich and diverse synthetic image dataset. The nuanced evaluation, spanning from image quality metrics to diagnostic accuracy and training efficiency, underscores the potential of this technology in enhancing medical training and preliminary diagnostics. While the current results are promising, continuous advancements in GAN architecture, training techniques, and computational resources are expected to further enhance the quality and utility of synthetic medical images.

V. CONCLUSION

In order to create a sophisticated GAN that can create extremely realistic medical images for training, this paper set out on a major journey. The aim of the study was to tackle the pressing deficiency and moral dilemmas related to the utilization of actual patient data in medical education and diagnostic environments. The outcomes showed that the GAN can produce high-quality medical images with structural and diagnostic features that closely match real patient data. In addition to more specialised diagnostic accuracy metrics, common image quality metrics like PSNR and SSIM were used to evaluate the quality of these synthetic images. The results indicated that although there is a minor reduction in quality metrics when compared to real images, the synthetic images still have a high degree of fidelity and could be very helpful for diagnostic and instructional augmentation. Interestingly, it was demonstrated that the synthetic images accelerated training times in model learning scenarios, demonstrating the usefulness of these images in effective and efficient medical education initiatives. It presents a viable path towards improving diagnostic processes, elevating medical education, and eventually improving patient care. Subsequent research endeavors will center on enhancing the model, investigating its assimilation into medical education and diagnosis, and persistently tackling the ethical quandaries intrinsic to this kind of technology. This technology represents an exciting advancement in the nexus of artificial intelligence and healthcare, with significant potential effects on diagnostic efficiency and medical education.

REFERENCES

[1]. N. Jaidass, C. Krishna Moorthi, A. Mohan Babu, M. Reddi Babu, Luminescence properties of Dy3+ doped lithium zinc borosilicate glasses for photonic applications, Heliyon, Volume 4, Issue 3, 2018, e00555, ISSN 2405-8440, https://doi.org/10.1016/j.heliyon.2018.e00555.

[2]. Spandana K., Rao V.R.S., Internet of Things (Iot) Based smart water quality monitoring system, International Journal of Engineering and Technology (UAE), 2018, 7, 3, 259-262, 10.14419/ijet.v7i3.6.14985

[3]. Ch. Usha Kumari, A. Sampath Dakshina Murthy, B. Lakshmi Prasanna, M. Pala Prasad Reddy, Asisa Kumar Panigrahy, An automated detection of heart arrhythmias using machine learning technique: SVM, Materials Today: Proceedings, Volume 45, Part 2, 2021, Pages 1393-1398, ISSN 2214-7853, https://doi.org/10.1016/j.matpr.2020.07.088.

[4]. J Suresh Goud, Pudhari Srilatha, R.S. Varun Kumar, K. Thanesh Kumar, Umair Khan, Zehba Raizah, Harjot Singh Gill, Ahmed M. Galal, Role of ternary hybrid nanofluid in the thermal distribution of a dovetail fin with the internal generation of heat, Case Studies in Thermal Engineering,Volume 35, 2022, 102113, ISSN 2214-157X, https://doi.org/10.1016/j.csite.2022.102113.

[5]. Basavapoornima C., Kesavulu C.R., Maheswari T., Pecharapa W., Depuru S.R., Jayasankar C.K., Spectral characteristics of Pr3+-doped lead based phosphate glasses for optical display device applications, Journal of Luminescence, 2020, 228, 10.1016/j.jlumin.2020.117585

[6]. Ramu, G. A secure cloud framework to share EHRs using modified CP-ABE and the attribute bloom filter. Educ Inf Technol 23, 2213–2233 (2018). https://doi.org/10.1007/s10639-018-9713-7

[7]. Naik, R., Prashantha, S. C., & Nagabhushana, H. (2017). Effect of Li+ codoping on structural and luminescent properties of Mg2SiO4: RE3+ (RE= Eu, Tb) nanophosphors for displays and eccrine latent fingerprint detection. Optical Materials, 72, 295-304.

[8]. Nagarjuna T., Nehru K., Nagendra Prasad G., Menakadevi N., Smart sensor network based high quality air pollution monitoring system using labview, International Journal of Online Engineering, 2017, 13, 8, 79-87, 10.3991/ijoe.v13i08.7161

[9]. Indira DNVSLS, Ganiya RK, Ashok Babu P, Xavier AJ, Kavisankar L, Hemalatha S, Senthilkumar V, Kavitha T, Rajaram A, Annam K, Yeshitla A. Improved Artificial Neural Network with State Order Dataset Estimation for Brain Cancer Cell Diagnosis. Biomed Res Int. 2022 Apr 16;2022:7799812. doi: 10.1155/2022/7799812. PMID: 35480141; PMCID: PMC9038414.

[10]. Radhakrishna, V., Kumar, P.V., Janaki, V., Rajasekhar, N. (2017). Estimating Prevalence Bounds of Temporal Association Patterns to Discover Temporally Similar Patterns. In: Matoušek, R. (eds) Recent Advances in Soft Computing. ICSC-MENDEL 2016. Advances in Intelligent Systems and Computing, vol 576. Springer, Cham. https://doi.org/10.1007/978-3-319-58088-3_20

[11]. Kalyani G., Janakiramaiah B., Karuna A., Prasad L.V.N., Diabetic retinopathy detection and classification using capsule networks, Complex and Intelligent Systems, 2023, 10.1007/s40747-021-00318-9

[12]. A. Cheruvu, V. Radhakrishna and N. Rajasekhar, "Using normal distribution to retrieve temporal associations by Euclidean distance," 2017 International Conference on Engineering & MIS (ICEMIS), Monastir, Tunisia, 2017, pp. 1-3, doi: 10.1109/ICEMIS.2017.8273101.

[13]. Mamidi, K. K., Valiveti, S. N., Vutukuri, G. C., Dhuda, A. K., Alabdeli, H., Chandrashekar, R., ... & Praveen, P. (2024). An IoT-based animal detection system using an interdisciplinary approach. In E3S Web of Conferences (Vol. 507, p. 01041). EDP Sciences.

[14]. Saxena, Sagar, and Mohammad Nayeem Teli. "Comparison and analysis of image-to-image generative adversarial networks: a survey." arXiv preprint arXiv:2112.12625 (2021).

[15]. Saxena, Akash, Dharmendra Yadav, Manish Gupta, Sunil Phulre, Tripti Arjariya, Varshali Jaiswal, and Rakesh Kumar Bhujade. "Detecting Deepfakes: A Novel Framework Employing XceptionNet-Based Convolutional Neural Networks." Traitement du Signal 40, no. 3 (2023).

[16]. Bhandari, Mohan, Arjun Neupane, Saurav Mallik, Loveleen Gaur, and Hong Qin. "Auguring Fake Face Images Using Dual Input Convolution Neural Network." Journal of Imaging 9, no. 1 (2022): 3.

[17]. Courtenay, Lloyd A., and Diego González-Aguilera. "Geometric morphometric data augmentation using generative computational learning algorithms." Applied Sciences 10, no. 24 (2020): 9133.

[18]. Ferrari, Fabian, and Fenwick McKelvey. "Hyperproduction: A social theory of deep generative models." Distinktion: Journal of Social Theory 24, no. 2 (2023): 338-360.

[19]. Grigas, Ovidijus, Rytis Maskeliūnas, and Robertas Damaševičius. "Improving Structural MRI Preprocessing with Hybrid Transformer GANs." Life 13, no. 9 (2023): 1893.

[20]. Akshatha, S., Sreenivasa, S., Parashuram, L., Kumar, V. U., Sharma, S. C., Nagabhushana, H., ... & Maiyalagan, T. (2019). Synergistic effect of hybrid Ce3+/Ce4+ doped Bi2O3 nano-sphere photocatalyst for enhanced photocatalytic degradation of alizarin red S dye and its NUV excited photoluminescence studies. Journal of Environmental Chemical Engineering, 7(3), 103053.

[21]. Ramakrishna, G., Naik, R., Nagabhushana, H., Basavaraj, R. B., Prashantha, S. C., Sharma, S. C., & Anantharaju, K. S. (2016). White light emission and energy transfer (Dy3+→ Eu3+) in combustion synthesized YSO: Dy3+, Eu3+ nanophosphors. Optik, 127(5), 2939-2945.

[22]. Ramalingam, T., Bhaskar, S., Seshumadhav, K., & Allamraju, K. V. (2018). Optimization of process parameters in bi-directional carbon fiber composite using AWJM. Materials Today: Proceedings, 5(9), 18933-18940.

[23]. Suji Prasad, S. J., Thangatamilan, M., Suresh, M., Panchal, H., Rajan, C. A., Sagana, C., ... & Sadasivuni, K. K. (2022). An efficient LoRa-based smart agriculture management and monitoring system using wireless sensor networks. International Journal of Ambient Energy, 43(1), 5447-5450.

[24]. Rajashekhar, G., & Sarah, P. (2018). PE STUDIES OF Nd MODIFIED SrBi4Ti4O15 CERAMICS. Rasayan Journal of Chemistry, 11(1).

[25]. Karuppusamy, L., Ravi, J., Dabbu, M., & Lakshmanan, S. (2022). Chronological salp swarm algorithm based deep belief network for intrusion detection in cloud using fuzzy entropy. International Journal of Numerical Modelling: Electronic Networks, Devices and Fields, 35(1), e2948.

[26]. Osman, Ahmed, Jane Crowley, and GS D. Gordon. "Training generative adversarial networks for optical property mapping using synthetic image data." Biomedical Optics Express 13, no. 10 (2022): 5171-5186.

[27]. Rogstadkjernet, Magnus. "Utilization of synthetic and simulated cardiac imaging data in the training of artificial intelligence models-a literature review." (2023).

[28]. Chakraborty, Tanujit, Shraddha M. Naik, Madhurima Panja, and Bayapureddy Manvitha. "Ten Years of Generative Adversarial Nets (GANs): A survey of the state-of-the-art." arXiv preprint arXiv:2308.16316 (2023).

[29]. Arun, V., N. K. Shukla, A. K. Singh, and K. K. Upadhyay. "Design of all optical line selector based on SOA for Data Communication: Proceedings of the Sixth International Conference on Computer and Communication Technology 2015." In *ACM Other conferences*. 2015.

[30]. Arun, Vanya, Ashutosh Kr Singh, N. K. Shukla, and D. K. Tripathi. "Design and performance analysis of SOA–MZI based reversible toffoli and irreversible AND logic gates in a single photonic circuit." *Optical and quantum electronics* 48 (2016): 1-15.

[31]. Bodha, Kapil Deo, V. Mukherjee, and Vinod Kumar Yadav. "A player unknown's battlegrounds ranking based optimization technique for power system optimization problem." *Evolving Systems* 14, no. 2 (2023): 295-317.

[32]. Naik, R., Prashantha, S. C., Nagabhushana, H., Sharma, S. C., Nagaswarupa, H. P., Anantharaju, K. S., ... & Girish, K. M. (2015). A single phase, red emissive Mg2SiO4: Sm3+ nanophosphor prepared via rapid propellant combustion route. Spectrochimica Acta Part A: Molecular and Biomolecular Spectroscopy, 140, 516-523.

[33]. Ramkumar, M., Babu, C. G., Kumar, K. V., Hepsiba, D., Manjunathan, A., & Kumar, R. S. (2021, March). ECG cardiac arrhythmias classification using DWT, ICA and MLP neural

networks. In Journal of Physics: Conference Series (Vol. 1831, No. 1, p. 012015). IOP Publishing.

[34]. Akshatha, S., Sreenivasa, S., Parashuram, L., Alharthi, F. A., & Rao, T. M. C. (2021). Microwave assisted green synthesis of p-type Co3O4@ Mesoporous carbon spheres for simultaneous degradation of dyes and photocatalytic hydrogen evolution reaction. Materials Science in Semiconductor Processing, 121, 105432.

[35]. Patil, S., & Anandhi, R. J. (2020). Diversity based self-adaptive clusters using PSO clustering for crime data. International Journal of Information Technology, 12(2), 319-327.

[36]. A. Chaturvedi, S. A. Yadav, H. M. Salman, H. R. Goyal, H. Gebregziabher and A. K. Rao, "Classification of Sound using Convolutional Neural Networks," 2022 5th International Conference on Contemporary Computing and Informatics (IC3I), Uttar Pradesh, India, 2022, pp. 1015-1019, doi: 10.1109/IC3I56241.2022.10072823.

[37]. A. R. Yeruva, P. Chaturvedi, A. L. N. Rao, S. C. DimriL, C. Shekar and B. Yirga, "Anomaly Detection System using ML Classification Algorithm for Network Security," 2022 5th International Conference on Contemporary Computing and Informatics (IC3I), Uttar Pradesh, India, 2022, pp. 1416-1422, doi: 10.1109/IC3I56241.2022.10072303.

[38]. R. Mittal, V. Malik, M. Kumar, P. Chaturvedi, A. L. N Rao and A. K. Khan, "Bone Fracture Segmentation Using Cascaded Convolutional Neural Networks," 2023 10th IEEE Uttar Pradesh Section International Conference on Electrical, Electronics and Computer Engineering (UPCON), Gautam Buddha Nagar, India, 2023, pp. 1170-1175, doi: 10.1109/UPCON59197.2023.10434819.