Explainable GAN for Enhanced Medical Image Denoising and Pneumonia Detection

Mohnish Karthikeyan B
SCOPE
Vellore Institute of Technology
Chennai, India
mohnishkarthikeyan.b2021@vitstudent.ac.in

Navaneetha Krishnan S
SCOPE
Vellore Institute of Technology
Chennai, India
navaneethakrishnan.s2021@vitstudent.ac.in

H G Leerish Arvind
SCOPE
Vellore Institute of Technology
Chennai, India
leerish.arvind2021@vitstudent.ac.in

Geetha S
SCOPE
Vellore Institute of Technology
Chennai, India
geetha.s@vit.ac.in

***Abstract*—Medical imaging is often beset by the pernicious effects of noise arising from equipment malfunctions or environmental perturbations, thereby complicating the diagnostic process. While traditional denoising methodologies—such as Gaussian filters, smoothing techniques, and various statistical approaches—have been extensively employed, they fail to leverage the transformative potential of contemporary advancements in artificial intelligence. Generative Adversarial Networks (GANs) have emerged as formidable instruments for the generation of denoised images. However, the inherent opacity of GANs frequently obstructs the comprehension of their decision-making mechanisms, engendering apprehensions regarding their reliability in critical medical applications. This research introduces a explainable GAN model that not only produces high-fidelity denoised chest X-ray images but also provides transparent and interpretable rationales for each generated output. Additionally, a robust and elucidative Convolutional Neural Network (CNN) is employed to ascertain the presence of pneumonia, thereby augmenting diagnostic accuracy. The confluence of explainability ensures that clinicians can place their trust in the system's outputs, ultimately enhancing patient outcomes.**

***Index Terms*—Medical Imaging, Generative Adversarial Networks, Image Denoising, Explainable AI, Pneumonia Detection, Convolutional Neural Networks, Diagnostic Accuracy, Interpretability**

I. Introduction

The proliferation of noisy medical images, particularly chest X-rays, presents formidable challenges to the precision of diagnostic methodologies. Medical imaging devices, susceptible to a myriad of hardware and software anomalies, frequently introduce artifacts and noise that, if left unmitigated, can culminate in erroneous diagnoses and misguided treatment strategies. Traditional denoising techniques, including Gaussian filtering, smoothing algorithms, and other statistical interventions, have been employed to ameliorate noise in medical imaging. While these methods exhibit a degree of efficacy, they do not capitalize on the revolutionary advancements in artificial intelligence that possess the potential to significantly enhance medical image processing.

Moreover, the advent of Generative Adversarial Networks (GANs) has heralded a new epoch in image generation and enhancement, showcasing remarkable capabilities in the domain of medical image denoising. However, the black-box nature of GANs remains a salient limitation, as it precludes users—especially within the medical community—from grasping and trusting the intricate processes that underpin image generation. Given that medical imaging directly impacts patient care, it is imperative to devise systems that not only yield high-quality images but also provide transparent and interpretable insights into the image generation process. This necessity underscores the importance of explainable AI (XAI), which seeks to illuminate the decision-making pathways of complex AI systems, thereby fostering trust and understanding among healthcare professionals.

In light of these challenges, this research endeavors to bridge the chasm between advanced AI methodologies and the exigent requirements of medical imaging. By proposing an explainable GAN architecture specifically designed for the denoising of chest X-rays, we aim to enhance the quality of medical images while simultaneously addressing the critical need for interpretability. Furthermore, to augment the clinical applicability of our framework, we integrate an explainable Convolutional Neural Network (CNN) for the detection of pneumonia within the generated denoised images. This synergistic approach not only amplifies image quality but also equips physicians with cogent justifications for the system's outputs, thereby fostering trust and improving diagnostic accuracy. The emphasis on explainability is paramount, ensuring that the system's behavior remains transparent and that its outputs are clinically sound, thereby facilitating its integration into real-world healthcare environments.

The integration of artificial intelligence into medical imaging has the potential to revolutionize diagnostic practices, yet it also raises critical ethical and practical considerations. As healthcare increasingly relies on AI-driven solutions, the imperative for transparency and accountability becomes paramount. Clinicians must not only trust the outputs of these advanced systems but also comprehend the rationale behind them to make informed decisions regarding patient care. This research addresses these concerns by developing an explainable framework that elucidates the decision-making processes of the AI models employed. By providing interpretable insights alongside high-quality denoised images and accurate pneumonia detection, we aim to empower healthcare professionals with the tools necessary to navigate the complexities of modern medical diagnostics, ultimately leading to improved patient outcomes and enhanced trust in AI technologies.

II. Literature Review

Nimitha et al. propose a multi-image super-resolution architecture using a Generative Adversarial Network (GAN) to enhance the resolution of MRI images, particularly for prostate cancer diagnosis. The architecture utilizes multi-stage feature extraction with residual blocks and attention networks, while reducing computational complexity with a simplified discriminator. A key innovation is the use of perceptual loss, optimized through a fine-tuned VGG19 network. The experimental results demonstrate superior performance over existing methods, achieving a peak signal-to-noise ratio (PSNR) of 30.58 dB and structural similarity index measure (SSIM) of 0.8105. The method significantly improves image quality without introducing false positives, making it a promising approach for medical image analysis. [1]

Anoushka Popuri et al. discuss the transformative approach of Generative Adversarial Networks (GANs) in synthetic data generation, emphasizing their competitive framework comprising a generator and discriminator. This approach excels in various applications, including image generation, style transfer, super-resolution, and image-to-image translation. Despite challenges like mode collapse and training instability, advancements such as DCGAN, CGAN, and WGAN have improved image quality and recognition tasks. Future research is focused on inter-domain transfers, reduced supervision, and ethical considerations, indicating the ongoing evolution and impact of GANs across diverse domains. [2]

Dhruv Sharma et al. highlight the integration of GANs with Artificial Intelligence and Machine Learning (AIML) in medical image processing, enhancing diagnostic accuracy and disease prediction. Their approach improves medical image quality and report summarization, addressing complex data analysis challenges. Key issues include ensuring data quality, interpretability, and seamless integration into clinical workflows, ultimately aiming to enhance patient care through advanced AI technologies. [3]

Robin Kumar et al. demonstrate how GANs have revolutionized medical image processing by providing solutions for image reconstruction, denoising, segmentation, and synthesis. They emphasize the effectiveness of GANs in generating high-quality images from noisy or incomplete data, particularly in modalities like MRI and CT. Despite advancements, challenges remain in optimal image reconstruction, artifact removal, and maintaining image quality, especially in fast MRI reconstruction and cross-modality synthesis. [4]

Sindhura et al. explore the use of Deep Convolutional GANs (DCGANs) to generate synthetic, realistic medical images, addressing the challenge of limited datasets in medical imaging. Their study successfully generated high-quality synthetic images from a dataset of CT images of vertebral column fractures, validated through a Visual Turing Test that showed experts struggled to differentiate synthetic from real images, highlighting the potential for GAN-based augmentation in medical imaging. [5]

Mohan et al. apply GANs to enhance brain tumor diagnosis by generating synthetic MRI images, effectively addressing data scarcity issues. Their work significantly expanded a dataset, increasing training effectiveness and improving model accuracy from 62% to 91% through image preprocessing, GAN training, and post-processing techniques. [6] Marzieh Esmaeili et al. investigate the application of GANs in anomaly detection (AD) within medical imaging, noting significant challenges due to limited annotated data and the complexity of abnormalities. Their comparative analysis of GAN-based AD methods across multiple datasets revealed variable performance, stressing the need for improved robustness and generalizability to ensure clinical reliability. [7]

Rajan Prasad Tripathi et al. propose a novel approach for breast cancer diagnosis that leverages GANs combined with segmentation techniques to generate synthetic mammograms closely resembling real images. This integration enhances the training dataset for diagnostic models, improving clinical relevance and accuracy, while also supporting medical education and training, thereby aiming to improve patient outcomes while considering ethical implications. [8]

Showrov Islam et al. conduct a comprehensive review of GANs in medical imaging, examining applications, algorithms, datasets, and preprocessing techniques. They address challenges such as optimization instability, privacy concerns, and traditional evaluation metrics inadequacies, while also suggesting future research directions to improve multimodal image augmentation and enhance GAN performance and privacy in medical applications. [9]

Yuhui Ma et al. introduce a bi-directional GAN framework to improve medical image quality by addressing issues like non-uniform illumination and imbalanced intensity. Their approach demonstrates superior performance across various medical imaging modalities, significantly enhancing the accuracy of clinical interpretation and decision-making in diagnostics. [10] Muthulakshmi et al. emphasize the critical role of GANs in enhancing medical imaging through denoising, data augmentation, and classification. They discuss the synergy between CNNs and ensemble learning methods in transforming diagnostic accuracy and reliability while advocating for further refinement of these methodologies for better patient outcomes. [11]

Manas Gupta et al. focus on convolutional autoencoders for medical image denoising, highlighting their effectiveness in reducing noise and improving reconstruction quality across several datasets. Their method showcases superior performance compared to existing techniques, indicating its potential in medical imaging applications. [12] Mufeng Geng et al. propose a content-noise complementary learning strategy within a GAN framework for medical image denoising. Their approach effectively balances noise reduction and detail retention, showing robust generalization capabilities across diverse datasets, suggesting significant potential for clinical applications. [13]

Ajmal Mohammed et al. review various CNN architectures and enhancements, including GANs and transfer learning, in the context of medical image denoising. They identify ongoing challenges such as computational complexity and data scarcity, underscoring the transition from traditional methods to advanced deep learning techniques. [14] Rajesh Patil et al. explore effective denoising techniques for multi-modal medical images, comparing Wavelet Transform and Singular Value Decomposition for noise removal. Their findings highlight the importance of tailoring denoising approaches based on the type of noise present in the images. [15] Zeng Jian et al. present the constrained least square filter as a robust method for denoising medical images, particularly in preserving edge detail while effectively reducing noise. Their quantitative analysis indicates superior results compared to traditional filtering techniques, highlighting its potential to improve diagnostic accuracy. [16]

Muthulakshmi et al. further discuss advancements in medical imaging through innovative techniques in image denoising, data augmentation, and classification, stressing the need for ongoing research to refine these methods and explore new applications to enhance imaging quality. [17] Guofen Wang et al. analyze medical image fusion technology, emphasizing the importance of noise reduction in multimodal imaging data integration. Their novel algorithm combines hybrid variation and sparse representation, achieving improved denoising and fusion outcomes validated through extensive experiments. [18]

Filza Akhlaq et al. report on advancements in bone anomaly detection using deep learning techniques, implementing a two-module pipeline for fracture classification that enhances reliability and interpretability through Explainable AI methods. [19] Miguel Fontes et al. highlight the significance of example-based Explainable AI techniques in medical imaging, which provide intuitive explanations to enhance the interpretability of AI systems, ultimately fostering better patient outcomes. [20]

Mina Nikolić et al. demonstrate the integration of Explainable AI methods in medical image classification, using tools to improve model transparency and accuracy, particularly in sensitive healthcare applications. [21] Padmapriya et al. discuss a computer-aided diagnostic system for brain tumor classification that leverages Explainable AI to enhance accuracy and interpretability, promoting timely diagnosis and improving patient outcomes. [22]

III. Proposed Work

Medical imaging is often hindered by noise, which can obscure vital details necessary for accurate diagnosis. The initial phase of our methodology involves the meticulous introduction of synthetic noise into the medical imaging dataset. Various noise typologies including Gaussian, salt and pepper, low frequency, quantization and speckle noises are introduced with varying probabilities, simulating realistic degradation scenarios in medical imaging. This synthetic corruption serves as the foundation for evaluating our model's robustness in denoising tasks. By diversifying the noise conditions, we ensure that our model generalizes well across disparate noise patterns, thus preparing it for real-world clinical applications where image quality may be compromised due to external factors.

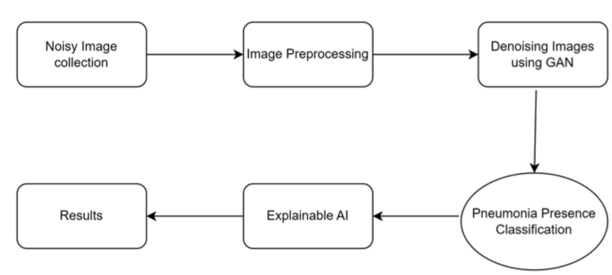

Fig. 1. Proposed Workflow

A. GAN Architecture for Denoising

The Generative Adversarial Network (GAN) architecture harnesses the UNet structure as the generator and a Convolutional Neural Network (CNN)-based Discriminator. The adversarial interplay between these two entities engenders a high-fidelity reconstruction of images, devoid of spurious noise. UNet, operates as a fully convolutional network meticulously designed for image-to-image transformation tasks. It incorporates an encoder-decoder framework with symmetric skip connections, which serve to bridge the encoder and decoder layers, effectively preserving spatial information. This retention of spatial integrity is paramount, as it enables UNet to capture fine-grained details essential for medical image restoration.

The encoder path, comprising sequential convolutional and pooling layers, progressively extracts hierarchical feature representations from the input. As each layer subsumes finer details into higher-level features, the model becomes adept at recognizing complex structures, an invaluable attribute when working with medical imagery. Conversely, the decoder path employs transpose convolutional layers to upsample the latent representations back to the original image dimensions, reinstating spatial resolution.

The skip connections unify the encoder and decoder at corresponding layers, reinstating lost spatial details, which ultimately augments the fidelity of the denoised image output. The final layer of the generator emits a refined denoised image, which is juxtaposed against the original noise-free image to evaluate the reconstruction accuracy. This reconstructed image is then subject to scrutiny by the Discriminator model to validate its authenticity.
The Discriminator, a convolutional neural network, is tasked with discerning the authenticity of the images generated by the UNet. Its architecture consists of progressive convolutional layers interspersed with batch normalization and LeakyReLU activation, which serves to accentuate the model's discriminative power. As the input image traverses through these layers, the model learns to extract distinguishing features that separate real images from synthesized ones, thus sharpening its adversarial proficiency.

The culmination of the Discriminator's pipeline is a sigmoid layer that outputs a probability score, delineating the likelihood of an image being real or generated. Through adversarial training, where the generator and Discriminator are iteratively optimized, the generator's capacity to produce realistic denoised images is markedly enhanced. This interplay is critical, as it drives the GAN toward a Nash equilibrium where the generator's output is virtually indistinguishable from real data, culminating in an optimal denoising model.

B. Pneumonia Detection with a CNN

Subsequent to denoising, the reconstructed images are processed by a Convolutional Neural Network (CNN) to ascertain the presence of pneumonia. The CNN is meticulously trained to discern subtle radiographic patterns indicative of pneumonia, leveraging the high-quality, denoised images produced by the GAN. By mitigating the obfuscating effects of noise, the GAN enhances the CNN's detection accuracy, ensuring that the subtle textural cues that typify pneumonia are more readily identifiable.

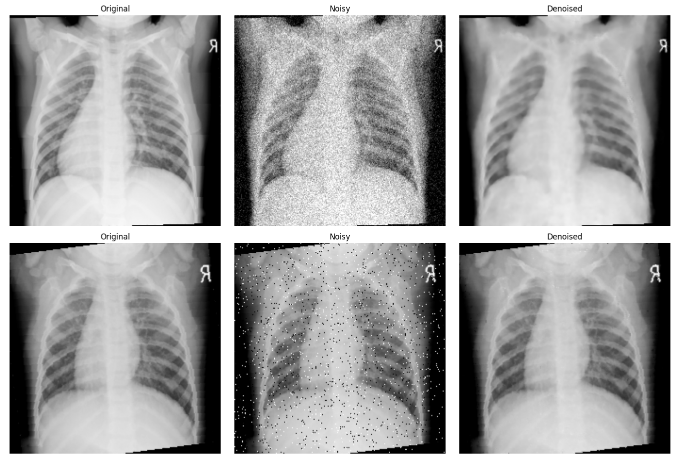

Fig. 2. Visual representation of Denoising

Each layer in the CNN abstracts increasingly complex features, with initial layers capturing basic edges and textures, while deeper layers capture intricate radiographic patterns associated with pulmonary pathology. This hierarchical learning mechanism, coupled with the denoised inputs, enhances the model's predictive accuracy, providing clinicians with reliable diagnostic insights.

C. Explainability via Grad-CAM

In medical imaging applications, model interpretability is crucial, as clinicians must understand the underlying rationale for AI-based diagnostic decisions. For this purpose, we employ Gradient-weighted Class Activation Mapping (Grad-CAM), a powerful explainability technique that elucidates the CNN's decision-making process by highlighting areas of the image that significantly impact its predictions.

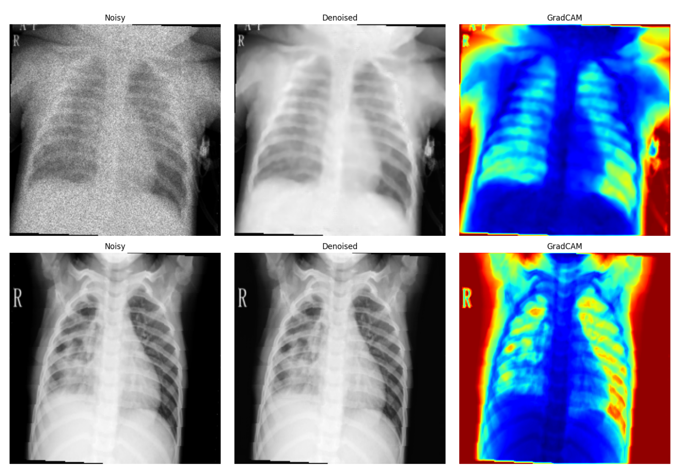

Fig. 3. Explanation of Model feature extraction using GradCAM

Grad-CAM operates by computing gradients of the classification score concerning the feature maps of a specific CNN layer, typically one of the deeper layers where the model captures complex visual cues. By applying these gradients, Grad-CAM generates a heatmap that emphasizes regions within the chest X-ray that strongly influence the pneumonia prediction. This approach provides a visual interpretability layer, allowing clinicians to corroborate the AI's predictions with their domain knowledge.

In this study, Grad-CAM is implemented using the LayerGradCam function from the Captum library, which integrates seamlessly with PyTorch-based CNNs. The resultant heatmaps are overlaid onto the original chest X-ray images, illustrating the regions the model focuses on when making a diagnostic decision. This transparency is pivotal, as it provides clinicians with a tangible explanation of the model's conclusions, reinforcing trust in its diagnostic utility.

IV. Results and Discussion

In this study, we evaluated the performance of an explainable Generative Adversarial Network (GAN) model for denoising chest X-ray images and diagnosing pneumonia. The model was trained to handle noisy images, achieving an accuracy of 81.75% for pneumonia detection after denoising. The results were analyzed based on the generator loss curve and the confusion matrix to determine the model's efficacy and areas for improvement.

The generator loss graph (Fig. 4) shows a steady decline across the epochs, indicating effective training. Initially, the generator loss was high, reflecting challenges in producing realistic, denoised images. However, with further training, the generator successfully minimized the loss, stabilizing at around 0.9 after approximately 50 epochs. This reduction in generator loss suggests that the GAN model adapted well to the noise in the dataset, progressively producing high-fidelity denoised images that closely resembled noise-free versions.

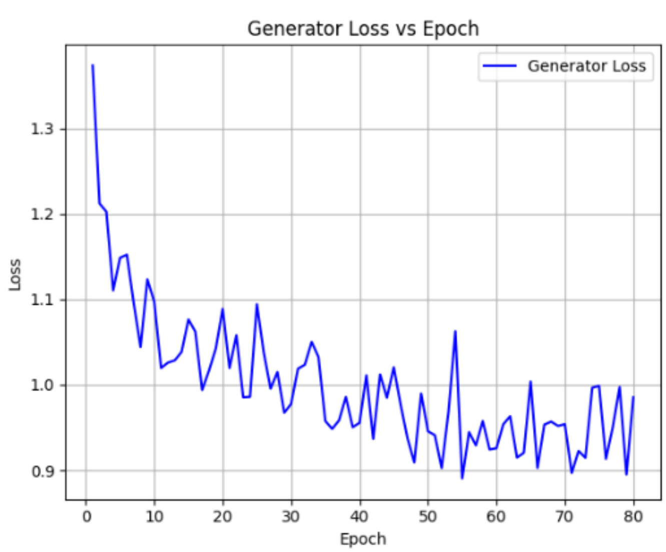

Fig. 4. Training Loss Curve for the Generator

The confusion matrix (Fig. 5) provides further insights into the model's classification performance. The model correctly classified 149 normal cases and 361 pneumonia cases, achieving an overall satisfactory balance between sensitivity and specificity. However, there were 85 false positives (normal images classified as pneumonia) and 29 false negatives (pneumonia images classified as normal). The slightly higher false positive rate may indicate the model's sensitivity toward identifying pneumonia features, potentially leading to an over-diagnosis of pneumonia cases.

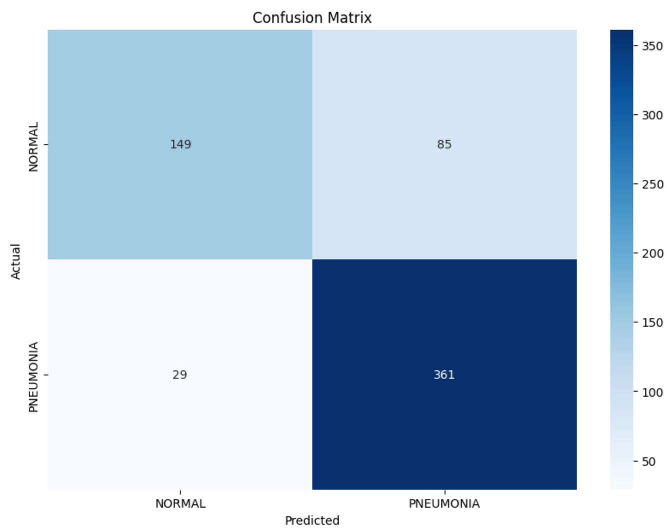

Fig. 5. Confusion Matrix of the CNN model

The quantitative metrics derived from the confusion matrix emphasize our model's effectiveness in handling noisy medical images for pneumonia detection. With an accuracy of 81.75%, a recall of 92.6%, and an F1 score of 86.4%, the model showcases a balanced performance between identifying pneumonia cases accurately while avoiding excessive false positives. High recall and F1 scores underscore the model's robustness in detecting pneumonia, which is crucial in reducing the risk of missed diagnoses in clinical settings. However, the lower specificity (63.6%) suggests that while the model is highly sensitive to pneumonia, it may overpredict the presence of pneumonia in normal cases. This outcome indicates a preference for reducing false negatives, an approach often favored in medical diagnostics to ensure critical cases are not overlooked.

Compared to traditional denoising and classification models for chest X-rays, our model offers a significant advantage by leveraging a GAN-based approach for image enhancement combined with an interpretable CNN for diagnosis. Traditional models, often reliant on techniques like Gaussian filtering or statistical denoising, lack the adaptive capabilities provided by GANs, especially in handling varied noise patterns and intensities. Additionally, conventional CNN models for pneumonia detection, while effective in noise-free datasets, often struggle with noisy images due to a lack of integrated denoising mechanisms. In contrast, our model's integrated GAN-based denoiser effectively reconstructs high-quality images, allowing the CNN classifier to achieve superior detection performance.

Moreover, explainability techniques like Grad-CAM provide our model with a significant edge by allowing clinicians to visualize the decision-making process. Most existing models either lack interpretability or rely solely on diagnostic outputs without transparency. By offering interpretable visualizations, our model aligns with clinical standards, enhancing its suitability for real-world applications where clinician trust and insight are paramount.

The combination of GAN-based denoising and a CNN for pneumonia detection has demonstrated effectiveness in enhancing diagnostic clarity. By filtering out noise, the GAN improves the quality of chest X-ray images, making it easier for the CNN to identify subtle patterns associated with pneumonia. The integration of Grad-CAM for interpretability further strengthens the model, as clinicians can verify the AI's predictions, fostering trust and usability in clinical settings.

V. Conclusion

This study introduces an explainable GAN-based model for denoising chest X-ray images and diagnosing pneumonia with an accuracy of 81.75%. By employing a UNet architecture for denoising and a CNN for classification, the model effectively minimizes noise, thereby enhancing diagnostic accuracy. Integrating Grad-CAM further enables interpretability, allowing clinicians to visualize regions that influence predictions, which is vital for adopting AI in critical medical applications. The findings underscore the potential of combining GANs with explainability techniques to improve medical image processing, particularly by reducing noise-related diagnostic errors in resource-limited settings.

Future improvements could involve developing advanced GAN architectures or hybrid models to further enhance denoising and diagnostic precision. Expanding the model's training to include diverse datasets with varied noise patterns would improve its generalizability to real-world imaging conditions. Additionally, extending the model to detect other respiratory conditions, such as tuberculosis, would increase its clinical utility. Real-world testing in healthcare environments could provide practical insights, while integrating interpretability methods like SHAP or LIME alongside Grad-CAM could enhance clinicians' understanding of the model's predictions, strengthening its role as a reliable diagnostic aid.

References

[1] U. Nimitha and P. M. Ameer, "Multi image super resolution of MRI images using generative adversarial network," Journal of Ambient Intelligence and Humanized Computing, vol. 15, no. 4, pp. 2241–2253, Feb. 2024, doi: 10.1007/s12652-024-04751-9.

[2] A. Popuri and J. Miller, "Generative Adversarial Networks in Image Generation and Recognition," 2023 International Conference on Computational Science and Computational Intelligence (CSCI), Las Vegas, NV, USA, 2023, pp. 1294-1297, doi: 10.1109/CSCI62032.2023.00212.

[3] D. Sharma, S. Singh, M. R. Patil and A. Subhan, "Medical Image Processing, Disease Prediction and Report Summarization Using Generative Adversarial Networks and AIML," 2024 2nd World Conference on Communication & Computing (WCONF), RAIPUR, India, 2024, pp. 1-5, doi: 10.1109/WCONF61366.2024.10692015.

[4] R. Kumar and R. Malik, "A Review on Generative Adversarial Networks used for Image Reconstruction in Medical imaging," 2021 9th International Conference on Reliability, Infocom Technologies and Optimization (Trends and Future Directions) (ICRITO), Noida, India, 2021, pp. 1-5, doi: 10.1109/ICRITO51393.2021.9596487.

[5] S. D. N, R. M. Pai, S. N. Bhat and M. P. M. M, "Synthetic Vertebral Column Fracture Image Generation by Deep Convolution Generative Adversarial Networks," 2021 IEEE International Conference on Electronics, Computing and Communication Technologies (CONECCT), Bangalore, India, 2021, pp. 1-4, doi: 10.1109/CONECCT52877.2021.9622527.

[6] B. M. G. et al., "Enhancing Brain Tumor Diagnosis with Generative Adversarial Networks," 2024 14th International Conference on Cloud Computing, Data Science & Engineering (Confluence), Noida, India, 2024, pp. 846-851, doi: 10.1109/Confluence60223.2024.10463384.

[7] M. Esmaeili et al., "Generative Adversarial Networks for Anomaly Detection in Biomedical Imaging: A Study on Seven Medical Image Datasets," in IEEE Access, vol. 11, pp. 17906-17921, 2023, doi: 10.1109/ACCESS.2023.3244741.

[8] R. P. Tripathi, S. K. Khatri, D. Van Greunen and D. Ather, "Enhancing Breast Cancer Diagnosis Through Segmentation-Driven Generative Adversarial Networks for Synthetic Mammogram Generation," 2023 3rd International Conference on Technological Advancements in Computational Sciences (ICTACS), Tashkent, Uzbekistan, 2023, pp. 1078-1082, doi: 10.1109/ICTACS59847.2023.10389935.

[9] S. Islam et al., "Generative Adversarial Networks (GANs) in Medical Imaging: Advancements, Applications, and Challenges," in IEEE Access, vol. 12, pp. 35728-35753, 2024, doi: 10.1109/ACCESS.2024.3370848.

[10] Y. Ma et al., "Structure and Illumination Constrained GAN for Medical Image Enhancement," in IEEE Transactions on Medical Imaging, vol. 40, no. 12, pp. 3955-3967, Dec. 2021, doi: 10.1109/TMI.2021.3101937.

[11] V. Muthulakshmi and K. Ramalakshmi, "Advancements in Medical Imaging Based on Image Denoising, Data Augmentation, and Classification with Computational Techniques," 2024 5th International Conference on Electronics and Sustainable Communication Systems (ICESC), Coimbatore, India, 2024, pp. 119-125, doi: 10.1109/ICESC60852.2024.10690154.

[12] M. Gupta, A. Goel, K. Goel and J. Kansal, "Medical Image Denoising using Convolutional Autoencoder with Shortcut Connections," 2023 5th International Conference on Smart Systems and Inventive Technology (ICSSIT), Tirunelveli, India, 2023, pp. 1524-1528, doi: 10.1109/ICSSIT55814.2023.10061131.

[13] M. Geng et al., "Content-Noise Complementary Learning for Medical Image Denoising," in IEEE Transactions on Medical Imaging, vol. 41, no. 2, pp. 407-419, Feb. 2022, doi: 10.1109/TMI.2021.3113365.

[14] A. Mohammed and S. Punniakodi, "A Comprehensive Study on Medical Image Denoising using Convolutional Neural Networks," 2023 Second International Conference on Advances in Computational Intelligence and Communication (ICACIC), Puducherry, India, 2023, pp. 1-5, doi: 10.1109/ICACIC59454.2023.10435104.

[15] R. Patil and S. Bhosale, ”Efficient Denoising of Multi-modal Medical Image using Wavelet Transform and Singular Value Decomposition,” 2023 IEEE IAS Global Conference on Emerging Technologies (GlobConET), London, United Kingdom, 2023, pp. 1-6, doi: 10.1109/GlobConET56651.2023.10150051.

[16] Z. Jian and L. Yin, ”Medical ankle image denoising based on constrained least square filter,” 2022 16th ICME International Conference on Complex Medical Engineering (CME), Zhongshan, China, 2022, pp. 178-181, doi: 10.1109/CME55444.2022.10063269.

[17] V. Muthulakshmi and K. Ramalakshmi, ”Advancements in Medical Imaging Based on Image Denoising, Data Augmentation, and Classification with Computational Techniques,” 2024 5th International Conference on Electronics and Sustainable Communication Systems (ICESC), Coimbatore, India, 2024, pp. 119-125, doi: 10.1109/ICESC60852.2024.10690154.

[18] G. Wang, W. Li, J. Du, B. Xiao and X. Gao, ”Medical Image Fusion and Denoising Algorithm Based on a Decomposition Model of Hybrid Variation-Sparse Representation,” in IEEE Journal of Biomedical and Health Informatics, vol. 26, no. 11, pp. 5584-5595, Nov. 2022, doi: 10.1109/JBHI.2022.3196710.

[19] F. Akhlaq, S. Ali, A. S. Imran, S. M. Daudpota and Z. Kastrati, ”Diving Deep into Bone Anomalies on the FracAtlas Dataset Using Deep Learning and Explainable AI,” 2024 International Conference on Engineering & Computing Technologies (ICECT), Islamabad, Pakistan, 2024, pp. 1-6, doi: 10.1109/ICECT61618.2024.10581288.

[20] M. Fontes, J. D. S. De Almeida and A. Cunha, ”Application of Example-Based Explainable Artificial Intelligence (XAI) for Analysis and Interpretation of Medical Imaging: A Systematic Review,” in IEEE Access, vol. 12, pp. 26419-26427, 2024, doi: 10.1109/ACCESS.2024.3367606.

[21] M. Nikolić, D. Janković, A. Stanimirović and L. Stoimenov, ”The Integration of Explainable AI Methods for the Classification of Medical Image Data,” 2024 11th International Conference on Electrical, Electronic and Computing Engineering (IcETRAN), Nis, Serbia, 2024, pp. 1-6, doi: 10.1109/IcETRAN62308.2024.10645095.

[22] S. T. Padmapriya and M. S. G. Devi, ”Computer-Aided Diagnostic System for Brain Tumor Classification using Explainable AI,” 2024 IEEE International Conference on Interdisciplinary Approaches in Technology and Management for Social Innovation (IATMSI), Gwalior, India, 2024, pp. 1-6, doi: 10.1109/IATMSI60426.2024.10502596.