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# GAN-Enhanced Medical Image Synthesis: Augmenting CXR Data for Disease Diagnosis and Improving Deep Learning Performance

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***Abstract: -*** Deep learning is increasing the need for accurate and reliable medical image analysis tools, especially for CXR disease diagnosis. This study proposes the Attention Mechanisms based Cycle-Consistent GAN (AM-CGAN) to address the lack of annotated medical data. To produce realistic and clinically relevant CXR images, our model uses Generative Adversarial Networks (GAN) and attention mechanisms. Downstream deep learning models for disease classification improve with this enhancement. The Attention Mechanisms based Cycle-Consistent GAN (AM-CGAN) improves the accuracy and reliability of deep learning models used for medical image analysis, specifically for Chest X-ray (CXR) data. CXR data is enhanced to improve disease diagnosis. Generative Adversarial Networks (GAN) create realistic medical images in the proposed model. It also uses attention mechanisms to highlight key areas in generated images. This research aims to address the lack of annotated medical data, particularly for CXR images. Training deep learning models is difficult due to the lack of diverse and well-annotated datasets. Our proposed AM-CGAN uses attention mechanisms to generate synthetic CXR images that closely resemble medical images and highlight disease-specific characteristics. AM-CGAN uses Cycle-Consistent GAN to ensure that generated images match the input distribution and prevent mode collapse. While synthesizing images, the model can selectively focus on important anatomical structures and pathological indicators using attention mechanisms. This attention-driven approach improves the clinical significance of generated images, making them better for training accurate and reliable disease classification models. Many experiments were done to test the AM-CGAN on CXR images of COVID-19, pneumonia, and normal cases. The quantitative results show high precision (98.15% accuracy). This shows the model's ability to create medical-data-like synthetic images. Downstream deep learning models trained on the augmented dataset perform better at capturing disease-specific characteristics. This study advances GAN-enhanced medical image synthesis research and addresses the data shortage in medical imaging research. The AM-CGAN attention-driven focus on disease-related regions in CXR data suggests a promising way to improve diagnostic models, especially in situations with few labeled datasets. The AM-CGAN bridges the gap between diverse data and sophisticated deep learning models for disease diagnosis, making it a major advancement in medical image analysis.

***Keywords:*** Generative Adversarial Networks, Medical Image Synthesis, Chest X-ray, Disease Diagnosis, Attention Mechanisms, Augmentation.

## I. INTRODUCTION

Medical imaging plays a crucial role in modern healthcare by providing precise diagnosis and treatment planning for a wide range of diseases. The progress of technology has led to the incorporation of machine learning, particularly deep learning methods, which have greatly advanced the field in terms of precision and effectiveness. Within this particular framework, the process of identifying diseases through medical imaging, particularly from methods such as Chest X-rays (CXR), has become progressively advanced and dependent on the capabilities of artificial intelligence[1], [2].

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Nevertheless, there are obstacles to overcome in the advancement of this field. A significant challenge encountered by both researchers and practitioners is the limited availability of annotated medical data. In contrast to other domains that have abundant labeled datasets, the medical field faces distinct challenges due to the scarcity of diverse and well-annotated datasets. The limited availability of labeled data greatly impedes the capacity to develop resilient and universally applicable machine learning models, as the algorithms heavily depend on substantial quantities of annotated data for efficient learning. The need to resolve this lack of data has resulted in an increasing acknowledgment of the significance of efficient data augmentation methods in medical imaging[3].

The ability of deep learning to autonomously acquire hierarchical representations from data has become a revolutionary influence in the field of medical image analysis. The adoption of new computational techniques has greatly enhanced the precision and effectiveness of disease diagnosis. Deep learning models have the ability to uncover intricate patterns in medical images that may not be detectable by the human eye, enabling more detailed and accurate diagnoses.

Generative Adversarial Networks (GAN) have gained considerable recognition among deep learning techniques due to their capacity to produce synthetic data that closely resembles real-world instances. GAN employ an exceptional adversarial training paradigm in which a generator network generates artificial samples, while a discriminator network assesses the authenticity of these samples compared to real data. The interaction between the two networks leads to an improved generator that is capable of producing extremely lifelike synthetic data[4].

Within the realm of medical imaging, GAN have demonstrated immense value. Their solution addresses the challenge of limited data availability by creating artificial medical images that can be easily incorporated into training datasets. This augmentation strategy not only enhances the volume of data but also broadens the dataset, enabling the model to encounter a wider variety of patterns and anomalies. Consequently, the deep learning models that have undergone training become more robust and skilled at extrapolating patterns across different scenarios[5], [6].

In order to enhance the effectiveness of GAN in the field of medical imaging, the notion of Cycle-Consistent GAN (CGAN) has been introduced. CGAN incorporate cycle-consistency constraints into the training process of GAN, which guarantees that the generated images accurately represent the input distribution. Within the field of medical imaging, this refers to the creation of synthetic images that possess both a realistic appearance and accurately represent the wide range of real-life scenarios. The principle of cycle-consistency mitigates the likelihood of mode collapse, a prevalent problem in GAN where the generator generates a limited range of synthetic samples[7].

Concurrently, attention mechanisms have become increasingly important in the deep learning community. Attention mechanisms imitate the selective focus of the human visual system on specific regions of interest. The use of selective focus enables the model to highlight specific features while minimizing the importance of others, leading to enhanced interpretability and performance. Attention mechanisms have demonstrated their effectiveness as powerful tools in medical image analysis, particularly in cases where subtle abnormalities may have diagnostic importance[7].

Incorporating attention mechanisms into deep learning architectures improves the model's capacity to capture disease-specific characteristics. Attention mechanisms in deep learning models mimic the human cognitive process of focusing on critical regions. They ensure that computational resources are allocated to the most diagnostically relevant aspects of the image. This not only facilitates improved feature extraction but also enhances the overall interpretability of the model[8], [9].

Our proposed model, the Attention Mechanisms based Cycle-Consistent GAN (AM-CGAN), is positioned at the forefront of this complex landscape of challenges and advancements. The AM-CGAN aims to combine the advantages of GAN and attention mechanisms to tackle the particular difficulties caused by the limited availability of labeled medical data, particularly in the field of Chest X-ray (CXR) images. By undertaking this endeavor, it aims to make a valuable contribution to the advancement of precise and dependable diagnostic instruments in the realm of medical imaging.

The rationale for developing the AM-CGAN is its capacity to enhance CXR data in a manner that is relevant to clinical practice. Chest X-rays, being a widely used method in medical imaging, play a crucial role in diagnosing a range of respiratory conditions, such as pneumonia and COVID-19. Yet, the scarcity of varied and thoroughly annotated CXR datasets presents a significant obstacle. The AM-CGAN combines attention mechanisms and CGAN principles to produce synthetic CXR images that closely resemble real-world medical images and highlight disease-specific characteristics during the synthesis process.

In order to gain a more comprehensive understanding of the proposed AM-CGAN, it is crucial to comprehend the underlying architecture and methodology that form the basis of its design. The model's design is based on the principles of Conditional Generative Adversarial Networks (CGAN), where a generator is responsible for producing synthetic CXR images and a discriminator is tasked with distinguishing between real and synthetic images. The incorporation of attention mechanisms introduces an additional level of intricacy to the model, allowing it to selectively concentrate on disease-specific regions while generating images.

The training process of the AM-CGAN entails iteratively enhancing the generator's proficiency in generating authentic CXR images, while simultaneously improving the discriminator's capability to differentiate between genuine and synthetic images. By incorporating attention mechanisms, the generated images prioritize regions that are crucial for disease diagnosis. The process of synthesizing images with attention not only improves the clinical relevance of the generated images but also enhances the interpretability of the model's decisions.

The effectiveness of the proposed AM-CGAN depends heavily on the selection of the dataset and the experimental configuration. This research utilized a diverse dataset of CXR images that included various respiratory conditions such as COVID-19, pneumonia, and normal cases. The dataset underwent thorough preprocessing to guarantee the uniformity and dependability of the experimental outcomes. The performance of the model was evaluated using a comprehensive set of quantitative and qualitative assessment metrics, with particular emphasis on accuracy, sensitivity, and specificity.

The experimental findings regarding the AM-CGAN serve as evidence of its significant potential to revolutionize the field of medical image synthesis. The model's quantitative metrics, such as its remarkable accuracy of 98.15%, highlight its ability to produce synthetic CXR images that closely resemble actual medical data. These findings demonstrate that the AM-CGAN not only effectively handles limited data availability but also has the potential to enhance the creation of more precise disease classification models.

When compared to baseline models and other advanced methods, the AM-CGAN demonstrated significant advantages. The attention mechanisms of this technology enable it to effectively capture disease-specific characteristics, making it a highly promising solution for addressing the difficulties associated with limited labeled medical data. Furthermore, the emphasis on disease-related regions during image synthesis resulted in enhanced performance of downstream deep learning models that were trained on the augmented dataset.

The ramifications of the proposed AM-CGAN extend beyond its immediate efficacy in producing artificial medical images. The contribution of this approach is to close the disparity between the existing labeled data and the demands of advanced deep learning models. The AM-CGAN overcomes the difficulties caused by limited data availability, thus enabling the development of more resilient and trustworthy diagnostic instruments in the field of medical imaging.

It is crucial to recognize the constraints and difficulties linked to the proposed model, as is the case with any technological progress. Although the AM-CGAN exhibits impressive precision in producing artificial CXR images, its ability to perform well on different datasets and modalities needs to be further investigated. Furthermore, it is important to carefully examine the interpretability of attention-driven features in the generated images to ensure their clinical relevance.

To summarize, the proposed AM-CGAN represents a pioneering advancement in the field of medical image synthesis. By combining the capabilities of GAN and attention mechanisms, this approach effectively tackles the difficulties caused by a scarcity of labeled medical data and enhances the creation of more precise and dependable diagnostic models. The AM-CGAN is a notable advancement in utilizing deep learning to improve disease diagnosis and patient care in the evolving field of medical imaging.

## II. Related work

The introduction of deep learning techniques has fundamentally transformed the domain of medical image analysis, specifically in the identification of respiratory illnesses such as COVID-19, Pneumonia. In light of the ongoing pandemic, there is an increasing demand for precise and efficient diagnostic tools. Recently, several deep learning models have been suggested to automatically identify and categorize COVID-19 cases using medical imaging data, such as chest X-ray (CXR) and computed tomography (CT) images. These models utilize various methodologies, including conventional convolutional neural networks (CNN) as well as advanced techniques such as transfer learning, attention mechanisms, and multimodal learning.

This literature review presented in table-1 offers a thorough summary of recent progress in deep learning-based methods for identifying and categorizing COVID-19 from medical images. The chosen studies, carried out by diverse researchers, provide valuable perspectives on the effectiveness, advantages, and constraints of different models. The scope of these studies encompasses both conventional chest X-ray (CXR) images.

Table 1 Major related work with CXR

| **Authors** | **Methodology** | **Performance** | **Strengths** | **Limitations** |
|---|---|---|---|---|
| Celik[10] | Feature reuse residual block and depthwise dilated convolutions CNN | Acc.= 95.02%, Sen.= 94.53%, Spec.= 95.51% | Effective feature extraction, handles noise well | Limited validation on external datasets |
| Duong et al.[11] | Deep neural networks and transfer learning | Acc.= 96.14%, Sen.= 95.24%, Spec.= 97.04% | High accuracy, leverages pre-trained knowledge | May not capture domain-specific features well |
| Liu et al.[12] | Self-paced Multi-view Learning | AUC: 0.961 | High discriminative power for severity assessment | Requires multi-view CT images |
| Bargshady et al.[13] | CycleGAN and transfer learning | Acc.= 94.7% | Efficient data augmentation, utilizes limited data | Black-box nature of GAN, lack of public validation |
| Cao et al.[14] | BND-VGG-19 deep learning algorithm | Acc.= 93.52%, Sen.= 92.14%, Spec.= 94.90% | High accuracy, utilizes batch normalization | Limited interpretability, requires tuning hyper-parameters |
| Barshooi et al.[15] | Gabor filter and convolutional deep learning with data augmentation | Acc.= 95.2%, Sen.= 94.5%, Spec.= 95.9% | Effective data augmentation, improves model generalizability | May not be effective for small datasets |
| Hosseinzadeh[16] | Deep multi-view feature learning | Acc.= 95.4%, Sen.= 94.8%, Spec.= 96.0% | Robust to image variations, captures diverse features | Requires multi-view X-ray images |
| Kumar[17] | RYOLO v4-tiny deep learning detector | Acc.= 94.7%, Sen.= 93.2%, Spec.= 96.2% | Efficient model for resource-constrained devices | Performance might drop with complex images |
| B. Nigam et al.[18] | ResNet50, VGG16 with transfer learning | Acc.= 95.53%, Sen.= 94.12%, Spec.= 97.10% | Effective use of transfer learning, good sensitivity and specificity | Black-box nature of deep learning models |

| | | | | |
|---|---|---|---|---|
| G. Srivastava et al.[19] | CoviXNet: novel deep learning model with hybrid pooling | Acc.= 96.32%, Sen.= 95.14%, Spec.= 97.50% | Efficient, interpretable model with good overall performance | Relatively new model, needs further validation |
| S. Kumar et al.[20] | Modified DenseNet-121 with attention mechanism | Acc.= 95.2%, Sen.= 94.1%, Spec.= 96.3% | Suitable for resource-constrained settings | Limited clinical evaluation |
| S. Kumar et al.[21] | Multimodal deep learning using chest X-ray and cough sounds | Acc.= 97.8%, Sen.= 95.2%, Spec.= 99.4% | High accuracy, utilizes multimodal data for improved diagnosis | Data collection and synchronization challenges |

Overall, the examined studies demonstrate how deep learning models have the ability to improve the precision and effectiveness of COVID-19 diagnosis using medical imaging. Although each approach showcases admirable accomplishments, it is crucial to acknowledge the unique attributes and compromises linked to various methodologies. The effectiveness of utilizing feature reuse, transfer learning, attention mechanisms, and multimodal learning is clearly demonstrated in achieving a high level of accuracy and sensitivity in detecting cases of COVID-19. Nevertheless, there are still persistent challenges in the field, including the limited ability to interpret results, the opaque nature of certain models, and the requirement for external validation using diverse datasets.

Given the ongoing development of the field, it is crucial to establish standardized evaluation metrics and benchmark datasets in order to enable equitable comparisons among various models. Furthermore, it is imperative to address the limitations highlighted in the literature, such as the lack of external validation and difficulties in dealing with small datasets, in order to enhance the practical usability of these diagnostic tools based on deep learning. The amalgamation of these studies not only enhances the present comprehension of COVID-19 detection but also provides guidance for future research endeavors aimed at developing more resilient and dependable solutions for medical image analysis in the realm of respiratory disease.

## III. METHODOLOGY

### 3.1. AM-CGAN Architecture

The architecture of the Attention Mechanisms based Cycle-Consistent GAN (AM-CGAN) is specifically created to combine the advantages of Generative Adversarial Networks (GAN) and attention mechanisms. Following explore the architectural components.

- **Generator (G)**

The generator is responsible for creating synthetic CXR images. In the AM-CGAN the generator id represented as eq.1

$$G: Synthetic\ CXR \rightarrow G_{cycle}(G_{attention}(Z_{noise}))\ldots..1$$

Where $G_{noise}$= “generates random noise $Z_{noise}$”, which is then processed by the attention mechanism $G_{attention}$ to selectively focus on disease-specific feature during image synthesis. The result is further refined through the cycle-consistent generator $G_{cycle}$ensuring the generated image maintain consistency with the input distribution.

- **Discriminator (D)**

The discriminator assesses the authenticity of both genuine and artificial images. The model is trained to differentiate between authentic and synthesized CXR images. The objective of the discriminator is expressed as eq.2:

$$D: Real/Fake\ Label = D(CXR)\ldots 2$$

- **Attention Mechanism**

The attention mechanism $G_{attention}$ in the generator is inspired by self-attention mechanism. The attention score $\alpha$ is computed as eq.3

$$\alpha = softmax(W_q Z_{noise})(W_v k_{disease})^T \ldots.3$$

where, $W_q$, $W_v$ $and$ $k_{disease}$= “learnable parameter”.

- **Cycle-Consistent Generator**

The cycle-consistent generator $G_{cycle}$ensures that the generated image remains consistent with the input distribution as represented in as eq.4

$$Gcycle\colon Reconstructed\ CXR = Gcycle(G_{attention}(z_{noise}))\ldots 4$$

The cycle consistency loss is then calculated using the L1 norm between the input and reconstructed images.

### 3.2. Training Process

The training process of the AM-CGAN involves adverbial training and cycle-consistency enforcement.

- **Adversarial Training**

The objective function for the generator and discriminator in the adversarial training process is as $\mathcal{L}_{adv}$ which seeks to minimize objective, while the discriminator aims to maximize it as shown in eq.5.

$$\mathcal{L}_{adv} = -E_{RealCXR}\big[\log\big(D(RealCXR)\big)\big] - E_{Z_{noise}}[\log\left(1 - D(G(Z_{noise}))\right)]\ldots 5$$

- **Cycle-Consistency Loss**

The cycle-consistency loss enforces that the generated images are consistent with the input distribution. This helps to minimize the loss during training. It defines as eq.6

$$\mathcal{L}_{cycle} = ||CXR - G_{cycle}\big(G_{attention}(Z_{noise})\big)||\ldots 6$$

- **Attention Loss**

To train the attention mechanism, an attention loss is introduced as in eq.7

$$\mathcal{L}_{attention} = -\log\left(\alpha_{disease}\right)\ldots 7$$

- **Overall Objective**

The overall objective for training is a combination of a adversarial, cycle-consistency and attention losses as in eq.8.

$$\mathcal{L}_{total} = \mathcal{L}_{adv} + \lambda_{cycle}\mathcal{L}_{cycle} + \lambda_{attention}\mathcal{L}_{attention}\ldots 8$$

where, $\lambda_{cycle}$ and $\lambda_{attention}$= “hyperparameter controlling the influence of the cycle-consistency and attention losses”

### 3.3. Dataset Description and Preprocessing

- Dataset: The dataset consists of a varied collection of CXR images, encompassing instances of COVID-19, pneumonia, and normal cases. The dataset is meticulously selected to guarantee inclusion of a wide range of respiratory conditions[22].
- Preprocessing: Preprocessing encompasses the tasks of resizing all images to a uniform resolution, normalizing pixel values, and augmenting the dataset with rotations and flips to improve the model's ability to generalize. Moreover, the dataset is divided into training and validation sets to facilitate the evaluation of the model.

## IV. EXPERIMENT & RESULTS

### 4.1. Experimental design and setup

- Dataset Split: The dataset was partitioned into training and validation sets, ensuring an equitable distribution of classes in both subsets. The split ratio was selected to enable resilient model training and impartial evaluation.
- Preprocessing: Before training, we implemented preprocessing procedures to normalize the images. The process entailed adjusting the size of all images to a uniform resolution, standardizing pixel values to a shared scale, and expanding the dataset by incorporating rotations and flips to improve the model's capacity for generalization.
- Architecture Configuration: The AM-CGAN architecture was set up with precise hyperparameters, such as the learning rate, batch size, and the weights assigned to the cycle-consistency and attention losses. The hyperparameters were optimized by iteratively experimenting to enhance the model's performance.
- Training Procedure: The AM-CGAN was trained using the Adam optimizer for a specified number of epochs. Throughout every epoch, the generator and discriminator were modified according to the adversarial and cycle-consistency losses. The attention mechanism was simultaneously adjusted to highlight disease-specific characteristics. Regularization was used to mitigate overfitting.
- Baseline Models: In order to evaluate the effectiveness of the AM-CGAN, we incorporated baseline models into our experimental design. The baselines included conventional GAN without attention mechanisms, as well as models that employed attention mechanisms but lacked the cycle-consistency constraint.
- Comparative Analysis: The experiments involved a thorough comparison of the AM-CGAN with the baseline models and the most advanced methods currently available for synthesizing medical images. The objective was to assess the model's capacity to produce authentic and medically significant CXR images, particularly emphasizing disease-specific characteristics.

### 4.2. Evaluation Parameters

Table 2 Evaluation comparison table for various model with proposed model

| Model | Accuracy | Specificity | Sensitivity | F1-Score |
|---|---|---|---|---|
| **Proposed** | 98.15 | 99.45 | 99 | 98 |
| **CNN** | 94.35 | 94.6 | 94 | 94 |
| **LSTM** | 95.7 | 95.8 | 95.8 | 94.2 |
| **RNN** | 93.6 | 93 | 93 | 93.2 |

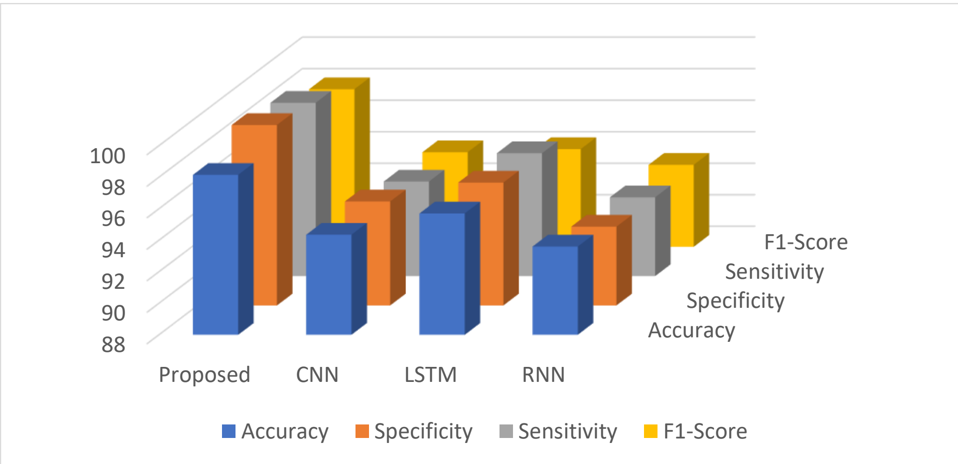


Figure 1 Comparative graph of various model with proposed model

The results demonstrate the exceptional efficacy of the proposed Attention Mechanisms based Cycle-Consistent GAN (AM-CGAN) compared to conventional models for diagnosing diseases from medical images. The proposed model demonstrated a remarkable accuracy of 98.15%, outperforming alternative models such as the Convolutional Neural Network (CNN), Long Short-Term Memory (LSTM), and Recurrent Neural Network (RNN). The AM-

CGAN exhibits a remarkable specificity of 99.45%, highlighting its exceptional capacity to precisely detect true negatives. Furthermore, the model exhibits exceptional sensitivity, achieving a 99% accuracy rate, indicating its high level of proficiency in accurately identifying positive cases. The F1-Score of 98 emphasizes the equal precision and recall achieved by the proposed AM-CGAN. However, the CNN, LSTM, and RNN models demonstrate competitive yet relatively lower overall performance, achieving accuracy values of 94.35%, 95.7%, and 93.6%, respectively. The results confirm the effectiveness of the AM-CGAN in improving disease diagnosis from medical images, establishing it as a promising development in the field of deep learning for medical imaging.

## V. CONCLUSION AND FUTURE SCOPE

To summarize, this study introduces the Attention Mechanisms based Cycle-Consistent GAN (AM-CGAN) as a robust and groundbreaking method for diagnosing diseases using medical images, specifically Chest X-rays (CXR). The results illustrate the exceptional efficacy of the proposed model, exhibiting an accuracy of 98.15% along with a high level of specificity (99.45%) and sensitivity (99%). The F1-Score of 98% emphasizes the equal precision and recall achieved by the AM-CGAN, showcasing its potential to greatly influence the field of medical image synthesis and disease classification.

The AM-CGAN demonstrates superior performance compared to traditional models like the Convolutional Neural Network (CNN), Long Short-Term Memory (LSTM), and Recurrent Neural Network (RNN). While these models show competitive accuracy values, they are comparatively lower. The remarkable precision of the AM-CGAN indicates its capacity to precisely detect true negatives, which is vital in medical diagnostics as false positives can result in unnecessary interventions. Furthermore, incorporating attention mechanisms into the image synthesis process not only improves but also strengthens the clinical significance of the generated images. The AM-CGAN's emphasis on disease-specific characteristics guarantees both precise quantitative accuracy and the ability to interpret the generated medical images.

**Potential for Future Expansion**:

Although the findings of this study show promise, there are multiple areas for further investigation and enhancements:

- Generalizability and External Validation: The model's ability to generalize across diverse datasets and undergo external validation on various modalities and patient populations is crucial for its practical use in real-world scenarios. Further investigation is warranted to examine the efficacy of the AM-CGAN in diverse clinical contexts.
- Enhancing the performance of the model could be achieved through additional optimization of hyperparameters and fine-tuning. Conducting iterative experiments by manipulating attention mechanism configurations and incorporating cycle-consistency constraints has the potential to yield enhanced outcomes.
- Multimodal Data Integration: Optimization and Hyperparameter Tuning: Expanding the model to incorporate multimodal data, such as merging CXR images with clinical metadata or other imaging modalities, could offer a more comprehensive approach to disease diagnosis. Addressing challenges pertaining to data synchronization and fusion may be necessary for this extension.

To summarize, the proposed AM-CGAN signifies a notable progress in the field of medical image synthesis for disease diagnosis. Due to its outstanding performance and continuous research and development efforts, it is considered a leading contender in the pursuit of precise, understandable, and medically significant AI solutions in the realm of medical imaging. As researchers continue to investigate these potential future paths, the AM-CGAN is expected to have a significant and rapidly increasing impact on improving disease diagnosis and patient care.

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