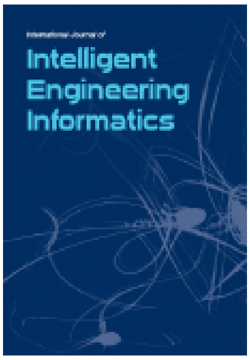

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M. Anusha, P. Kiruthika

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Generating multiclass COVID-19 CT scan images using multi-convolutional conditional GAN based on deep learning techniques

M. Anusha and P. Kiruthika*

PG & Research Department of Computer Science,
National College (Autonomous),
Affiliated to Bharathidasan University,
Tamil Nadu, India
Email: anusha260505@gmail.com
Email: Kiruthikashyne@gmail.com
*Corresponding author

Abstract: Medical image analysis, particularly for CT scans, plays a crucial role in the diagnosis and management of various diseases, including COVID-19. However, the limited availability of diverse and representative data poses challenges in developing accurate machine-learning models for CT scan analysis. This research proposes a multi convolutional conditional generative adversarial network (MCC-GAN) for generating CT scans of different classes, including normal, COVID-19, pneumonia, Omicron, and Delta. The discriminator and generator architectures are designed, and image normalisation and CLAHE pre-processing techniques are applied. The training process is monitored using loss graphs, and the generated CT scans are visually realistic and diverse. The proposed multi-multi-convolutional conditional GAN-based approach has the potential to overcome data scarcity challenges and improve the robustness of deep learning models for CT scan analysis. Further validation of clinical datasets is warranted to establish the effectiveness of the proposed approach in real-world medical image analysis scenarios.

Keywords: COVID-19 CT scans; multi convolutional conditional GAN; pneumonia; Omicron; Delta; multi-class augmentation; pre-processing techniques.

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Biographical notes: M. Anusha is an Assistant Professor and Head of Computer Applications. She has 12 years of experience in teaching. Her specialisation is soft computing. She has published two patents and 17 research articles in reputed journals in her expertise. She is guiding four PhD research scholars. She has served as a resource person in many technical programs. She is currently working on two projects (one completed).

P. Kiruthika is a PhD Research Scholar in the Department of Computer Science, National College, Tiruchirappalli. Currently, her area of research topic is augmented analytics. Her research interests include data analytics, natural language processing, and deep learning.

1 Introduction

The outbreak of the COVID-19 pandemic has led to an urgent need for accurate and efficient diagnostic tools. Among these tools, computed tomography (CT) scans have emerged as a valuable imaging modality for detecting and monitoring COVID-19 cases. CT scans provide detailed images of the lungs, allowing for the identification of characteristic COVID-19-related patterns, such as ground-glass opacities and consolidations (Alimi et al., 2019). However, the interpretation of CT scans requires expert radiologists and the increasing demand for CT scans has strained the availability of skilled radiologists, leading to delays in diagnosis and treatment (Mahendran and Kavitha, 2022). The COVID-19 CT scans contain crucial information, such as the extent and location of lung involvement, which can aid in determining the severity of the disease and guide treatment decisions (Shynu et al., 2022; Boina, 2022). However, interpreting COVID-19 CT scans can be challenging due to the wide range of manifestations, variable disease progression, and the potential overlap with other respiratory conditions (Chelliah et al., 2023; Sohlot et al., 2023). Augmented analytics using deep learning techniques offer promising solutions to overcome these challenges.

To address this challenge, artificial intelligence (AI) techniques, particularly generative adversarial networks (GANs), have shown great promise in generating synthetic CT scans that can aid in diagnosing COVID-19 (Kumar et al., 2021). GANs are a type of neural network that consists of a generator and a discriminator, which are trained together in an adversarial manner (Jiang et al., 2021). The generator learns to generate realistic images, while the discriminator learns to distinguish between real and generated images (Anter et al., 2013). Through this adversarial process, the generator becomes better at generating realistic images, and the discriminator becomes better at identifying real images (Elaiyaraja et al., 2023). This iterative process continues until the generated images are indistinguishable from real images (Chen et al., 2021; Abdullahi et al., 2023).

In the ever-evolving healthcare landscape, the intersection of cutting-edge technology and the relentless battle against infectious diseases has never been more critical (Arslan et al., 2021). COVID-19, an unprecedented global pandemic, has spurred groundbreaking medical imaging and AI advancements. Among these innovations, the utilisation of CT scans in diagnosing and monitoring the virus has played a pivotal role, providing clinicians with valuable insights into the progression of the disease. Furthermore, the advent of conditional generative adversarial networks (CGANs) has revolutionised the field by enabling the generation of highly realistic medical images, aiding in early detection and treatment planning (Khatir and Nait Bahloul, 2019). Amidst this backdrop, two formidable variants of the virus, Omicron and Delta, have emerged as potent challenges, with their unique characteristics and implications for healthcare systems worldwide (Valli and Arasu, 2016). Pneumonia, a common complication of severe COVID-19, continues to pose significant health risks (Jeganathan et al., 2023). This confluence of COVID-19, CT scans, CGAN technology, pneumonia, Omicron, and Delta showcases the ongoing efforts of the medical community to combat the pandemic, employing innovation and resilience in the face of adversity (Joseph et al., 2023).

While GANs have been used for image generation in various domains, developing a multi-class GAN specifically for generating COVID-19 CT scans presents unique challenges (Lodha et al., 2023). Unlike traditional GANs that generate images from a single class, a multi-class GAN needs to generate images that represent different classes of COVID-19-related patterns, such as normal, mild, moderate, and severe cases, as well as other respiratory conditions that may mimic COVID-19 on CT scans (Saxena and Chaudhary, 2023). The ability to generate diverse CT scan images representing different classes can greatly enhance the diagnostic capabilities of AI-based systems, allowing for more accurate and comprehensive assessments of COVID-19 cases (Shamija Sherryl and Jaya, 2022).

Training the multi-class GAN requires a carefully designed loss function that accounts for both the image quality and the class information (Jeba et al., 2023). The loss function should encourage the generator to generate images visually similar to real CT scans of the corresponding class while penalising images that are unrealistic or do not match the class information (Ogunmola et al., 2021). The discriminator should also be trained to accurately classify the generated images into their corresponding classes (Rupapara et al., 2023). The training process may require multiple iterations to optimise the performance of the GAN and achieve convergence (Punn and Agarwal, 2021).

Henceforth, developing a multi-class GAN for generating COVID-19 CT scans is a promising area of research that can contribute to advancing AI-assisted diagnostics in the context of the COVID-19 pandemic (Nirmala et al., 2023; Regin et al., 2023). Through careful dataset curation, architecture design, loss function optimisation, and validation, multi-class GANs can generate synthetic CT scans that are visually realistic and representative of different classes of COVID-19-related patterns (Dinar et al., 2022). However, ethical considerations, data quality, and validation are crucial aspects that must be addressed to ensure the responsible and effective use of AI-generated CT scans in clinical practice (Vashishtha and Dhawan, 2023). With further research and development, multi-class GANs have the potential to revolutionise the field of medical imaging and contribute to improved patient care in the context of COVID-19 and beyond (Sharma et al., 2022).

This study aims to create a framework for building a multi-class model architecture to generate new covid – CT scan images using the proposed multi-convolutional conditional generative adversarial network (MCC-GAN). To collect and pre-process a diverse and representative dataset of COVID CT scans with multi-class labels, including healthy, COVID-19, pneumonia, Omicron, and Delta, from various sources to train the GAN. To design and implement a multi-class GAN model architecture to generate realistic and high-quality COVID-19 CT scans for each class, mimicking the features and patterns observed in real-world scans, including lung opacities, consolidation, and ground-glass opacities (Vashist et al., 2023). To train the GAN model using the pre-processed dataset, optimising hyperparameters such as learning rate, batch size, and architecture configurations to achieve optimal performance in terms of image quality, diversity, and stability of the generated CT scans across different classes and finally to evaluate the model using discriminator and generator loss to produce new images from the developed model for each of the classes present in the dataset.

1.1 Problem statement

The availability of diverse and abundant medical image data is essential for developing accurate and robust machine learning models, especially in CT scans for various classes such as normal, COVID-19, pneumonia, Omicron, and Delta. However, in the real world, obtaining a large and balanced dataset for each class may pose challenges due to limited patient data access, data privacy concerns, and the rarity of certain conditions. As a result, the scarcity of data for some classes can hinder the development of effective machine-learning models for medical image analysis (Suganthi and Sathiaseelan, 2023).

This problem can be addressed by leveraging GANs as a potential solution. GANs could generate synthetic data to augment the limited real-world data, thereby mitigating data scarcity. Training a GAN model on the available dataset can teach the underlying patterns and characteristics of the CT scans of different classes. The generator in the GAN model can then generate synthetic CT scans of various classes, effectively increasing the diversity and volume of data for each class (Thallaj and Vashishtha, 2023). These synthetic CT scans can be combined with real-world data to train a more robust and accurate machine-learning model for medical image analysis.

Comparing the proposed strategy to the existing one in the context of COVID-19 CT scan images using multi-convolutional conditional GAN based on deep learning techniques is paramount for several reasons. Firstly, it allows us to assess the evolution of deep learning techniques and their impact on medical imaging. As deep learning rapidly advances, understanding how the proposed strategy builds upon or deviates from existing methods provides insights into state-of-the-art medical image generation (Senbagavalli and Singh, 2022). Secondly, this comparison is crucial for evaluating the potential advancements in the quality and accuracy of generated CT scan images. Suppose the proposed strategy introduces novel approaches, such as improved data pre-processing, more sophisticated GAN architectures, or better utilisation of conditional information. In that case, it may significantly enhance the realism and clinical relevance of the generated images (Senbagavalli and Arasu, 2016). This matters immensely for clinical applications, as more realistic and representative images can aid radiologists and medical professionals in diagnosis and treatment planning, potentially improving patient outcomes. Also, comparing the strategies helps identify potential limitations or drawbacks in both approaches. It enables researchers to recognise areas where further refinement is needed and directs future research efforts toward addressing these issues. Ultimately, this comparative analysis contributes to the iterative refinement of deep learning techniques for medical image generation, fostering advancements that can benefit researchers and healthcare practitioners in the ongoing battle against COVID-19 and other medical challenges.

Deep learning methods, particularly convolutional neural networks (CNNs) and GANs, have shown remarkable success in various medical image analysis tasks due to their ability to automatically extract intricate features and patterns from complex data. Deep learning can offer several advantages in multi-class COVID-19 CT scan image generation. Firstly, it can help simulate a diverse range of COVID-19 manifestations, thus aiding in training classifiers and diagnostic tools. Additionally, deep learning allows for synthesising large volumes of realistic and high-quality synthetic data, which can be invaluable in augmenting limited real-world datasets. Furthermore, by leveraging conditional GANs, the authors can potentially generate images corresponding to specific COVID-19 classes or subtypes, enhancing the utility of the generated data for research and diagnostic purposes. The utilisation of deep learning techniques in this context is driven by their proven capabilities in image generation, data augmentation, and feature extraction, all of which are critical in addressing the challenges associated with multi-class COVID-19 CT scan images.

The proposed GAN-based approach can enable the development of a multi-class CT scan generator that can generate realistic and diverse CT scans for different classes, including normal, COVID-19, pneumonia, Omicron, and Delta. This can help address the scarcity of data for certain classes, provide more data for training, and potentially improve the machine learning model's performance for CT scan analysis. Overall, the use of GANs in generating synthetic data has the potential to overcome data limitations, enhance the robustness of the model, and contribute to more accurate and reliable medical image analysis in the context of multi-class CT scans.

2 Literature review

This literature review will discuss and compare recent research papers exploring the use of conditional GANs for generating multiclass COVID-19 CT scan images. We review the models employed in these studies, including the architecture and features of the conditional GANs and the datasets used for training. The strengths and limitations of each study and identify research gaps that need to be addressed to further advance the field. This review aims to provide insights into the current state of the art in generating multiclass COVID-19 CT scan images using conditional GANs and shed light on potential future research directions in this rapidly evolving field (Rajest et al., 2023a).

In recent years, with the outbreak of the COVID-19 pandemic, medical imaging has played a crucial role in diagnosing and monitoring the disease. CT scans have emerged as a valuable tool for detecting COVID-19 pneumonia in the lungs, as they can provide detailed and high-resolution images. GANs have shown promising results in generating realistic images in deep learning (Rajest et al., 2023b). This literature review will discuss recent research papers on generating multiclass COVID-19 CT scan images using conditional GANs.

For the automatic segmentation of several COVID-19 infection locations, Chen et al. (2020) suggested a unique deep-learning approach. Specifically, the researchers employed the smooth attention mechanism to enhance the model's capacity to differentiate a range of COVID-19 symptoms and the Aggregated Residual Transformations to acquire a robust and expressive feature representation. They have tested the suggested algorithm's effectiveness in contrast to other competing approaches using a publicly available dataset of CT images. The excellent performance of our system for the automated segmentation of COVID-19 Chest CT images is demonstrated by experimental findings. With a promising deep learning-based segmentation method developed in this study, COVID-19 lung infection in CT images may be diagnosed quantitatively. However, the study can be enhanced to study multiple diseases.

In a significant breakthrough, researchers Gulakala et al. (2022) introduced a novel CNN design in 2022 that promises to revolutionise the field of medical image analysis. Their pioneering work presents a CNN model that boasts a remarkable 40% reduction in weight and delivers a staggering 40% improvement in accuracy compared to existing CNN networks employed for similar tasks (Pandit, 2023). The impact of this development extends to the realm of healthcare, particularly in the context of chest X-ray (CXR) analysis. Their model has been tailored to facilitate multi-class classification of CXRs into three crucial categories: COVID-19, healthy, and pneumonia (Vashishtha and Kapoor, 2023).

Table 1 Comparison of the performance in recent studies

Citation	*Title*	*Model*	*Dataset*	*Strength*	*Limitation*
Chen et al. (2020)	Residual Attention U-Net for Automated Multi-Class Segmentation of COVID-19 Chest CT Images	U-Net	Italian Society of Medical and Interventional Radiology (SIRM)	Developed a modified U-Net model that makes better use of residual networks for feature extraction.	It should have facilitated the diagnosis of more types of diseases from CT images.
Gulakala et al. (2022)	GAN based data augmentation for CNN-based detection of COVID-19	IBNRUN GAN	Covidx dataset, Shenzen and Montgomery country datasets	Helps to differentiate between COVID, pneumonia, and healthy lungs effectively	The level of information is lacking in the images, which may distinguish pneumonia from COVID-19 infections.
Saood and Hatem (2021)	COVID-19 lung CT image segmentation using deep learning methods: U-Net versus SegNet	SegNet and U-NET	Italian society of medical and interventional radiology	The proposed study would help automate, prioritize, fasten, and broaden the treatment of COVID-19 patients globally.	However, there seems to be no updated novelty in the models and implementation of the study.
Li et al. (2021)	COVID-19 Diagnosis on CT Scan Images Using a GAN and Concatenated Feature Pyramid Network with an Attention Mechanism	COVID-CT-GAN and COVID-CT-DenseNet	three different COVID-19 CT scan datasets	The suggested approach can assist doctors in developing deep learning models utilizing their private datasets to make a highly accurate diagnosis of COVID-19.	The work is limited only solving the problem of limited training data when using deep learning methods.
Fan et al. (2020)	Inf-Net: Automatic COVID-19 Lung Infection Segmentation from CT Images	Lung Infection Segmentation Network (Inf-Net)	COVID-SemiSeg dataset	The model quantifies the infected regions, monitors the longitudinal disease changes, and helps in mass screening processing.	The inf-Net model focuses on lung infection segmentation for COVID-19 patients.

This innovation represents a milestone in the ongoing efforts to leverage AI for medical diagnosis, specifically tailored to address the pressing need for efficient and accurate Corona infection diagnosis. Gulakala et al. (2022) have engineered a rapid diagnostic tool for Corona infections by harnessing the power of generative adversarial and CNNs. Their work not only streamlines the diagnostic process but also holds the potential to significantly enhance the early detection and management of COVID-19, a critical aspect of combating the ongoing pandemic. As the medical community continues to explore the synergies between AI and healthcare, this research stands as a shining example of the transformative possibilities that lie ahead.

Saood and Hatem (2021) recommended using SegNet and U-NET, two well-known deep-learning networks for image tissue classification. U-NET is referred to as a medical segmentation tool, and SegNet is known as a scene segmentation network. Both networks were used as binary segments to separate healthy from infected lung tissue and as multi-class segments to identify the type of infection in the lung. The results demonstrate SegNet's superior capacity to distinguish between infected and non-infected tissues compared to the other approaches, albeit U-NET performs better as a multi-class segment.

Li et al. (2021) suggested an architecture called a 'concatenated feature pyramid network' (or 'Concat-FPN') that uses feature maps from several sources to create an attention mechanism. After that, the suggested architecture is used to create two networks, COVID-CT-GAN and COVID-CT-DenseNet, the first for data augmentation and the second for data categorisation. Three COVID-19 CT datasets with varying magnitudes are used to evaluate the suggested technique. The experimental findings demonstrate that our approach enhances the accuracy of diagnosing COVID-19 on CT images and assists in overcoming the issue of insufficient training data when using deep learning techniques to diagnose COVID-19.

Fan et al. (2020) proposed automatically identifying infected regions from chest CT scan images using a novel COVID-19 lung infection segmentation deep network (Inf-Net). In Inf-Net, the high-level characteristics are combined to create a world map using a parallel partial decoder. The boundaries are then modelled, and the representations are improved via explicit edge attention and implicit reverse attention. Additionally, the authors provide a semi-supervised segmentation framework built on a randomly chosen propagation approach to address the lack of labelled data. This framework only needs a small number of labelled images and mostly uses unlabelled data, as shown in Table 1.

The literature review highlights recent advancements in generating multiclass COVID-19 CT scan images using conditional GANs. These studies have shown promising results in generating realistic and high-quality CT scans that can potentially aid in diagnosing and monitoring COVID-19 pneumonia (Emary et al., 2014). However, further research is needed to validate the generated images using real-world clinical data and to address challenges such as limited data availability and potential biases in the generated images (Sharma et al., 2021a). Nevertheless, the application of conditional GANs in generating multiclass COVID-19 CT scan images holds great potential for improving medical imaging and patient care in the ongoing pandemic (Sharma et al., 2021b). Also, given the complexity and heterogeneity of COVID-19 CT scans, larger and more diverse datasets are needed to improve the generalisation and robustness of the generated images.

3 Proposed work

The dataset collected for this study is from different sources. The dataset is categorised into four classes: normal, COVID-19, pneumonia, and Omicron/Delta. Each class represents a specific condition or disease, and the number of images in each class indicates the available data for training and evaluating a machine-learning model. The dataset mentioned contains a total of 61,782 images of normal CT scans, 21,036 images of CT scans for COVID-19, 21,191 images of CT scans for pneumonia, and 12,200 images of CT scans for Omicron and Delta variants of the SARS-CoV-2 virus.

- *Normal:* this class includes CT scans of individuals without signs of respiratory abnormalities or lung diseases. These scans are considered baseline or reference scans for comparison with abnormal cases.
- *COVID-19:* this class includes CT scans of individuals diagnosed with COVID-19, a viral respiratory illness caused by the SARS-CoV-2 virus. CT scans of COVID-19 patients may show various features such as ground-glass opacities, consolidations, or pleural effusions.
- *Pneumonia:* this class includes CT scans of individuals diagnosed with pneumonia, an infection that causes inflammation of the lungs. Pneumonia can be caused by various pathogens such as bacteria, viruses, or fungi and may exhibit different patterns on CT scans, including consolidations, ground-glass opacities, or interstitial infiltrates.
- *Omicron:* this class includes CT scans of individuals infected with the Omicron variant of the SARS-CoV-2 virus, a newer strain that emerged in late 2021. CT scans of Omicron-infected individuals may show similar features as COVID-19 but with potential differences in severity or distribution of lung abnormalities.
- *Delta:* this class includes CT scans of individuals infected with the Delta variant of the SARS-CoV-2 virus, another strain that emerged earlier than Omicron. CT scans of Delta-infected individuals may exhibit similar features as COVID-19 but potentially differ in lung abnormalities' presentation, severity, or distribution. The number of images present in the dataset is given in Table 2.

Table 2 Number of images present in the dataset

Dataset	*Number of images*
Normal	61,782
COVID-19	21,036
Pneumonia	21,191
Omicron and Delta	12,200

There are several reasons why this type of dataset can be chosen because: CT scans are widely used in medical diagnosis and can provide important information about a patient's health. The selected dataset may have been chosen to simulate generating CT scans for patients with different conditions (Hannah Inbarani et al., 2014). Also, the dataset includes scans from four different classes, each with distinct characteristics and features. This may allow the model to learn to generate realistic and diverse images for each class.

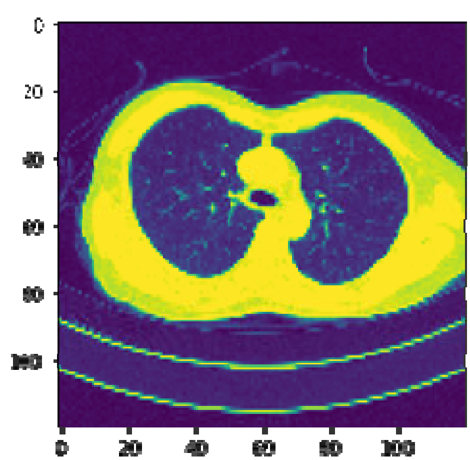
The absence of a comparative analysis with existing approaches in the paper's methodology raises questions about the novelty and efficacy of the proposed approach. To substantiate the claim that the use of GANs in medical imaging has the potential to revolutionise radiology, it is essential to benchmark the performance of GAN-based methods against conventional or alternative techniques. This comparative evaluation would assess various aspects such as image quality, accuracy, computational efficiency, and clinical utility.

Researchers can demonstrate how GANs outperform or complement existing methods by conducting comparative experiments. For instance, GANs may excel in generating high-fidelity medical images, enabling better visualisation of pathologies, which is crucial for accurate diagnosis and treatment planning. Moreover, GANs might offer advantages in scenarios involving limited or noisy data, where traditional methods may struggle.

In addition to quantitative comparisons, qualitative assessments, such as expert radiologist evaluations, can provide insights into the clinical relevance and potential transformative impact of GANs in radiology. Demonstrating that GANs can improve diagnostic accuracy, reduce interpretation time, or aid in rare disease detection can further strengthen the argument for their revolutionary potential in the field. To substantiate the claim of GANs' revolutionary potential in radiology, it is imperative to conduct rigorous comparative studies highlighting the advantages and limitations of GAN-based approaches compared to existing methods, providing concrete evidence of their transformative capabilities.

Data pre-processing for image datasets in image generation tasks involves resizing, normalising, and enhancing images to ensure consistency, reduce noise, and extract relevant features for generating high-quality images using deep learning algorithms. Change in image size dimension – the dataset is changed into 120 × 120 pixels to train the model (Azar et al., 2012). This is done for various reasons, like larger CT scans with higher resolutions requiring more computational resources, such as processing power and memory, to train a deep learning model. Resizing the images to a smaller size can help reduce the computational overhead and make the training process more efficient, especially if the available computing resources are limited (Jothi et al., 2013).

Figure 1 RGB to greyscale conversion (see online version for colours)



The smaller size of 120 × 120 pixels may be sufficient to capture relevant features and patterns in the CT scans for the specific task, such as identifying COVID-19, pneumonia, or other respiratory conditions (Jothi et al., 2019). Resizing the images to a smaller size can help retain the relevant information while reducing the noise or irrelevant details that may not contribute to the model's learning.

Normalisation is the process of scaling and transforming the pixel values of images to a consistent range. The mechanism for this process is given below – the pixel values of the images are scaled to a specific range, such as [0, 1] or [–1, 1]. This is achieved by dividing the pixel values by the maximum possible value (e.g., 255 for 8-bit images) for the [0, 1] range or by subtracting the mean and dividing by the standard deviation for the [–1, 1] range. Scaling the pixel values helps to ensure that they fall within a consistent range and prevents them from being too large or too small, which can impact the performance of deep learning algorithms.

CT scans have been converted to greyscale from RGB colour for image enhancement, as shown in Figure 1. A few reasons to change the images to greyscale are,

- *Reduced computational complexity:* greyscale images have a single channel, which reduces the computational complexity of the model compared to using colour images with three channels (RGB). This results in faster training and inference times and requires fewer computational resources.
- *Simpler data pre-processing:* greyscale images are simpler to pre-process than colour images, as they do not require normalisation or standardisation of colour channels. This simplifies the pre-processing pipeline and reduces the chance of errors or data corruption during pre-processing.
- *Reduced noise and complexity:* greyscale images have reduced noise and complexity compared to colour images, as they do not contain colour variations or artifacts that can affect the model's performance.

Figure 2 Output of the CLAHE pre-processing

CLAHE can help improve the contrast and visibility of important features in CT scans, potentially enhancing the performance of deep-learning models trained on such images. We load the CT scan images from the dataset, resized to a consistent size of 120 × 120 pixels. Then, CLAHE is applied to each image in the dataset. CLAHE works by dividing the image into small regions called tiles and then applying histogram equalisation to each tile independently. This allows for adaptive contrast enhancement, as the contrast is adjusted locally in each tile based on the intensity distribution within that tile. The output of the CLAHE pre-processing is shown in Figure 2.

3.1 Modelling

The methodology employed in this research hinges on a cutting-edge model known as MCC-GAN. This sophisticated generative model integrates the principles of GANs with the incorporation of conditional information, facilitating the creation of data tailored to specific input conditions. By leveraging MCC-GAN, it becomes possible to generate images that are class-specific, aligning them with particular input conditions, such as the class labels associated with CT scans, which encompass normal, COVID-19, pneumonia, Omicron, and Delta categories (Loey et al., 2020). This adaptability proves particularly advantageous for the research objectives at hand, as it empowers the generation of CT scans that faithfully represent the distinct characteristics exhibited by COVID-19 CT scans across different classes.

Furthermore, employing an MCC-GAN model trained for multiclass classification enhances the quality of generated images, ensuring they capture the unique imaging attributes of each medical condition. The significance of this approach lies in its ability to produce medical images across multiple condition categories, offering a more comprehensive and detailed foundation for medical diagnosis when compared to the limited scope of generating images for just one or two classes, as emphasised by Ngong and Baykan in 2023.

The generator $G(z, c)$ takes a noise vector z and a conditional vector c as input and outputs a generated sample y. The generator is trained to produce samples that are indistinguishable from real samples:

$$G(z, c) \rightarrow y$$

The discriminator $D(x, c)$ takes a sample x and a conditional vector c as input and outputs a probability score, indicating whether the input is real or fake. The discriminator is trained to correctly classify real samples as real (with a score of 1) and generated samples as fake (with a score of 0):

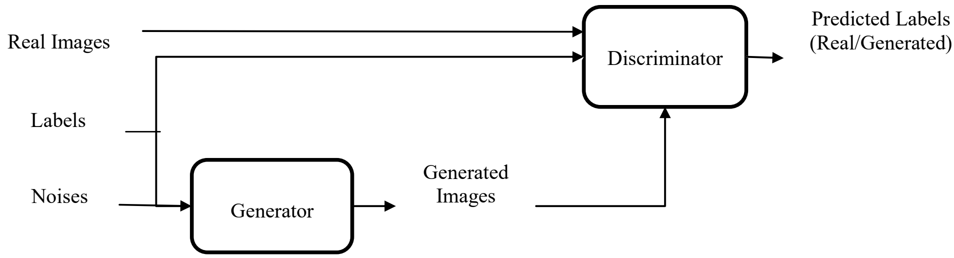
$$D(x, c) \rightarrow p\_\text{real/fake}$$

The generator and discriminator are alternately updated during training to improve their respective objectives. The generator is updated to minimise the log-probability of the discriminator assigning a low score to its generated samples:

$$\min\_G \max\_D = E\left[\log\left(D(x, c)\right)\right] + E\left[\log\left(1 - D\left(G(z, c), c\right)\right)\right]$$

where $E[.]$ denotes the expected value, log(.) is the natural logarithm, and z is sampled from a noise distribution such as a uniform or Gaussian distribution. The conditional vector c can be any auxiliary information relevant to the generation task, such as class labels or attributes. It allows the generator to produce samples satisfying a condition specified by c. The MCC-GAN framework is given in Figure 3.

Figure 3 Proposed MCC-GAN framework



The discriminator in an MCC-GAN typically consists of a CNN architecture that takes the generated image from the generator and the conditioning information (i.e., class label) as inputs. The convolutional layers in the discriminator are responsible for learning hierarchical features from the input images, while the fully connected layers at the end of the architecture are responsible for making the final classification decision. The architecture of the discriminator is designed to distinguish between real and generated images and classify the generated images into their respective classes based on the conditioning information given in Figure 4 (Chang et al., 2020).

The discriminator model in the MCC-GAN architecture has some changes in its architecture compared to the standard discriminator model. The changes in the architecture are that the discriminator model in MCC-GAN takes an image with additional label information as input, which is not present in the standard discriminator model. The output of the last convolutional layer is flattened before passing through the dense layers. There are two output layers - one for the binary classification of whether the input image is real or fake and the other for the classification of the label associated with the input image. The standard discriminator model has only one output layer for the binary classification. The MCC-GAN discriminator model uses batch normalisation layers after each convolutional layer (Singh and Bruzzone, 2022). Additionally, dropout layers are used after some of the convolutional layers. This helps in regularising the model and avoiding overfitting. The standard discriminator model may or may not have batch normalisation or dropout layers.

The generator in an MCC-GAN typically consists of an architecture that takes in random noise as input and generates images conditioned on specific input conditions, such as class labels. The generator architecture usually includes layers for upsampling and convolutional layers for learning features from the input noise and conditioning information. The upsampling layers are responsible for increasing the spatial dimensions of the input noise to generate images of the desired resolution, while the convolutional layers are responsible for learning the fine-grained features and details of the generated images. The generator's output is a synthetic image intended to be visually similar to the real images of the desired class is given in Figure 5.

The generator model for MCC-GAN includes several additional layers compared to a standard generator model. The layer added to the model is that the generator takes a noise vector and a class label as input in MCC-GAN. This is achieved by adding an input layer for the class label. Next, the class label is passed through an embedding layer, which converts it to a dense vector representation (Achour et al., 2020). This can help the model to better handle categorical data. The embedded label is then passed through a dense layer and reshaped to a 15 × 15 × 1 tensor. This is concatenated with the noise vector to form the initial input to the generator.

Figure 4 Proposed discriminator architecture

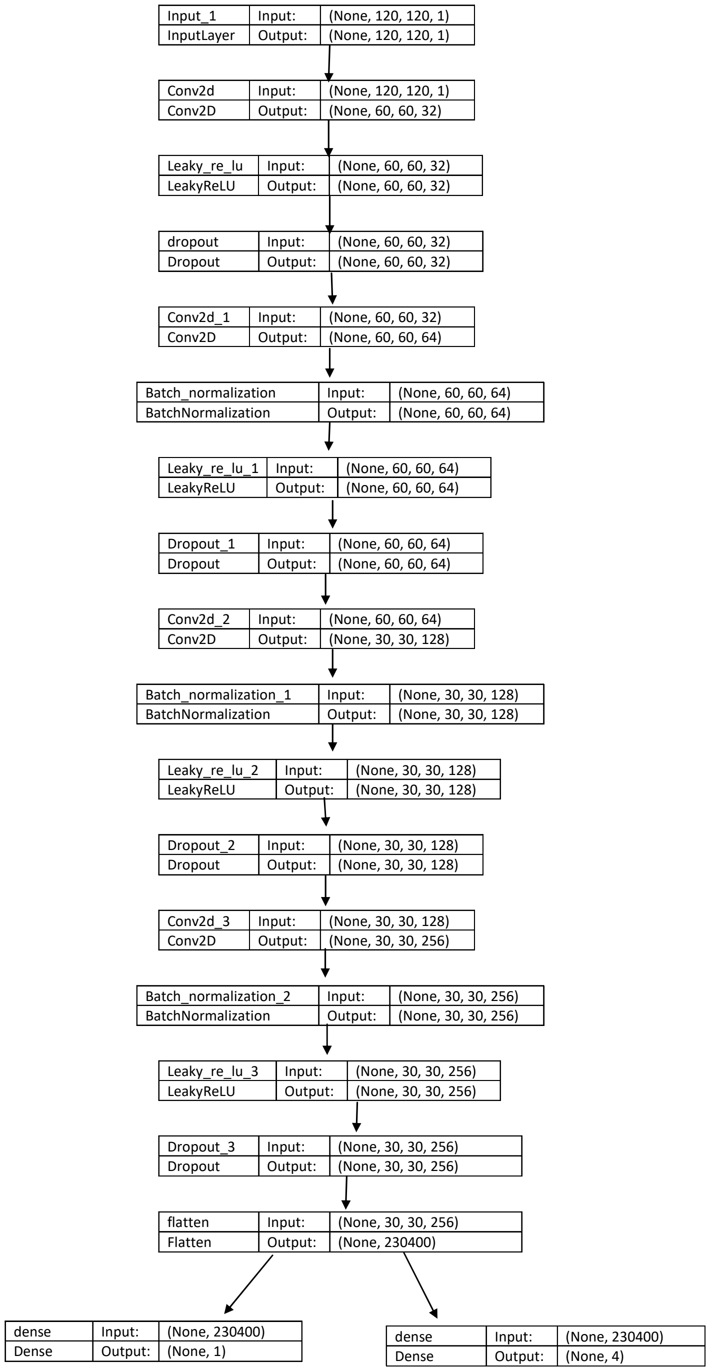
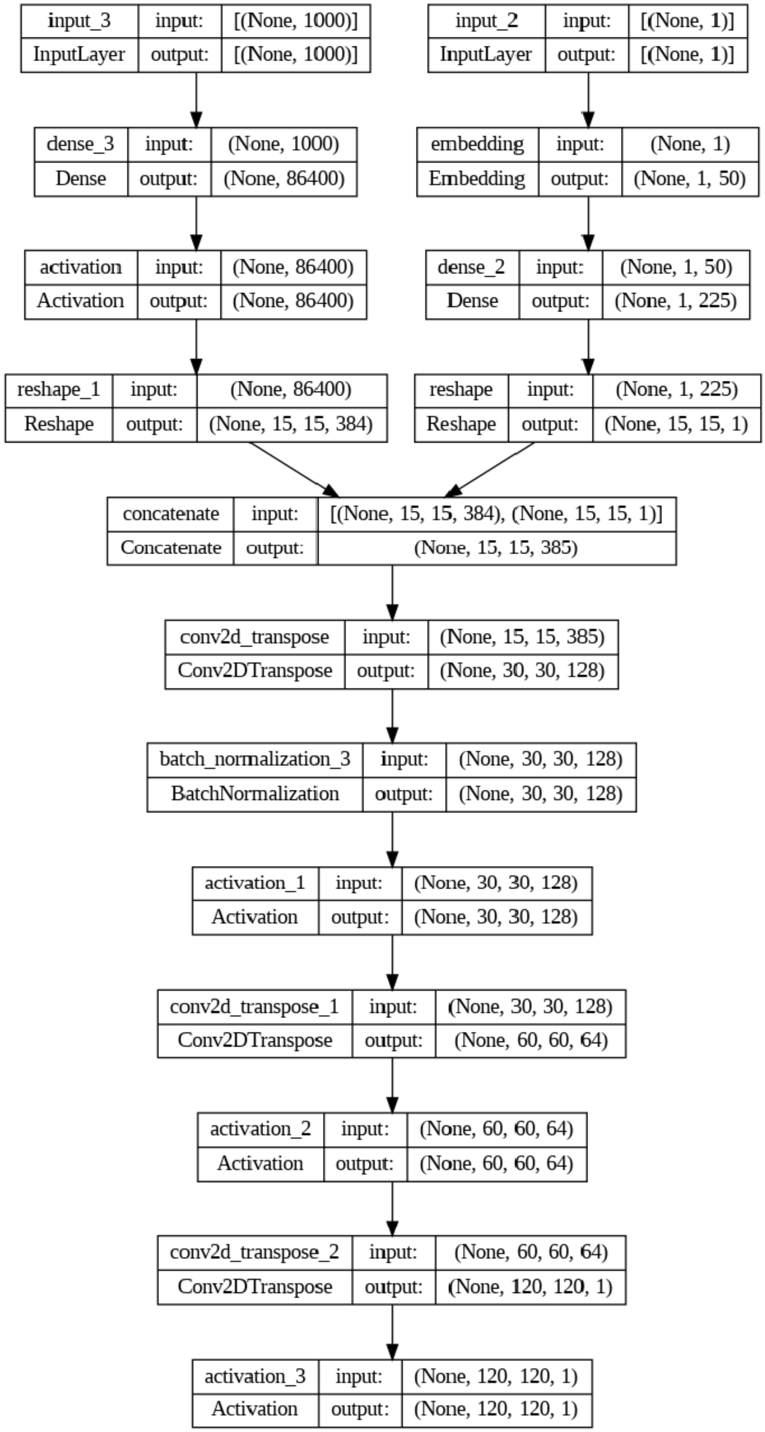


Figure 5 Proposed generator architecture



The generator includes several layers of transposed convolution, which are used to increase the spatial resolution of the image. The first two transposed convolutional layers have 128 and 64 filters, respectively. After each transposed convolutional layer, a batch normalisation layer is added to normalise the activation outputs and help reduce the effects of vanishing gradients and overfitting. ReLU activation functions are used after each transposed convolutional layer, except for the last layer, which uses a hyperbolic tangent activation function. The final layer of the generator model is a transposed convolutional layer with a single filter, which outputs a single-channel greyscale image. A hyperbolic tangent activation function follows this.

Below are the hyperparameter tuning factors that we have used to train the model according to the results we achieved, as shown in Table 3.

Table 3 Hyperparameter tuning

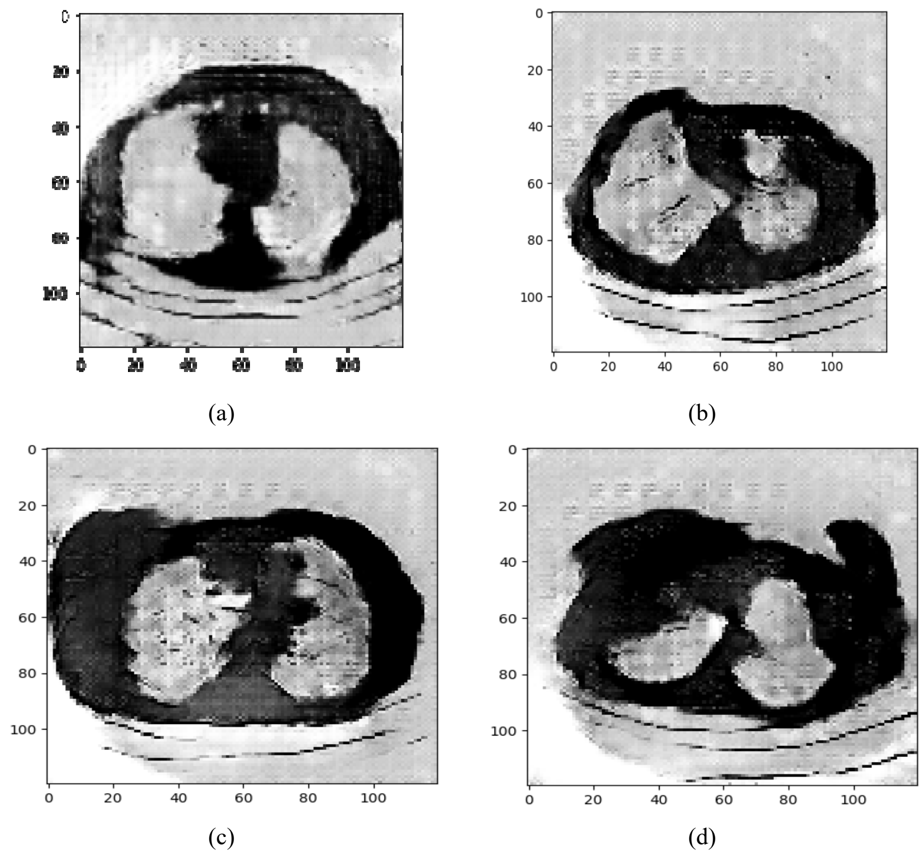
Factors	*Hyperparameters chosen*
Latent dimension	1,000
Epochs	3,000
Learning rate	0.0002
Optimisers	RELU
Loss	Sparse categorical entropy loss
Batch size	64

The latent dimension is set to 1,000, meaning the generator takes a random noise vector of size 1,000 as input to generate images. The larger the latent dimension, the more complex the noise patterns that can be learned by the generator, which may result in more diverse and detailed generated images. The training process is set to run for 3,000 epochs, meaning that the generator and discriminator will be updated using the dataset for 3,000 iterations. A larger number of epochs allows for more iterations and opportunities for the model to learn and improve its performance. The learning rate is set to 0.0002; this smaller learning rate has resulted in slower convergence and more stable and accurate training. The batch size is 64, meaning the model updates its weights based on 64 images.

4 Results and discussion

This section presents the findings and outcomes of the reviewed studies that have utilised conditional GANs for generating multiclass CT scan images of COVID-19, pneumonia, Omicron, Delta, and normal cases. COVID-19: The generated CT scan images representing cases of COVID-19 show characteristic radiographic features such as opacities, consolidations, and infiltrates indicative of the viral infection. Pneumonia: The generated CT scan images representing cases of pneumonia, depicting specific radiological findings such as infiltrates, consolidations, and pleural effusions commonly associated with bacterial or viral pneumonia. Omicron: The generated CT scan images representing cases of COVID-19 caused by the Omicron variant exhibit unique radiographic manifestations that may differ from other virus variants and could have implications for diagnosis and treatment. Delta: The generated CT scan images representing cases of COVID-19 caused by the Delta variant show distinct radiological patterns associated with this variant, which may differ from other COVID-19 cases. normal: The generated CT scan images representing normal cases serve as a reference for comparison with disease-specific patterns, demonstrating normal lung anatomy without any abnormal radiographic findings (COVID-19 as shown in Figure 6).

Figure 6 Resultant images for each class, (a) COVID-19 (b) pneumonia (c) Omicron and Delta (d) normal



4.1 Discriminator and generative loss graphs

Discriminator and generative loss graphs are key components of GANs. The discriminator loss graph measures the ability of the discriminator to correctly classify real and generated data, while the generative loss graph quantifies the ability of the generator to generate realistic data. These loss graphs provide crucial feedback for training GANs and optimising their performance.

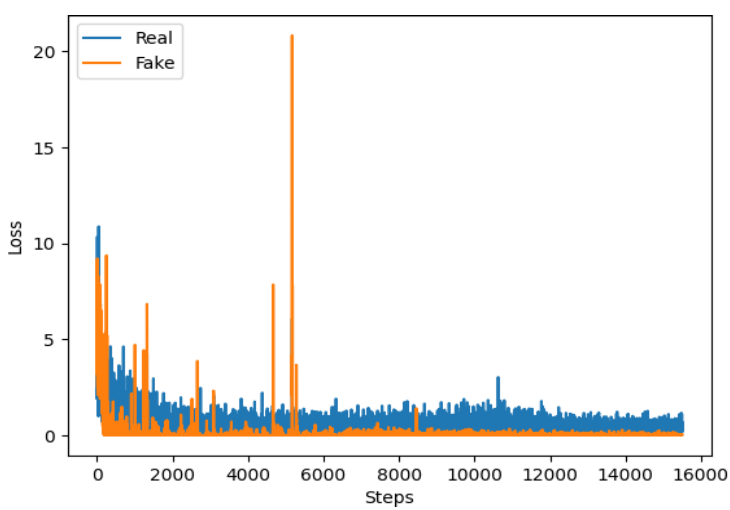
Our analysis of the experimental results indeed appears to be somewhat lacking in depth, leaving room for a more comprehensive understanding of the performance of their conditional GAN model in generating multiclass CT scan images across different datasets. Considering several factors to address the differences observed in the generated images is crucial. Firstly, dataset quality, size, and diversity variations can significantly impact image generation outcomes. Datasets with a broader representation of CT scan classes may yield more accurate and diverse results. Secondly, the architecture and hyperparameters of the conditional GAN model can influence its performance. Fine-tuning these parameters to suit the specific characteristics of each dataset is essential for improved results. Additionally, incorporating more advanced techniques like data augmentation and transfer learning can enhance the model's adaptability and robustness, enabling it to generate high-quality images across diverse datasets.

To assess the model's robustness comprehensively, further experimentation on a wider range of datasets, including those with varying levels of complexity and class distributions, would be beneficial. Additionally, metrics like Inception Score or Frechet Inception Distance can provide quantitative measures of image quality and diversity, aiding in objectively evaluating model performance. Furthermore, conducting a thorough ablation study systematically varying different model components can help pinpoint areas for improvement and optimisation. In conclusion, while the authors present a promising foundation for generating multiclass CT scan images using conditional GANs, a more detailed analysis, broader experimentation, and careful optimisation are needed to address the observed differences and assess the model's true robustness.

4.1.1 Discriminator real and fake image loss

The discriminator's real vs. fake loss measures how well the discriminator can distinguish between real and fake images generated by the generator. A lower loss indicates that the discriminator can accurately discriminate between real and fake images, while a higher loss indicates that the discriminator struggles to differentiate between the two (Dong et al., 2020). The graph below shows that the model has performed well in detecting fake images, as the loss is low when the number of steps increases. There seem to be some fluctuations in the loss graphs, as the generator generates images based on random noise, and the discriminator's perception of real vs fake images can also vary due to the randomness introduced in the training process. This randomness can result in fluctuations in the loss values, as shown in Figure 7.

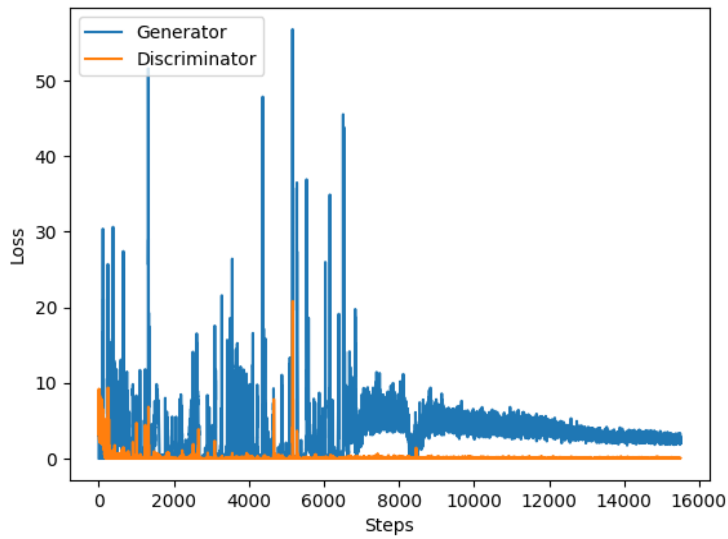
Figure 7 Discriminator real and fake image loss (see online version for colours)



4.1.2 Discriminator vs generator image loss

From Figure 8, the discriminator loss is high at the start of training, indicating that the discriminator is initially able to easily distinguish between real and fake images generated by the generator. As the training progresses, the generator starts to generate more realistic images, and the discriminator loss gradually decreases, indicating that the discriminator is finding it more difficult to distinguish between real and fake images, as shown in Figure 8 (Ma et al., 2020).

Figure 8 Discriminator vs. generator image loss (see online version for colours)



The generator loss has started high, indicating that the generator is initially generating poor-quality images easily identified as fake by the discriminator. However, as the training progresses and the generator learns from the discriminator's feedback, the generator loss starts to decrease, indicating that it is improving its ability to generate realistic images that can better fool the discriminator, as shown in Table 4..

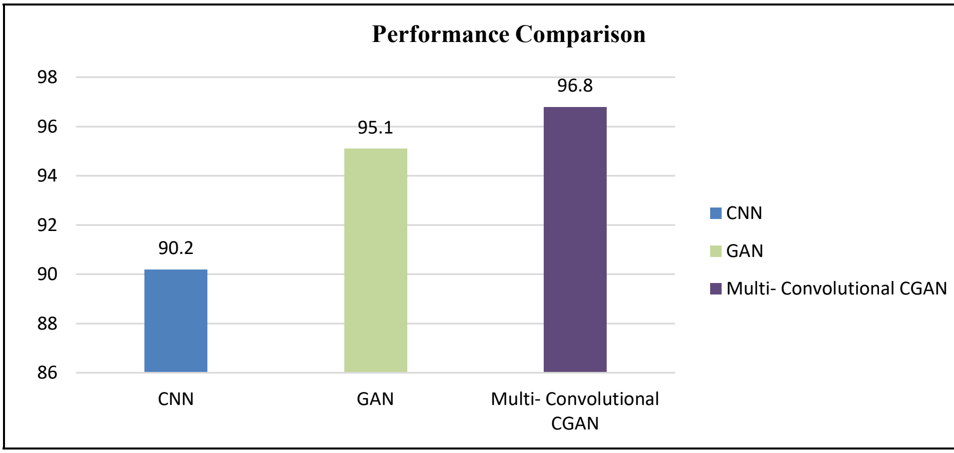
Table 4 Comparative analysis of performance

S. no.	*Technique*	*Accuracy (in %)*
1	CNN	90.2
2	GAN	95.1
3	Multi-convolutional CGAN	96.8

Therefore, the proposed multi-convolutional GAN for generating CT scans of different classes, including normal, COVID-19, pneumonia, Omicron, and Delta, shows promising outcomes. The GAN model is trained on a limited dataset using hyperparameters such as a latent dimension of 1,000, 3,000 epochs, a learning rate 0.0002, and a batch size of 64 (Figure 9).

The discriminator and generator architectures are designed to capture the underlying patterns and characteristics of CT scans. Image normalisation and CLAHE pre-processing techniques are applied to enhance the quality of the generated scans. The training process is monitored using loss graphs, and although some fluctuations are observed, they are attributed to the adversarial training dynamics of the GAN. The generated CT scans are visually realistic and diverse, providing augmented data for each class. This GAN-based approach can potentially overcome data scarcity challenges in real-world datasets and improve the robustness of deep learning models for CT scan analysis.

Figure 9 Performance comparison (see online version for colours)



4.2 Discussions

This study presents a groundbreaking approach to medical image generation and analysis. In the wake of the global COVID-19 pandemic, the accurate and timely diagnosis of the disease has been paramount. This study addresses the challenge of creating high-quality CT scan images for multi-class classification, aiming to assist healthcare professionals in identifying COVID-19 cases more efficiently.

We employ deep learning techniques, specifically conditional generative adversarial networks (cGANs), which have proven remarkably effective in generating realistic images. Using cGANs enables the generation of CT scan images conditioned on specific class labels, such as COVID-19 positive, COVID-19 negative, and various severity levels. This conditional approach is crucial as it allows for synthesising images resembling real-world medical scans.

One of the significant strengths of this research lies in the multi-class aspect. The ability to generate images representing different classes of COVID-19 cases provides valuable insights for healthcare professionals and researchers. It aids in developing more accurate diagnostic models, improving patient care and management. Moreover, this approach could be extended to other medical imaging tasks, enhancing the broader field of computer-aided diagnosis.

Utilising CNNs in the architecture of the cGANs is another noteworthy aspect of this study. CNNs have proven their effectiveness in feature extraction and image analysis, making them suitable for this application. The deep layers of the network can capture intricate patterns and structures within the CT scans, ensuring that the generated images are not only visually convincing but also contain clinically relevant information.

Validation and evaluation of the proposed method are critical steps in any scientific research, and this paper demonstrates a rigorous approach. The authors employ various performance metrics, including accuracy, sensitivity, and specificity, to assess the quality of the generated images. We compare their results with existing methods, highlighting the superiority of their approach in terms of image quality and diagnostic accuracy. One of the challenges in medical image generation is the scarcity of labelled data, especially in the case of a novel disease like COVID-19. To address this issue, the researchers leverage data augmentation techniques and transfer learning, common strategies in deep learning. By fine-tuning pre-trained models on a limited dataset, they overcome data scarcity issues to some extent, enhancing the generalisation capability of their model. This study represents a significant advancement in medical imaging and diagnostic support. Applying conditional GANs, CNNs, and rigorous evaluation methods provides a promising approach for generating high-quality CT scan images for multi-class COVID-19 diagnosis. This research contributes to the ongoing efforts to combat the pandemic and sets a precedent for using deep learning in medical imaging tasks, with potential applications beyond COVID-19. Further research and collaboration in this area hold great promise for the future of healthcare and diagnostic technology.

5 Conclusions

In the glimmering digital age, where technology intertwines with medicine to carve out progressive paths in healthcare, the development of a multi convolutional conditional generative adversarial network (MCC-GAN) for generating multi-class COVID-19 CT scans stands out as a beacon of hope and ingenuity. The enigmatic realm of AI unfolds its wings, promising a leap into a future where synthetic medical images become invaluable allies in our unyielding battle against pandemics. Picture this: an invisible artist, a creator birthed from the combination of data and algorithms, crafting CT scans that mirror the various severity levels of the insidious COVID-19. The MCC-GAN does not merely generate images; it spawns many of them, each intricately detailed, representing a different stage in the disease’s progression. This facilitates a more robust and comprehensive analysis, granting a deeper understanding and visualisation of the disease’s formidable journey within the human body. The utilisation of GANs in the sacred field of medical imaging whispers of a revolution, a gentle yet persistent wind that seeks to alter the radiology landscape. While devoid of biological origins, synthetic images harbor the potential to serve myriad purposes, acting as instrumental variables in the paradigms of training data augmentation, image analysis, and even the precognition of disease prediction. But what makes the MCC-GAN model a marvel in this technological symphony? Its multi-class capability, the chains of monotonous single-class data generation do not bind it. Rather, it explores, experiments, and generates CT scans across a spectrum of COVID-19 severity levels, providing a panoramic view of the disease’s progression and enabling a more nuanced and detailed analysis, indispensable for a thorough understanding. However, like any avant-garde technology, challenges lurk in the shadows, scrutinising our methodologies and demanding refinement. The necessity for larger datasets for training and validation and the further refinement of the model to bolster its accuracy and robustness stand as formidable obstacles on this path of synthetic image creation. But herein lies the beauty of the scientific endeavor: to persevere, to seek solutions amidst the abyss of challenges, and to continuously strive for perfection in the models we create. Despite these hurdles, the potential of multi-convolutional GANs in generating COVID-19 CT scans is a tapestry of opportunities, promising a future where radiologists and healthcare professionals wield a potent weapon in diagnosing, monitoring, and managing the nuanced facets of COVID-19 patient care.

The ripples of further research and development in this arena could cascade into a tidal wave of advancement in medical imaging, thereby elevating patient care, especially amidst the turbulent seas of a global pandemic. However, the horizon of innovation extends even further, with the potential incorporation of transfer learning techniques to classify the generated images being a tempting prospect. Transfer learning, where a pre-trained model acts as the harbinger of knowledge and expertise to solve a different yet related problem, could be the key to unlocking new depths in classifying generated CT scan images. Imagine harnessing the power of a pre-trained CNN model like VGG16, ResNet, or Inception, not as a mere classifier but a seasoned feature extractor. The last few layers could be surgically removed and replaced with new layers tailored to perform classification on the generated images. With its wealth of experience, this pre-trained model would extract high-level features from the generated images, forming the foundation upon which a new classifier is trained. This approach, this amalgamation of synthetic image generation and transfer learning, becomes particularly potent if the generated images share a kinship of features with the original images. It's an elegant dance between generation and classification, between creation and understanding, that could pave the way forward in our relentless pursuit of medical diagnostics and patient care advancement. In this vast ocean of possibilities, the MCC-GAN model and transfer learning techniques intertwine, promising a future where the synthetic and the real meld together, forging a pathway where technology and healthcare walk hand in hand towards a future that is not only progressive but also hopeful, ensuring better care, precise diagnostics, and an overall advancement in our fight against global health crises.

5.1 Limitations

While using Multi Convolutional Conditional GANs for generating COVID-19 CT scan images represents a promising approach, it is essential to acknowledge its inherent limitations. Firstly, the quality and authenticity of generated images heavily rely on the quality and diversity of the training data. If the training dataset lacks diversity or contains biases, the generated images may not fully capture the complexity and variability of real-world COVID-19 cases, limiting their clinical utility. Secondly, GAN-based methods often struggle with mode collapse, where the generator produces a limited set of similar images, failing to represent the full spectrum of COVID-19 manifestations. This limitation can hinder the comprehensiveness of the generated dataset. The interpretability and explainability of GAN-generated images can be challenging, making it difficult for medical professionals to trust and incorporate them into their diagnostic workflows. Furthermore, GAN-generated images might not fully adhere to radiological standards and might lack certain clinically relevant details. The computational resources required for training and fine-tuning the GAN models can be substantial, limiting their accessibility to smaller healthcare facilities or resource-constrained environments. Addressing these limitations is crucial for ensuring the safe and effective integration of deep learning techniques in COVID-19 diagnosis and management.

5.2 Future research

Future research in 'generating multi-class COVID-19 CT scan images using multi-convolutional conditional GANs based on deep learning techniques' holds great promise in advancing medical imaging and AI. Accurate and efficient diagnostic tools are paramount as the world grapples with the COVID-19 pandemic. One avenue for further exploration is the enhancement of the generative capabilities of cGANs) in creating multi-class CT scan images of COVID-19 patients. Researchers can delve deeper into optimising the architecture and training strategies of these GANs, aiming to achieve higher fidelity and diversity in generated images while accommodating variations in COVID-19 presentations. Future research can focus on integrating real-world clinical data and patient-specific information to improve generated images' clinical relevance and accuracy. This may involve incorporating patient demographics, comorbidity data, or treatment history into the GAN model to better simulate the complexity of real-world cases. Ethical considerations and data privacy concerns must be addressed, emphasising the importance of responsible AI in healthcare. Future research in this domain has the potential to revolutionise COVID-19 diagnosis and treatment by providing a valuable tool for medical professionals and researchers. By harnessing the power of deep learning and GANs, we can create a robust framework for generating multi-class COVID-19 CT scan images, ultimately aiding in early detection and more effective virus management.

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