

**SYNTHETIC DATA GENERATION FOR LUNG CANCER CT SCAN
USING DEEP CONVOLUTIONAL GENERATIVE ADVERSARIAL NETWORK**



UNIVERSITI TEKNIKAL MALAYSIA MELAKA

SYNTHETIC DATA GENERATION FOR LUNG CANCER CT SCAN
USING DEEP CONVOLUTIONAL GENERATIVE ADVERSARIAL NETWORK



This report is submitted in partial fulfillment of the requirements for the
Bachelor of [Computer Science (Artificial Intelligence)] with Honours.

FACULTY OF INFORMATION AND COMMUNICATION TECHNOLOGY
UNIVERSITI TEKNIKAL MALAYSIA MELAKA

2024

DECLARATION

I hereby declare that this project report entitled

SYNTHETIC DATA GENERATION FOR LUNG CANCER CT SCAN

USING DEEP CONVOLUTIONAL GENERATIVE ADVERSARIAL NETWORK

is written by me and is my own effort and that no part has been plagiarized

without citations.

STUDENT : _____ Date : 22 / 01 / 2024

(MUHAMMAD HAZIQ ISKANDAR BIN HANIZAL)

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I hereby declare that I have read this project report and found
this project report is sufficient in term of the scope and quality for the award of
Bachelor of [Computer Science (Artificial Intelligence)] with Honours.

SUPERVISOR : _____ Date : 5/2/2024

(Profesor Madya Ts. Dr. Choo Yun Huoy)

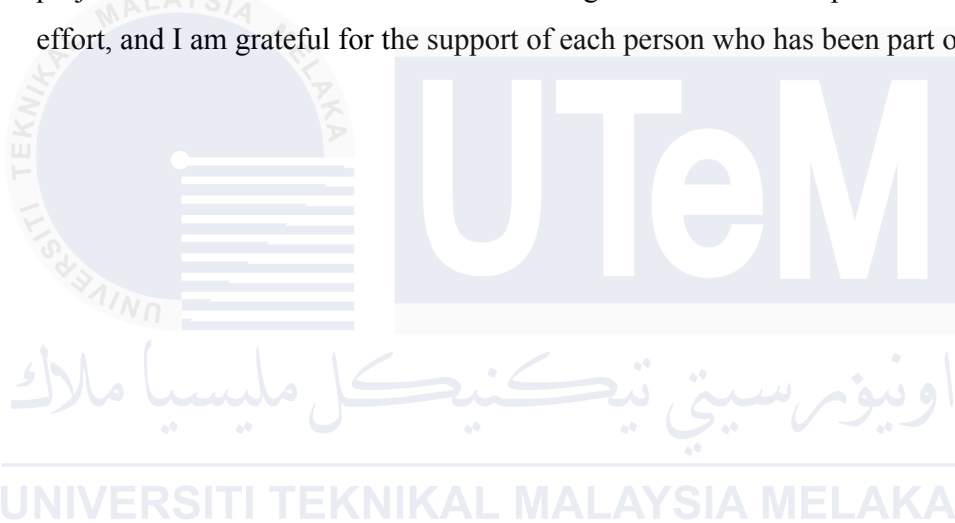
DEDICATION

I dedicate this work to my esteemed supervisor, Profesor Madya Ts. Dr. Choo Yun Huoy, whose guidance and expertise have been invaluable throughout this journey. My sincere gratitude extends to my academic advisor, Profesor Madya Ts. Dr. Zeratul Izzah Binti Mohd Yusoh, for her unwavering support and insightful advices throughout the completion of this project. To my friends and family, your encouragement and understanding have been a constant source of strength. This accomplishment is as much yours as it is mine.



ACKNOWLEDGEMENTS

I extend my heartfelt gratitude to the individuals who have played a significant role in the completion of this project. My sincere thanks to Profesor Madya Ts. Dr. Choo Yun Huoy, my Supervisor, for providing invaluable guidance, support, and encouragement throughout this research endeavor. Special appreciation goes to Profesor Madya Ts. Dr. Zeratul Izzah Binti Mohd Yusoh, my academic advisor, for her wisdom and insightful feedback during times of need. I am indebted to my friends and family for their unwavering encouragement and understanding during the challenging phases of this project. Their belief in me has been a driving force. This accomplishment is a collective effort, and I am grateful for the support of each person who has been part of this journey.



ABSTRACT

Lung cancer remains a leading cause of mortality, and early detection of the disease are needed to help control the nature of the cancer cells. However, usage of Predictive Modeling Systems that utilizes Artificial Intelligence to help medical experts in diagnosis are still in experimental phase due to lack of real data that helps create a reliable predicting systems. This project proposes a tool for synthetic data generation of lung cancer CT scans utilizing Deep Convolutional Generative Adversarial Networks (DCGANs) framework. The proposed tool aims to address the data scarcity issue by generating realistic and diverse synthetic CT scans. The images generated will facilitate improved training of AI models for accurate lung cancer diagnosis. The potential impact of this project lies in its ability to augment existing datasets, mitigate data biases, and boost the performance of computer-aided diagnosis systems in detecting diseases like lung cancer in their early phase.

ABSTRAK

Kanser paru-paru merupakan antara punca tertinggi yang menyebabkan kematian, dan pengesanan awal bagi penyakit ini adalah amat diperlukan untuk membantu mengawal tumbesaran sel-sel kanser. Walau bagaimanapun, penggunaan Sistem Permodelan Ramalan yang menggunakan Kepintaran Buatan untuk membantu pakar perubatan semasa proses diagnosis masih berada dalam fasa percubaan akibat kekurangan jumlah data yang membantu untuk mencipta sistem ramalan yang boleh dipercayai. Projek ini mencadangkan satu alat untuk menjana data sintetik imbasan CT kanser paru-paru menggunakan Rangkaian Adversarial Generatif Konvolusi Dalam (DCGANs). Alat yang dicadangkan bertujuan untuk menangani isu kekurangan data dengan menghasilkan imbasan CT sintetik yang realistic dan pelbagai. Imej yang dihasilkan akan memudahkan latihan model AI yang lebih baik untuk diagnosis kanser paru-paru yang tepat. Potensi projek ini terletak pada keupayaannya untuk menambah jumlah data yang sedia ada, mengurangkan bias data dan meningkatkan prestasi sistem diagnosis berbantuan komputer dalam mengesan penyakit seperti kanser paru-paru pada fasa awalnya.

TABLE OF CONTENTS

	PAGE
DECLARATION.....	II
DECLARATION.....	II
DEDICATION.....	III
ACKNOWLEDGEMENTS.....	IV
ABSTRACT.....	V
ABSTRAK.....	VI
TABLE OF CONTENTS.....	VII
LIST OF TABLES.....	XI
LIST OF FIGURES.....	XII
LIST OF ABBREVIATIONS.....	XIV
LIST OF ATTACHMENTS.....	XV
CHAPTER 1: INTRODUCTION.....	1
1.1 Introduction.....	1
1.2 Problem Statement.....	2
1.3 Project Question.....	2
1.4 Project Objective.....	2
1.5 Project Scope.....	3
1.6 Project Significance.....	3

1.7	Project Contribution (PC)	4
1.8	Report Organization.....	5
1.9	Conclusion	6
CHAPTER 2: LITERATURE REVIEW.....		7
2.1	Introduction.....	7
2.2	DCGAN-based Synthetic Data Generation for Lung Cancer	8
2.3	DCGANs: Principles and Application in Medical Image Generation.....	10
2.3.1	Understanding DCGANs	10
2.3.2	DCGANs for Medical Image Generation	11
2.3.3	Assessing effectiveness and benefits	12
2.4	Related Work: DCGAN in Lung CT Scan Generation.....	13
2.4.1	DCGAN Architecture for Synthetic Lung CT Scans	13
2.4.2	Lung-Specific Challenges.....	16
2.5	Ethical and Privacy Considerations: Protecting Patients in Malaysia	16
2.6	Synthetic Lung CT Scan Generation: Challenges and Future Directions.....	18
2.7	Conclusion	19
CHAPTER 3: PROJECT METHODOLOGY		21
3.1	Introduction.....	21
3.2	Project Management Framework.....	21
3.3	Project Milestones.....	24
3.4	Data Collection and Preprocessing	31
3.4.1	Data Acquisition	31

3.4.2	Data Preparation for Optimal Performance	32
3.4.3	Addressing Missing and Imbalance Data	33
3.5	DCGAN Architecture	33
3.6	Evaluation Metrics	34
3.7	Tool Development and Functionalities	35
3.8	Testing and Validation	36
3.9	Conclusion	36
CHAPTER 4: DESIGN		37
4.1	Introduction	37
4.2	System Architecture	37
4.3	Technical Specification	40
4.4	Data Flow Diagram (DFD)	43
4.5	User Interface Design	45
4.6	Algorithmic Design	47
4.7	Conclusion	49
CHAPTER 5: IMPLEMENTATION.....		50
5.1	Introduction	50
5.2	Coding and Programming Environment	50
5.3	DCGAN Implementation and Training	52
5.4	User Interface Implementation	58
5.4.1	Login Window	58
5.4.2	Main Interface Window	59

5.5	Summary	60
CHAPTER 6: ANALYSIS.....		61
6.1	Introduction.....	61
6.2	Quantitative Assessment of the Generated Images.....	61
6.2.1	Factors affecting IS and FID.....	61
6.2.2	Test Results.....	62
6.3	Summary of Quantitative Assessment	68
6.4	Tkinter Desktop App Testing and Analysis.....	70
6.4.1	Objectives and Testing Methodology	70
6.4.2	Functional Testing Scenarios.....	71
6.4.3	Results and Findings.....	72
6.4.4	Improvements and Recommendations.....	75
6.5	Summary.....	75
CHAPTER 7: CONCLUSION.....		77
7.1	Introduction.....	77
7.2	Project Summarization.....	77
7.3	Project Strengths and Weakness	78
7.4	Project Contribution.....	80
7.5	Future Work	80
7.6	Summary.....	81
TURNITIN ORIGINALITY REPORT		82
REFERENCES.....		90
APPENDIX.....		92

LIST OF TABLES

	PAGE
Table 1: Table of Project Contribution.....	4
Table 2: PSM1 Milestones.....	24
Table 3: PSM2 Milestones.....	28
Table 4: Table of Technical Specifications.....	42
Table 5 : Summary of Inception Score.....	69
Table 6: Summary of FID Scores.....	69



 UNIVERSITI TEKNIKAL MALAYSIA MELAKA

LIST OF FIGURES


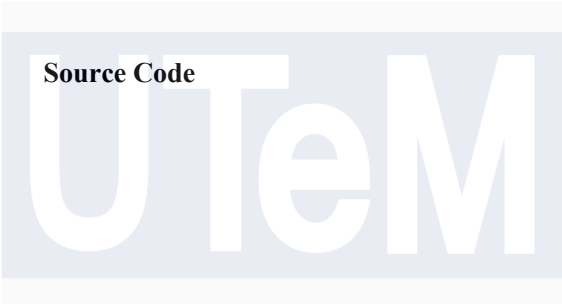
	PAGE
Figure 1: Example of a DCGAN Generator Network	10
Figure 2: Example of DCGAN Discriminator Network	11
Figure 3: Pix2PixHD Model Architecture	15
Figure 4: 6 Phases of CRISP-DM	21
Figure 5: Proposed System Architecture	38
Figure 6: Data Flow Diagram of the Proposed System	43
Figure 7: Wireframe of the Login Window	45
Figure 8: Mockup of the Login Window	45
Figure 9: Wireframe of the Main Window	46
Figure 10: Mockup of the Main Window	46
Figure 11: DCGAN Model Architecture	47
Figure 12: Generator Network of DCGAN	48
Figure 13: Python Logo	50
Figure 14: Tensorflow Logo	51
Figure 15: Tkinter Logo	51

Figure 16: Generator Network Definition	53
Figure 17: Discriminator Network Definition.....	53
Figure 18: Real Image Loading and Pre-processing.....	54
Figure 19: Pixel Normalization Technique	55
Figure 20: Function that Defines Training Step of DCGAN	55
Figure 21: Sample Image Generated at Epoch 200	56
Figure 22: Sample Image Generated at Epoch 400	56
Figure 23: Error Handling for Login Function	58
Figure 24: Successful Login Window	59
Figure 25: Inception Score over Different Epochs (Method 1)	63
Figure 26: FID over Different Epochs (Method 1)	63
Figure 27: Inception Score Comparison between Method of Image Generation	64
Figure 28: FID comparison Between Method of Image Generation.....	65
Figure 29: IS of Percentage of Images Generated over Epochs.....	66
Figure 30: FID Scores by Percentage of Images Generated.....	67

LIST OF ABBREVIATIONS

PSM	-	Projek Sarjana Muda
GANs	-	Generative Adversarial Networks
DCGANs	-	Deep Convolutional Generative Adversarial Networks
WHO	-	World Health Organization
NSCLC	-	Non-Small Cell Lung Cancer
SCLC	-	Small Cell Lung Cancer
CT	-	Computed Tomography
MRI	-	Magnetic Resonance Imaging
AI	-	Artificial Intelligence
PDPA	-	Personal Data Protection Act
CRISP-DM	-	Cross-Industry Standard Process for Data Mining
IS	-	Inception Score
FID	-	Fréchet Inception Distance
GPU	-	Graphic Processing Unit
RAM	-	Random Access Memory
DFD	-	Data Flow Diagram
UI	-	User Interface
GUI	-	Graphical User Interface

LIST OF ATTACHMENTS

	PAGE
 Appendix A	
 Source Code	19

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CHAPTER 1: INTRODUCTION

1.1 Introduction

Lung cancer is one of the top three most commonly diagnosed cancers. According to WHO, lung cancer is the leading cause of cancer-related deaths worldwide. For instance, approximately 2.21 million new cases of lung cancer were reported in 2020, making up 11.4% of all cancer diagnoses globally. Lung cancer occurs when genetic mutation of normal cells in the lungs happened resulting in uncontrollable growth and division of the cells. These mutations disrupt the normal mechanisms that regulate cell growth, division, and death, leading to the formation of a tumor. Lung cancer can be divided into two types, which is differentiated through the appearance under microscope, NSCLC and SCLC. NSCLC is the most common type of lung cancer, which accounts for about 80-85% of all lung cancers while SCLC accounts for about 10-15%, but spread more rapidly and is strongly associated with smoking habit.

Nowadays, there are many people at risk of lung cancer which smoking is proven to be the leading factor that triggers lung cancer. Even people without smoking habit are at risk due to the fact that they might be exposed to environment that have tobacco smoke which makes them a passive smoker. Overall, the five-year survival rate for NSCLC average at around 24% but can be higher at around 61% to 92% provided that the disease was diagnosed at early stages. The more aggressive SCLC have a very low five-year survival rate at approximately 7% according to the American Cancer Society. This mean that people who are diagnosed with SCLC are almost confirm to die within 5 years, depending on how fast the disease was diagnosed.

Although there is no cure, we can minimize our chance of developing lung cancer by avoiding bad habit such as smoking, exposure to carcinogenic substances, and unnecessary exposure to radiation such as Radon. Lung cancer can be diagnosed with Lung CT (**Computer Tomography**) scan, chest X-rays, MRI scans, or Biopsy (surgery). It is said that Lung CT scans are widely used in detecting lung cancer due to their ability to provide detailed images of the lungs.

1.2 Problem Statement

To improve the health of society, time taken to diagnose an illness should be as short and precise as possible. Medical experts can take advantage by utilizing predictive modeling system that can diagnose lung cancer at a high performance and accuracy. The main problem is that there is no deep learning model that can analyze medical images with high confidence since medical images are considered a privacy and sharing of them will violate the privacy act. As a result, acquiring real CT scans costs very heavily for companies that provide these deep learning model. Thus, medical experts cannot fully predictive modeling systems to assist them with diagnosis. Therefore, this project will tackle the privacy and data scarcity issue thus making lung cancer prediction model possible.

1.3 Project Question

How to generate synthetic Lung CT scans images that are identical to the genuine image? Which deep learning algorithm is appropriate for this type of task?

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1.4 Project Objective

This project embarks on the following objectives:

1. To train a Deep Convolutional Generative Adversarial Networks (DCGANs) that is able to generate synthetic lung CT scans that is statistically similar to real world data and diverse.
2. To design a tool that can generate synthetic lung CT scans for lung cancer disease using DCGANs.
3. To develop a tool that is able to reproduce Lung CT scans image that mimic the statistical pattern and properties of lung cancer data.

1.5 Project Scope

1. Data acquisition and preprocessing.
2. DCGANs architecture to generate lung cancer CT scans.
3. Assessment of the synthetic data generated.

1.6 Project Significance

The significance of this project lies in its potential to address a critical challenge in creating a predictive model for lung cancer diagnosis: data scarcity. Predictive model system can assist medical experts in early detection of lung cancer, but acquiring data to generate the system can be expensive, time-consuming, and ethically complex. This limited data availability obstructed the development and training of accurate AI models for lung detection.

This project proposes a solution to use DCGANs to generate realistic and diverse synthetic lung cancer CT scans. This synthetic data can be used to:

1. Augment existing datasets

Significantly increasing the amount of training data available, generalizability and robustness of AI models can be improved and thus, leading to more accurate diagnoses.

1. Reduce costs and improve access to diagnosis

Synthetic data can be generated much faster and cheaper than acquiring real CT scans. This can make lung cancer screening more accessible and affordable.

2. Develop and test new AI algorithms

With a good supply of synthetic data, researchers can experiment and refine new AI models for lung cancer detection without relying on limited patient data.

1.7 Project Contribution (PC)

This project will be extremely beneficial to researchers who intended to develop an artificial intelligence model to predict lung cancer. This project will assist in generating synthetic Lung CT scan images which is the most common medical images used to detect lung cancer. The images will be free of privacy and will mimic the statistical pattern and properties of lung cancer data for researchers to utilize.

Table 1: Table of Project Contribution

Contribution	Project Objective		Project Scope			Project Significance		
	1	3	1	2		1	2	3
Advancements in medical image synthesis for lung cancer detection.	1	3	1	2		1	2	3
Development of a DCGANs-based tool for synthetic lung CT scan generation.	2					1		
Enhanced evaluation metrics for medical image synthesis quality	3		1	2	3	1	2	3

1.8 Report Organization

Chapter 1: Introduction

This chapter discusses the project's background, problem statement, objective, scope, project contribution, and about the generation of synthetic Lung CT scan images.

Chapter 2: Literature Review

This chapter discusses a summary of previous works that are relevant to the project. This chapter also discusses which models are appropriate for this project.

Chapter 3: Project Methodology

This chapter discusses the methodology and flow of the process for the entire project, from the beginning to the end.

Chapter 4: Design

This chapter discusses the design to solve the problem as well as all of the requirements for this project.

Chapter 5: Implementation

This chapter discusses the environment setup, including which software and libraries will be used for this project.

Chapter 6: Testing

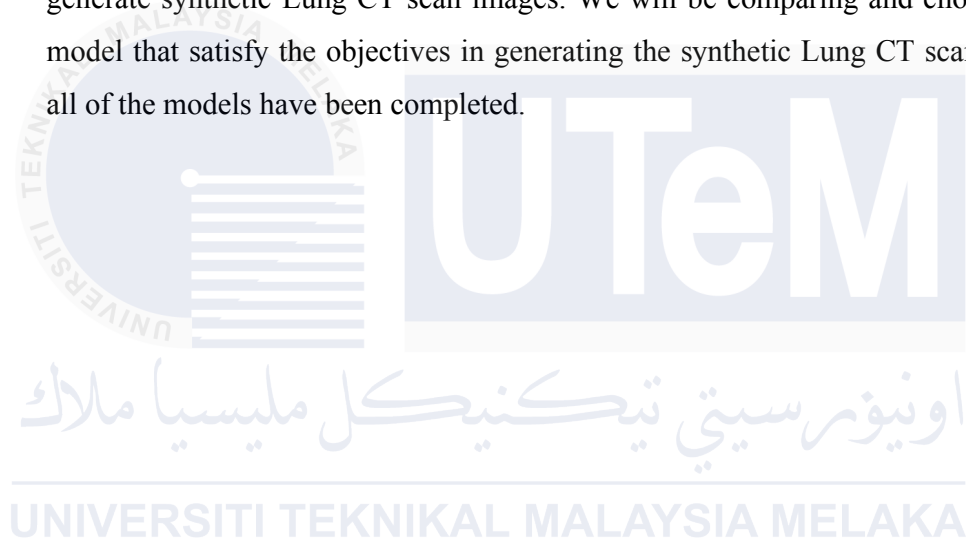
This chapter discusses the testing process and analyzes the results. In this chapter, the results will be compared, and the best model will be chosen.

Chapter 7: Project Conclusion

This is the chapter that summarizes the entire project and discusses the project's limitations as well as future work.

1.9 Conclusion

In conclusion, this project will use a Generative machine learning model to generate synthetic Lung CT scan images. We will be comparing and choosing the best model that satisfy the objectives in generating the synthetic Lung CT scan images after all of the models have been completed.



CHAPTER 2: LITERATURE REVIEW

2.1 Introduction

Lung cancer, one of the leading causes of death worldwide, claims an estimated 9.3 million lives annually (World Health Organization, 2023). Early detection and accurate diagnosis are crucial for effective treatment strategies, and Computed Tomography (CT) scans have become the cornerstone for lung cancer diagnosis due to their detailed visualization of lung tissues and lesion characterization. However, the availability of large-scale, real world annotated CT scan for lung cancer research and machine learning model development shows huge challenges for researchers. Not only that the process of acquiring the data is time-consuming and resource-intensive, it also raises concerns regarding patients' privacy and data sharing. In addition to that, the generalization of data and performance of the machine learning models will be hindered as a result from lack of diversity and variability of existing datasets. This causes application of the model to real-world scenarios in lung cancer diagnosis to become irrelevant.

Deep Convolutional Generative Adversarial Networks (DCGANs) offer a promising solution to these challenges by generating high-quality synthetic lung CT scans. DCGANs overcome data acquisition constraints, alleviate privacy concerns, and significantly increase dataset size and diversity. This augmented data can improve the performance of machine learning models, leading to more robust and generalizable algorithms for lung cancer diagnosis even with limited labeled data.

This literature review focuses on the current state of DCGAN-based synthetic data generation for lung cancer CT scans. We will delve into the principles of DCGANs and their specific applications in medical image generation tasks. By reviewing relevant research papers and studies, we will assess the effectiveness and benefits of using synthetic data to improve lung cancer diagnosis, treatment planning, and ultimately, patient care.

Furthermore, we will examine the ethical and privacy considerations surrounding synthetic data generation for medical applications, ensuring compliance with regulations and upholding patient confidentiality. Lastly, we will discuss the challenges and limitations of this approach, along with suggestions for future research directions to advance the field.

This in-depth review aims to provide a comprehensive understanding of DCGANs in the context of lung cancer CT scan generation, highlighting their potential benefits and challenges. We believe this will pave the way for further advancements in lung cancer research and clinical practice, ultimately contributing to improved patient outcomes.

2.2 DCGAN-based Synthetic Data Generation for Lung Cancer

Lung cancer is a global health burden, in which the death toll accounts for roughly 9.3 million in 2019 (World Health Organization, 2023). Early detection of the disease and accurate diagnosis are crucial in deciding for effective treatment and improved patient's condition. CT scans is the most used medical image for lung cancer diagnosis due to their detailed visualization of lung tissues and lesion characteristics. In order to speed the diagnoses process, researchers in the AI field have proposed AI models that assist medical experts in diagnosing lung cancer.

However, research and development of reliable AI models in classifying lung cancer using CT scans faces significant challenges due to limitations in real-world CT data availability. Acquiring CT scans is very time-consuming, resource-intensive, and raises ethical concerns involving patient privacy and data sharing. Furthermore, existing datasets often lack diversity in terms of demographic, disease presentations, and image quality, hindering the generalizability of trained models to real-world scenarios (Guo et al., 2023; Liu et al.,).

In response to these challenges, Deep Convolutional Generative Adversarial Networks (DCGANs) have emerged as a promising solution to augment existing datasets and generate high-quality, synthetic lung CT scans. DCGANs are a type of generative adversarial networks (GAN) architecture that is designed for handling image data. The architecture involves two competing neural networks: a generator network that learns to produce synthetic images, and a discriminator network that attempts to identify synthetic

and real images (Radford et al., 2015). The competing nature of these networks drives generator to create increasingly realistic and detailed synthetic images, making DCGANs suitable for medical images generation task, including CT scans.

The application of DCGANs for synthetic lung CT scans generation offers several benefits. Synthetic data can significantly increase the size and diversity of existing datasets. This will lead to improved training and performance of AI models for lung cancer detection and diagnosis. In addition to that, synthetic data anonymizes patient information, which alleviates concerns about data sharing and ethical implications associated with using real patient data. Finally, the ability to generate large amounts of synthetic data can reduce the need for expensive and time-consuming CT scan acquisition, reducing costs particularly in under-resourced settings.

While the potential of DCGANs for lung CT scan generation is promising, several challenges remain and need to be addressed. One of the challenges is to ensure the quality and realism of the generated synthetic data. In the context of lung cancer CT scans, the generated CT scans should accurately capture the anatomical structures and pathological characteristics of lung cancer lesions in order to be useful in training a robust and accurate machine learning model. The correct evaluation method for the generated scans needs to be developed to assess the fidelity and utility of the synthetic data compared to real patient scans.

The next challenge is that there is a need to consider the potential biases introduced by the generative models during the data generation process. Biased machine learning model will be produced because biases present in the training data can be amplified and reflected in the synthetic data. To ensure fairness and equitable performance of the models across diverse patient populations, it is important to address and alleviate these biases.

In conclusion, challenges in acquiring and annotating large-scale lung cancer CT scan datasets show the need to explore alternative approaches, such as synthetic data generation using generative machine learning models. The limitations of real data availability, privacy concerns, and dataset diversity can be overcome by utilizing these models. Researchers can enhance the development and evaluation of machine learning models by generating synthetic data that mimics real lung CT scan of lung cancer.

However, it is essential to address the challenges that may arise while using synthetic data generation, such as ensuring realism, evaluating quality, and alleviating biases to open the full potential of synthetic data generation in improving lung cancer diagnosis and treatment planning.

2.3 DCGANs: Principles and Application in Medical Image Generation

Demand for high-quality medical images for training and testing AI models purpose has brought Deep Convolutional Generative Adversarial Networks (DCGANs) to forefront of research. This section discusses the principles of DCGANs and explores their specific applications in generating synthetic lung CT scans, and finally observes the effectiveness and potential benefits to improve diagnosis, treatment planning, and patient care.

2.3.1 Understanding DCGANs

DCGANs are a specialized type of Generative Adversarial Network (GAN) architecture designed specifically for image generation tasks. DCGANs take advantage of the competitive nature of two neural networks:

Generator

The generator network learns to map random noise vectors into a realistic image, recreating the distribution of real images in the training data. In lung CT scans context, the generator aims to create synthetic CT scans that resemble real lung tissue structures and lesions. Figure 1 from Radford et al., 2015 shows an example of a DCGAN generator network.

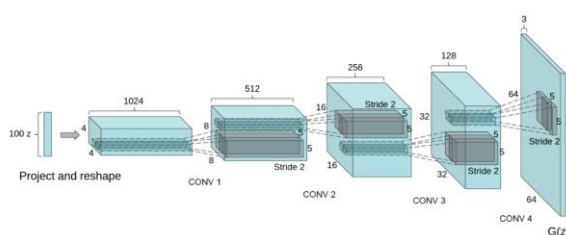


Figure 1: Example of a DCGAN Generator Network

Discriminator

On the other hand, discriminator network acts as evaluator, which attempts to distinguish real images from image generated by the generator network. By receiving feedback from the discriminator, generator will continue to improve its ability to produce realistic and faithful synthetic images until discriminator is unable to distinguish between real and fake images. Figure 2 shows an example of a DCGAN discriminator network.

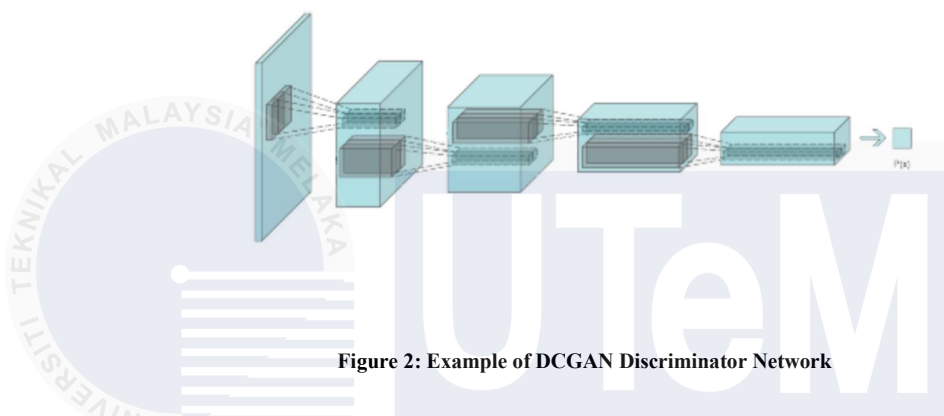


Figure 2: Example of DCGAN Discriminator Network

The adversarial training process between these two networks is crucial for DCGANs' success. As the generator improves its ability to generate more realistic images, the discriminator will adapt and improve its ability to distinguish fake images from real images. This process pushes both networks to achieve higher levels of performance, resulting in increasingly realistic and detailed synthetic images.

2.3.2 DCGANs for Medical Image Generation

The core strengths of DCGANs are their ability to handle complex image data and generate realistic images as output. This makes them particularly suitable for medical image generation tasks. In lung cancer diagnosis context, DCGANs have been utilized in few areas:

1. Augment existing datasets

By generating a large number of synthetic lung CT scans, DCGANs can increase the size and diversity of datasets significantly. This will lead to improved training and generalizability of AI models for lung cancer detection (Yu et al., 2023; Yang et al., 2022)

2. Mitigate data biases

Real-world CT scan data can often be biased towards certain demographic or disease presentation. DCGANs allow researchers to control their generation process and create synthetic data that address these biases, leading to AI models that is more accurate and fairer (Wang et al., 2021; Gong et al., 2020)

3. Generate patient-specific data

For personalized medicine, DCGANs can be conditioned on specific patient information to generate synthetic scans that recreate individual characteristics and disease progression. This can potentially aid in tailored treatment planning and drug response prediction (Liu et al., 2022; Qin et al., 2021)

2.3.3 Assessing effectiveness and benefits

Numerous studies have explored the effectiveness of DCGANs in generating synthetic lung CT scans. These studies have also pointed the potential benefits for improving lung cancer diagnosis and patient care. Among the key findings are:

1. Improved AI model performance

Studies from Zhang et al., 2023 and Han et al., 2022 have shown that AI models trained with augmented datasets containing synthetic CT scans have achieved higher accuracy in lung cancer detection compared to models trained on real data.

2. Reduced data acquisition costs and ethical concerns

Synthetic data reduces the need to acquire real CT scans. The process of acquiring real data can be time-consuming, expensive, and raises ethical concerns regarding patient privacy. DCGANs offer a cost-effective and ethically sound alternative according to Guo et al., 2023.

3. Enhanced early detection and personalized medicine

With access to larger and diverse data, DCGANs contribute to the development of AI models that are capable of earlier and more accurate lung cancer detection. Additionally, patient outcomes can be improved with patient-specific synthetic data that can facilitate personalized treatment planning (Qin et al., 2021)

In conclusion, DCGANs have emerged as a powerful tool for synthetic medical images generation, specifically in lung CT scans for improved lung cancer diagnosis and patient care. This review explored the core principles of DCGANs, highlighting their adversarial training process and ability to handle complex image data. By discussing their specific application in medical image generation, potential of DCGAN to address various challenges that hinder current AI models for lung cancer diagnosis are pointed out.

2.4 Related Work: DCGAN in Lung CT Scan Generation

DCGANs have been recognized to generate medical images. The principles and benefits of DCGANs have been discussed, specifically in lung CT scans generation for lung cancer diagnosis. This part will discuss the existing landscape of related research regarding DCGANs in generating lung CT scan. It will also highlight how this project sits within the broader context of DCGAN applications in this domain, highlighting synergies and identifying potential contributions to advance in further field.

2.4.1 DCGAN Architecture for Synthetic Lung CT Scans

The choice of DCGAN architecture plays an important role in the quality and realism of the generated lung CT scans. Researchers have studied various architectures, each with their own strengths and weaknesses, to address the challenges of generating medically accurate and anatomically complex lung tissues. Prominent examples of this research will be discussed in this part.

1. DeepSurv with Spatial Attention Mechanism

In their recent work, Yu et al. (2023) introduced a novel extension to the DeepSurv architecture. His team integrates spatial attention mechanisms into the generator network. This approach allows the generator to concentrate on critical anatomical details, particularly emphasizing lung nodules and vasculature within medical imaging data. The success of this enhanced DeepSurv model lies in its ability to generate high-fidelity representation of lung parenchyma, showcasing a remarkable capability to capture subtle variations in nodule texture and size. However, the incorporation of spatial attention mechanisms results in a higher computational complexity which increases training times and demanding substantial hardware resources. Despite these challenges, improved accuracy and detailed representations achieved by the suggested model demonstrate the potential of this approach in enhancing the performance of prediction models in medical imaging applications.

2. Pix2PixHD for High-Fidelity Image Synthesis

To address the quality of images generated by the network, Wang et al. (2020) introduced the pix2pixHD architecture, differentiated by its utilization of a multi-scale generator network and perceptual loss functions. This approach enables the generation of photorealistic images with remarkable sharpness and intricate details. Pix2pixHD stands out for its proficiency in generating visually stunning anatomical structures. The success of the model lies in its ability to capture fine-grained details, providing a level of realism that is appealing. However, there is an inherent trade-off in the team's effort of pursuing visual realism. The emphasis on achieving photorealistic images can result in a compromise on anatomical accuracy. This raises considerations about clinical relevance of the approach, emphasizing the needs to balance the visual fidelity and anatomical precision of the generated images. Despite the limitation, pix2pixHD represents a significant advancement in high-fidelity image synthesis, contributing to complex image

generation techniques in medical domain. Figure 4 shows the pix2pixHD architecture proposed by Wang et al. (2023)

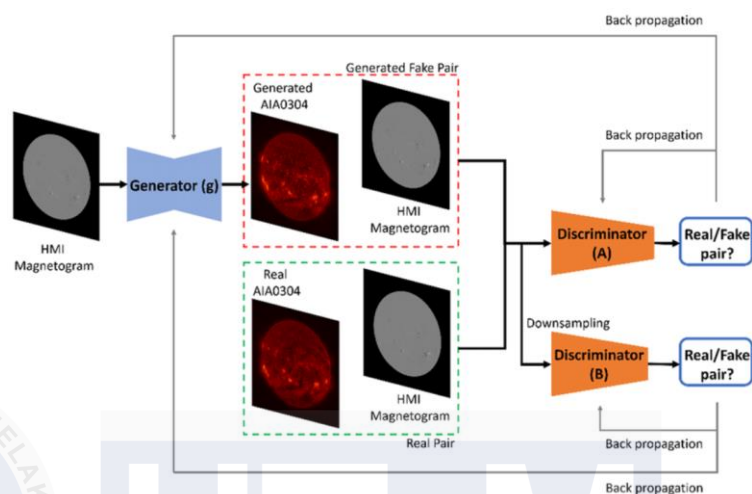


Figure 3: Pix2PixHD Model Architecture

3. CycleGAN for Unpaired Data Training

Yang et al. (2022) introduced the CycleGAN architecture, providing a novel solution for training on unpaired datasets, particularly involving real CT scans and images from alternative modalities such as PET scans. One of notable strengths of this approach is its ability to accommodate training data without demanding perfect pixel-wise alignment. The success of the proposed model lies in its flexibility, making it well suited for setting with limited availability of real CT scans. This adaptability enhances CycleGAN utility in medical imaging applications where access to paired datasets may be constrained. However, it is important to acknowledge the limitations of the approach employed by CycleGAN. This is due to the fact that this approach may introduce inconsistencies in anatomical features in the generated images, which affect the accuracy of the synthesized medical data. Furthermore, controlling specific aspects of the generated images can be challenging, which raises the need for careful consideration and validation in clinical applications. Despite the challenges, CycleGAN stands as a valuable tool for leveraging unpaired data in medical image synthesis.

2.4.2 Lung-Specific Challenges

The pursuit of hyper-realistic lung CT scans through generative models faces major challenges, but researchers are progressively moving forward to address the challenges. One major challenge lies in accurately replicating the appearance of the lung nodules, the suspicious lesions that are often associated with cancer. To address this, Zhang et al. (2023) propose incorporating domain-specific loss function into the training process. These function acts as filters, which will penalize generated scans that have unrealistic nodule shapes and textures. This approach effectively pushes the model towards generating more believable lesions.

Another significant challenge is capturing the anatomical complexity of the lungs. Liu et al. (2022) address this challenge by extracting the anatomical features prior, which acts essentially blueprints of spatial relationships, from real CT scans. These features are then fed into the generative model, guiding it to generate synthetic CT scans with accurate placements of lung lobes, airways, and the complex network of blood vessels, reproducing the natural organization of real lungs.

By tackling these challenges, researchers are steadily polishing generative models, bringing the generation of lung CT scan to a level where the lines between artificial and real data becomes blurry. This holds immense potential for medical research, training, and ultimately, early detection of lung cancer and better management of lung diseases.

2.5 Ethical and Privacy Considerations: Protecting Patients in Malaysia

While DCGANs offer immense potential for generating synthetic lung CT scans to improve lung cancer diagnosis, the ethical and privacy concerns surrounding synthetic data in medical applications require careful consideration. In Malaysia, specific regulations and cultural contexts requires thoughtful approach to ensure compliance and patient confidentiality is upheld (Ohm, 2019).

1. Patient Privacy and Confidentiality

Johnson & Waugh (2019) states that utilizing established anonymization techniques like k-anonymity, differential privacy, or federated learning can help researchers to hide individual identities while preserving data utility. This approach is suggested to prevent re-identification or unauthorized access to sensitive medical information which may lead to misuse of information.

2. Data Bias and Fairness

Biases present in the real-world datasets can be inherited and amplified by AI models trained on synthetic data. This can result in unfair and discriminatory outcomes for certain patient groups, particularly marginalized communities (Veale & Binns, 2017). Training data audit and employing bias mitigation techniques during synthetic data generation are important to promote fairness in AI-powered disease diagnosis systems.

3. Compliance with Regulations

Personal Data Protection Act 2010 (PDPA) governs the collection, storage, and use of personal data in Malaysia. This includes data related to healthcare. Synthetic data derived from patient information falls under the jurisdiction of the PDPA and must comply with its requirements (Azmi et al., 2022)

Addressing ethical and privacy concerns is not just a legal obligation but also an ethical imperative for implementing DCGANs for synthetic lung CT scans in a responsible and patient-centered manner. By obligating to Malaysian regulations, employing robust anonymization and bias mitigation techniques, researchers can leverage the power of synthetic data while upholding patient confidentiality and promoting fairness in lung cancer diagnosis and treatment. By prioritizing ethical considerations and fostering trust with stakeholders, full potential of synthetic data to improve health outcomes and well-being for all can be unleashed.

2.6 Synthetic Lung CT Scan Generation: Challenges and Future Directions

A lot of aspects have been discussed in previous parts and it is proven that DCGANs offer promising avenues for generating realistic lung CT scans. However, significant challenges and limitations remain to be addressed. Overcoming these obstacles and exploring new research directions will be very critical to unlock the full potential of synthetic data for improved lung cancer diagnosis.

1. Data Availability and Scarcity

Collecting and sharing of CT scans data in Malaysia can be challenging due to privacy concerns, data fragmentation across healthcare institutions, and limited resources. This results in obstruction in training robust DCGAN models and create challenges in generating diverse synthetic datasets.

Potential solution for this challenge will be to explore federated learning approaches to secure data sharing process and collaboration across institutions, anonymization techniques to protect patient privacy, and leveraging data augmentation to address limited data availability (Azmi et al., 2023)

2. Quality and Domain Specificity

Ensuring the realism and clinical accuracy of the synthetic CT scans is important for their practical application in diagnosis. Anatomical detail, nodule appearance, and tissue texture needs to be replicated successfully to create a reliable AI model for training and evaluation.

Domain-specific loss function implemented by Yu et al. (2023), incorporating prior knowledge from medical experts and utilizing CT scan-specific image quality metrics can improve the realism of the images generated. It can also improve the clinical relevance of the generated data so that diagnosis of lung cancer will be more accurate.

3. Regulatory and Ethical Landscape

Complex regulatory landscape surrounding medical data privacy and synthetic data generation in Malaysia is essential to be navigated. Compliance with the PDPA and ethical considerations must be prioritized to ensure responsible and patient-centered development of this technology. It is vital to engage with stakeholders, including policymakers, healthcare professionals, and patients, to create a clear and adaptable ethical framework for synthetic data utilization in Malaysia. (World Health Organization, 2019)

The future of generating lung CT scans is bright, but it extends beyond realism of the generated data. To overcome data scarcity and privacy concerns, secure data sharing via federated learning offers collaborative approach, though robust anonymization techniques and data security protocols are necessary for responsible implementation. Building trust in these AI models is equally important. Transparent, explainable DCGAN architectures and clear documentation of synthetic data generation processes are crucial to foster acceptance among healthcare professionals and patients. Engaging diverse communities and incorporating cultural perspectives into AI development will foster trust and ensure equitable access to these life-changing innovations. By tackling these challenges head-on, the true potential of lung CT scan generation in Malaysia can be unlocked, paving the way for a future of personalized medicine and improved healthcare for all.

2.7 Conclusion

Our comprehensive review delves into the captivating realm of deep convolutional generative adversarial networks (DCGANs) and their potential to revolutionize lung cancer diagnosis in Malaysia. We meticulously examined various DCGAN architectures specifically adapted for generating realistic lung tissue. The review critically explored the ethical and privacy considerations surrounding synthetic data in healthcare while addressing the inherent challenges of data scarcity, quality, and bias. By meticulously surmounting these obstacles and charting innovative research avenues, we can unlock the full potential of synthetic scans to save lives and enhance patient outcomes in Malaysia.

The future of Malaysian lung cancer research lies on a challenging yet promising path. Embracing collaborative data sharing practices, prioritizing fairness and interpretability in AI models, and meticulously tailoring AI development to the cultural context are all pivotal steps towards achieving this vision.



CHAPTER 3: PROJECT METHODOLOGY

3.1 Introduction

To achieve the goal of efficiently generating high-quality synthetic lung cancer CT scans with a Deep Convolutional Generative Adversarial Network (DCGAN), a robust and systematic methodology was adopted. This chapter outlines the chosen framework, data acquisition and preparation, model architecture and training, evaluation metrics, tool development, and validation strategies. Throughout each step, a focus was placed on maximizing efficiency, ensuring project completion within defined timelines and resources. By meticulously choosing methods and justifying every decision, we aimed to establish a reproducible and well-defined approach for delivering a valuable tool capable of generating synthetic images of lung CT scan.

3.2 Project Management Framework

This project's efficient delivery took advantage of the Cross-Industry Standard Process for Data Mining (CRISP-DM) framework. It is recognized for its structured approach to guiding data-driven initiatives. CRISP-DM includes six iterative phases, in which each phase plays an important role in navigating the complexities of extracting and applying insights from data. Figure 5 shows the six phase of CRISP-DM in guiding data mining process.

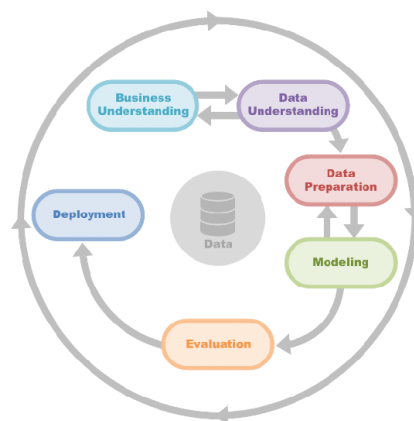


Figure 4: 6 Phases of CRISP-DM

1. Business Understanding

The initial phase of the CRISP-DM focuses on defining the project's objectives, aligning them with clinical needs and research goals. Potential applications of synthetic CT scans in lung cancer diagnosis, treatment planning, and algorithm development were explored. Clear understanding of the “why” behind this project served as a guide throughout subsequent phases.

2. Data Understanding

In the next phase, complexities of the data itself are explored. Reliable sources of lung cancer CT scan data are identified and acquired, ensuring ethical considerations and patient privacy were at the top of priorities. Understanding the data's properties, limitations, and potential biases influenced both data preparation and model development strategies.

3. Data Preparation

The data preparation phase is very crucial. In this phase, the raw data is transformed into a format suitable for DCGAN training. Normalization to ensure consistent scales is involved before passing the transformed data into the generator network. The thorough preparations established the groundwork for strong model training and the dependable creation of synthetic data.

4. Modeling

Designing and implementing the DCGAN architecture started in this phase. The cleaned and well-prepared data is equipped into the architecture for training. Model components, hyperparameter, and training protocols were selected utilizing the insights from previous phases. Each decision was evaluated and documented, to ensure reproducibility and efficient optimization of the model's performance.

5. Evaluation

Established metrics like Fréchet Inception Distance (FID) and Inception Score (IS) are employed to assess the success of the DCGAN model. These metrics objectively evaluated the quality and diversity of the generated synthetic CT scans, enabling monitoring of the model's progress and make informed adjustments for optimal performance.

6. Deployment

Finally, the trained model is transitioned into a readily utilizable tool. By utilizing Python Tkinter's user friendly interface capabilities, software application that integrates the DCGAN model were built and offers accessible functionalities for generating and manipulating synthetic CT scans. This user-centered approach will ensure the project's long term impact and facilitates its integration into real world research and clinical settings.

Following the structured and flexible guidelines of CRISP-DM proved instrumental in efficiently navigating the complexities of this research. Each phase, from defining project objectives and deploying the final tool, allowed continuous refining of methodologies based on new insights and adapt to unforeseen challenges. This will ensure that the project progresses efficiently towards our goals. By leveraging strengths of CRISP-DM, valuable tool for synthetic CT scan generation was successfully delivered, contributing to advancements in lung cancer research and diagnosis.

3.3 Project Milestones

This section presents the groundwork precisely throughout PSM1, making way for the successful development and implementation of the tool for generating synthetic lung cancer CT scans. The project progressed by first outlining the **Project Management Framework**, guided by the robust and iterative nature of CRISP-DM. Table 2 shows the milestones for PSM1. The table will show activities done throughout the duration of PSM1.

Table 2: PSM1 Milestones

WEEK	ACTIVITY	NOTE / ACTION
W1 (20/03 →24/03) (<3/10)	Select a suitable project topic and potential Supervisor	<input type="checkbox"/> Action – Student
W1 (20/03 →24/03) Meeting 1	Proposal PSM: Discussion with Supervisor	<input type="checkbox"/> Proposal Form – Ulearn <input type="checkbox"/> Action – Student
	Proposal assessment & verification	<input type="checkbox"/> Action – Supervisor
	Proposal Correction/Improvement	<input type="checkbox"/> Deliverable – Draft Proposal Form – email PIC
	Proposal Approval	<input type="checkbox"/> Action – Committee Action – Student email Committee for proposal approval
	Proposal Submission Proposal [PRJ-1]	<input type="checkbox"/> Action – Student <input type="checkbox"/> Upload approved proposal at Ulearn

W2 (27/03 → 31/03)	List of student with project title versus supervisor and evaluator	<input type="checkbox"/> Action – Committee – List at Ulearn
W3 (03/04 → 07/04) Meeting 2	Chapter 1	<input type="checkbox"/> Action – Student
W4 (10/04 → 14/04)	Chapter 1 Report Writing Progress 1 [PRJ-3]	<input type="checkbox"/> Log Progress – ePSM <input type="checkbox"/> Deliverable – Chapter 1 – ePSM Action – Student → Supervisor <input type="checkbox"/> Evaluate – ePSM <input type="checkbox"/> Action – Supervisor
W5 (17/04 → 21/04)	Chapter 2	<input type="checkbox"/> Action – Student
W6 (24/04 → 28/04)	MID-SEMESTER BREAK	
W7 (01/05 → 05/05) Meeting 3	Chapter 2 Report Writing Progress [PRJ-3]	<input type="checkbox"/> Log Progress – ePSM <input type="checkbox"/> Deliverable – Chapter 2 – ePSM <input type="checkbox"/> Action – Student → Supervisor <input type="checkbox"/> Evaluate – ePSM <input type="checkbox"/> Action – Supervisor
	Project Progress 1 [PRJ-2]	<input type="checkbox"/> Log Progress – ePSM <input type="checkbox"/> Progress Presentation 1 (KPI) <input type="checkbox"/> Action – Student → Supervisor <input type="checkbox"/> Evaluate – ePSM <input type="checkbox"/> Action – Supervisor
	Student Status	<input type="checkbox"/> Warning Letter 1 to Student

		<input type="checkbox"/> Action → Supervisor, Committee
W8 (08/05 → 12/05)	Chapter 3	<input type="checkbox"/> Action – Student
W9 (15/05 → 19/05)	Chapter 3 Report Writing Progress 1 [PRJ-3]	<input type="checkbox"/> Log Progress – ePSM <input type="checkbox"/> Deliverable – Chapter 3 – ePSM <input type="checkbox"/> Action – Student → Supervisor <input type="checkbox"/> Evaluate – ePSM <input type="checkbox"/> Action – Supervisor
W10 (22/05 → 26/05) Meeting 4	Chapter 4	<input type="checkbox"/> Action – Student
	Project Progress 2 [PRJ-4]	<input type="checkbox"/> Log Progress – ePSM <input type="checkbox"/> Progress Presentation 2 (KP2) <input type="checkbox"/> Action – Student → Supervisor <input type="checkbox"/> Evaluate – ePSM <input type="checkbox"/> Action – Supervisor
	Student Status	<input type="checkbox"/> Warning Letter 2 to Student <input type="checkbox"/> Action – Supervisor, Committee
W11 (29/05 → 02/06)	Chapter 4 Report Writing Progress 2 [PRJ-5]	<input type="checkbox"/> Log Progress – ePSM <input type="checkbox"/> Deliverable – Chapter 4 – ePSM <input type="checkbox"/> Action – Student → Supervisor <input type="checkbox"/> Evaluate – ePSM <input type="checkbox"/> Action – Supervisor
	PSM1 Draft Report Preparation	<input type="checkbox"/> Action – Student

	Determination of Student Status (Continue/Withdraw)	<input type="checkbox"/> Submit Student status to PSM/PD Committee <input type="checkbox"/> Action – Supervisor → Committee
W12 & W13 (05/06 → 16/06) Meeting 5	PSM1 Draft Report preparation	<input type="checkbox"/> Action – Student <input type="checkbox"/> Supervisor
W14 (19/06 → 23/06)	PSM1 Draft Report submission to SV & Evaluator Report Evaluation [PRJ9] [PRJ-10]	<input type="checkbox"/> Log Progress – ePSM <input type="checkbox"/> Deliverable – Complete PSM1 Draft Report – ePSM <input type="checkbox"/> Action – Student → Supervisor, Evaluator <input type="checkbox"/> Evaluate – ePSM <input type="checkbox"/> Action – Supervisor
	Schedule the presentation	<input type="checkbox"/> Presentation Schedule - ULearn <input type="checkbox"/> Action – Committee
W15 (26/06 → 30/06) FINAL PRESENTATION	Demonstration Supervisor [PRJ-6] Evaluator [PRJ-7]	<input type="checkbox"/> Log Record – ePSM <input type="checkbox"/> Action – Student <input type="checkbox"/> Evaluate – ePSM <input type="checkbox"/> Action – Supervisor, Evaluator
	Presentation Skill [PRJ-8]	<input type="checkbox"/> Log Record – ePSM <input type="checkbox"/> Action – Student <input type="checkbox"/> Evaluate – ePSM <input type="checkbox"/> Action – Evaluator

With solid foundation established in PSM1, PSM2 sets the stage for further refinement and impactful deployment. Table 3 shows the timeline of PSM2, which covers the rest of the project until the submission of project and thesis.

Table 3: PSM2 Milestones

WEEK	ACTIVITY	NOTE/ACTION
W1 (09/10 – 13/10) Meeting 1	Chapter 4	Action – Student
W2 (16/10 – 20/10)	Chapter 4	Action – Student
W3 & W4 (23/10 – 3/11) Meeting 2	Project Progress 1 [PRJ-1]	<ul style="list-style-type: none"> • Log Record – ePSM • Progress Presentation 1 (KP1) • Action – Student, Supervisor
		<ul style="list-style-type: none"> • Evaluate – ePSM • Action - Supervisor
W5 (06/11 – 10/11)	Chapter 5	<ul style="list-style-type: none"> • Action - Student
W6 (13/11 – 17/11)	Chapter 5 Report Writing Progress [PRJ-3]	<ul style="list-style-type: none"> • Log Record – ePSM • Deliverable-Chapter 5, ePSM • Action – Student, Supervisor
		<ul style="list-style-type: none"> • Evaluate – ePSM • Action - Supervisor
	Student Status	<ul style="list-style-type: none"> • Warning Letter 1

		<ul style="list-style-type: none"> Action-Supervisor,
<p>W7</p> <p>(20/11 – 24/11)</p> <p>Meeting 3</p>	Chapter 6	<ul style="list-style-type: none"> Action - Student
<p>W8</p> <p>(27 /11 – 1/12)</p>	MID – SEMESTER BREAK	
<p>W9</p> <p>(04/12 – 08/12)</p>	Chapter 6	<ul style="list-style-type: none"> Action - Student
<p>W10</p> <p>(11/12 – 15/12)</p>	Chapter 6	<ul style="list-style-type: none"> Log Record – ePSM Deliverable-Chapter6 (ePSM) Action – Student, Supervisor
	Report Writing Progress [PRJ-3]	<ul style="list-style-type: none"> Evaluate – ePSM Action - Supervisor
	Project Progress 2 [PRJ-2]	<ul style="list-style-type: none"> Log Record – ePSM Progress Presentation 2 (KP2) Action – Student, Supervisor
	Student Status	<ul style="list-style-type: none"> Warning Letter 2 Action - Supervisor
<p>W11</p> <p>(18/12 – 22/12)</p> <p>Meeting 4</p>	Chapter 7	<ul style="list-style-type: none"> Action - Student

W12 (25/12 – 29/12)	Chapter 7 Report Writing Progress [PRJ-3]	<ul style="list-style-type: none"> • Log Record – ePSM • Deliverable-Chapter7 (ePSM) • Action – Student, Supervisor
		<ul style="list-style-type: none"> • Evaluate – ePSM • Action – Supervisor
	PSM2 Draft Report Preparation	<ul style="list-style-type: none"> • Action – Student, Supervisor
	Determination of Student Status (Continue/Withdraw)	<ul style="list-style-type: none"> • Submit Student status to committee • Action–Supervisor, Committee
W13 (1/1 – 5/1) Meeting 5	PSM2 Draft Report Preparation	<ul style="list-style-type: none"> • Action – Student, Supervisor
W14 (8/1 – 12/1)	PSM2 Draft Report Submission to SV & Evaluator Report Evaluation [PRJ6][PRJ-10]	<ul style="list-style-type: none"> • Log Record – ePSM • Deliverable-PSM2 Draft Report (ePSM) • Action-Student,(SV, Evaluator)
		<ul style="list-style-type: none"> • Evaluate – ePSM • Action – SV,Evaluator
	Schedule the presentation	<ul style="list-style-type: none"> • Presentation Schedule – Ulearn • Action - Committee
W15 (15/1 – 19/1) FINAL PRESENTATION	Demonstration Supervisor [PRJ4][PRJ5] Evaluator [PRJ9]	<ul style="list-style-type: none"> • Log Record – ePSM • Action - Student
		<ul style="list-style-type: none"> • Evaluate – ePSM • Action – SV, Evaluator
		<ul style="list-style-type: none"> • Log Record – ePSM

	English Proficiency [PRJ7]	<ul style="list-style-type: none"> Action - Student
		<ul style="list-style-type: none"> Evaluate – ePSM Action - Supervisor
	Presentation Skill [PRJ8]	<ul style="list-style-type: none"> Log Record – ePSM Action - Student
		<ul style="list-style-type: none"> Evaluate – ePSM Action - Evaluator
W16 (22/1 – 26/1) Revision Week	Draft report correction.	<ul style="list-style-type: none"> Deliverable-EoS survey
	EoS Survey form.	<ul style="list-style-type: none"> Action - Student
	Submission of final complete report, corrected	<ul style="list-style-type: none"> Deliverable – Report (e-Thesis) Action-Student,Committee
W17 & W18 (29/1 – 9/2) Final Examination Week	Submission of the final complete report; updated and corrected with Plagiarism Report	<ul style="list-style-type: none"> Deliverable – PSM report, Plagiarism Report (OneDrive) Action – Student, Supervisor

3.4 Data Collection and Preprocessing

3.4.1 Data Acquisition

To develop a reliable synthetic CT scan generation, the dataset used was acquired from Kaggle.com, a reputable platform for curated datasets which is the IQ-OTH/NCCD which is publicly available. This dataset, containing a diverse collection of lung cancer CT scans, offered volume necessary for the training of DCGAN model.

3.4.2 Data Preparation for Optimal Performance

After obtaining the dataset, comprehensive preprocessing pipeline to prepare the data for GAN training is initiated.

1. Resizing

All images are resized to 112x168 pixels to ensure consistency in input dimensions for the model. This is because GANs are often sensitive to spatial structure.

2. NumPy Array Conversion

The image was then converted into a NumPy array. NumPy array is a fundamental structure within Python's scientific computing ecosystem. This will enable seamless model training and manipulation.

3. Pixel Normalization

Pixel normalization was applied to the training images to streamline model convergence and mitigate potential biases. This process centers the pixel values around 0 with a standard deviation of 1. This is applied to improve training stability and model generalization. Formula 1 shows the formula used to normalize the image pixel.

$$Image = \frac{(Image - 127.5)}{127.5}$$

Formula 1: Pixel normalization formula

3.4.3 Addressing Missing and Imbalance Data

The IQ-OTH/NCCD dataset contains no missing or imbalance data, avoiding the need for additional preprocessing techniques. However, it's important to acknowledge that challenges might arise in medical datasets, and methodology needs to be adapted accordingly. Strategies like imputation or resampling might be able to address this issue, ensuring data cleanliness and preventing potential biases.

By preparing the data through these strategic techniques, basis for successful model training was established. In addition to that, generation of high-quality synthetic lung cancer CT scans will be made possible.

3.5 DCGAN Architecture

In pursuit of synthesizing realistic lung cancer CT scans, the computational ability of Tensorflow was utilized to construct and train a Deep Convolutional Generative Adversarial Network (DCGAN). It comprises of a Generator network and Discriminator network which engage in adversarial training. The generator network employs convolutional transpose layers and Tanh activation to create synthetic images. On the other hand, Discriminator network utilizes convolutional layers and a dense layer for discernment. Hyperparameter, including batch size and learning rate guide the training process with the Adam optimizer and binary cross-entropy loss. Decisions made to the architectural settings were strategically made to maximize the performance of the model. The resulting DCGAN demonstrates potential to generate high-quality synthetic lung cancer CT scans.

3.6 Evaluation Metrics

Fréchet Inception Distance (FID) and Inception Score (IS) are commonly used evaluation metrics in assessing the quality of synthetic images generated by models like the DCGAN.

FID measures the similarity between the distribution of real-world data and generated data. Fréchet distance, a statistical measure, between distribution of feature vectors extracted from real and generated images is computed. The computation utilized a pre-trained InceptionV3 model. A lower FID indicates similarity between the distribution of real-world and generated data.

Inception Score (IS) evaluates the quality and diversity of the generated images. Just like FID, IS takes advantage of the InceptionV3 model to calculate the entropy of the class probabilities assigned to the generated images. It also calculates their average KL divergence. A higher IS suggests better quality and diversity. However, it has limitations and may not always correlate with visual appeal.

Benchmarks for success in FID and IS can vary based on specific goals of the project and the dataset characteristics. In ideal situation, a lower FID and a higher IS are desirable, but there is no universal threshold when it comes to FID and IS. Researchers often compare these metrics across different models or as relative indicators of model performance rather than establishing strict benchmarks. Choice of threshold should consider specific application of the model and trade-off between image quality and diversity.

3.7 Tool Development and Functionalities

In tool development context, the purpose is to create a user-friendly interface for researchers and medical experts involved in lung cancer research and medical imaging applications. The target audience of the tool will be professionals who seek an accessible platform to generate and explore synthetic lung cancer CT scans. For this project, the tool is implemented with Python Tkinter, offering a visually intuitive interface with key functionalities such as initiating image synthesis, and adjusting model hyperparameter.

Integration of the trained DCGAN model into the tool is a crucial aspect of its functionality. This involves assimilating the pre-trained model into the tool's backend, which allows users to leverage the generative capabilities of the DCGAN without requiring advanced technical knowledge. This integration ensures that users can explore the potential application of the model and generate synthetic images for further research purposes.

Usability and accessibility are emphasized through features designed to enhance user experience. Interactive parameter tuning and real-time feedback on model performance contribute to the tool's user-friendly nature. The purpose of these features is to make the tool accessible to a broader audience, invoking collaboration between domain experts and those with varying levels of technical expertise. Further details on development process, functionalities, and user interface design will be thoroughly explored in subsequent chapters, providing a comprehensive understanding of the implemented tool.

3.8 Testing and Validation

The final stage of project development includes solidifying the worth of the tool through testing and validation. This will ensure that the tool works as intended, delivers accurate results, and can be reliably employed by target users. Testing approach includes unit testing, where individual modules are inspected for core functionalities. Besides that, integration testing will be employed to ensure seamless interactions, functional testing covering diverse user scenarios, and regression testing to prevent unintended breaks in existing features. Validation process involves defining accuracy metrics related to the tool's purpose. Challenges in devising comprehensive test cases, obtaining diverse data, and addressing potential bias were acknowledged. The subsequent chapter will discuss the details of testing methodologies, validation metrics, and solution, showcasing thoroughness applied to ensure the tool's robustness. Through testing and validation, Tkinter creation's capabilities will be put to test, ensuring successful deployment in practical scenario.

3.9 Conclusion

This methodology outlined a comprehensive and data-driven approach for utilizing DCGAN on lung cancer CT scan. With CRISP-DM framework as guide, it prioritized systematic data management, model development and tool building. The incorporation of evaluation metrics, such as FID and IS, were included as medium to assess the generated images quality and diversity. User-focused Tkinter-integrated tool prioritized accuracy, reliability, and user-friendliness. By strictly addressing each phase, the methodology lays a solid groundwork for advancing clinical applications of AI in lung cancer diagnosis and research, promising improved patient outcomes. Subsequent chapters will discuss the detailed execution of this approach, showcasing its potential impact on the field.

CHAPTER 4: DESIGN

4.1 Introduction

This chapter delves into the complex design of the proposed system, strictly crafted to close the gap between data scarcity and impactful solutions. In this chapter, the system's architecture will be explained, revealing the interconnected components through diagram and clear explanations. Technical specifications will also be discussed, providing the foundation upon which this system thrives – the hardware, software, and programming languages chosen with purpose. Data flow diagram will be the guide to the information's journey within the system, which highlights key processes and storage points.

After that, the user interface, which will be the bridge of connection between the target user and the system's functionalities will be revealed. For image generation task, algorithmic design will be explored, which will be the link to solve the defined problems. The logic behind every design decision will be exposed, in consideration of research findings, project objectives, and limitations. This transparent exploration of the system's design clarifies its inherent potential, charting a course for future improvements with potential applications.

4.2 System Architecture

The success of any complex system hinges upon a well-defined architecture, which is a crucial foundation that becomes the building base of the system's functionalities and performance. For this project, the system architecture plays an important role in demonstrating smooth interaction between user input, image synthesis via a pre-trained DCGAN model, and interactive user interface built using Tkinter framework. This section explores the details of the system architecture, revealing the components and their connection to deliver the desired functionalities.

The desktop application is first contextualized and its core objective, which will then expose the reason behind choosing Tkinter as user interface framework. Subsequently, the DCGAN model is introduced and its significance within the system, which will highlight its role in image synthesis. The exploration of the architecture will then continue, presenting a visual representation and detailed explanation of its interconnected elements. Figure 6 shows the system architecture of the project.

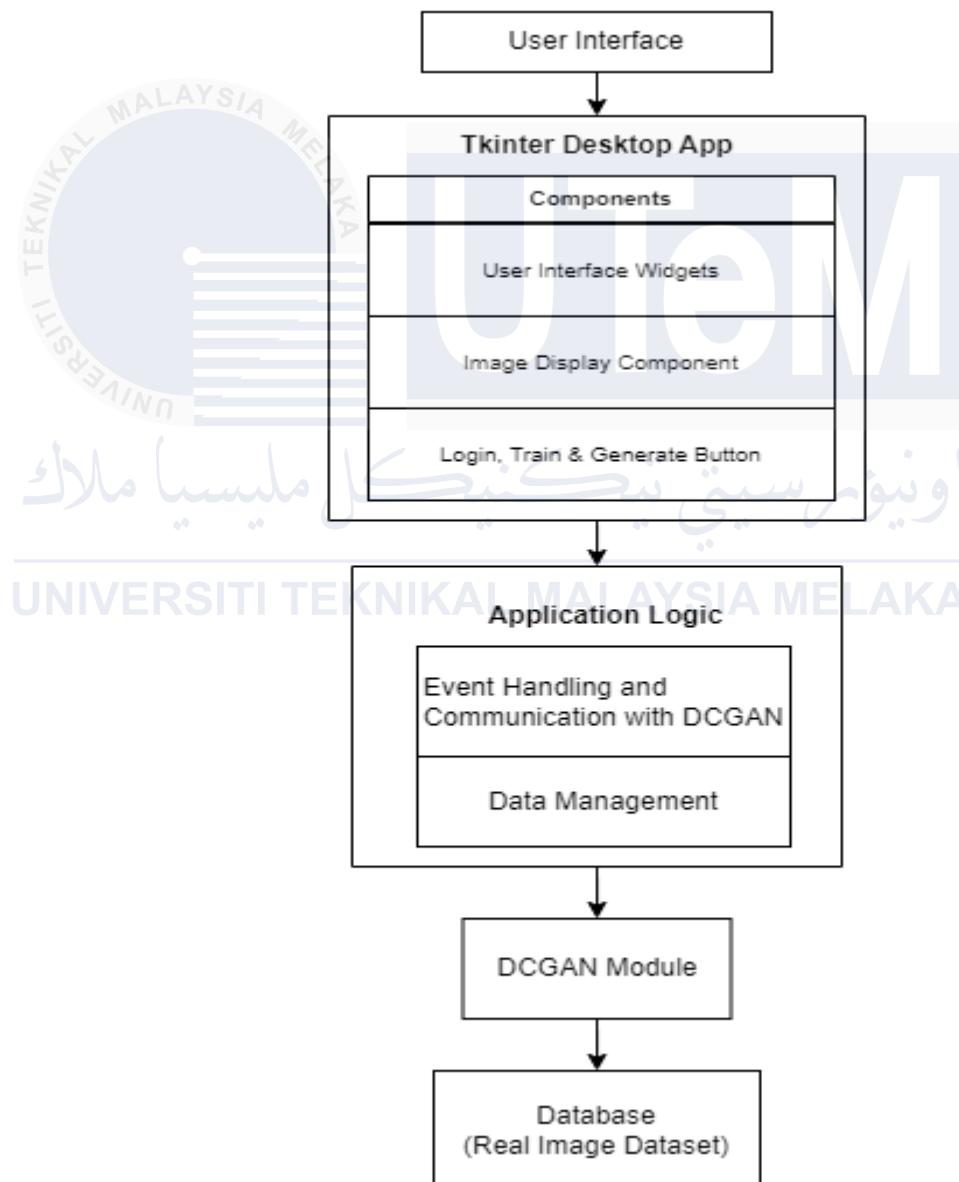


Figure 5: Proposed System Architecture

1. User Interface (Tkinter)

The Tkinter desktop application provides graphical user interface (GUI) intended for users to interact with the application. GUI includes widgets such as buttons, image display component, label, and other UI elements.

2. Application Logic

This layer manages interaction between the user interface and the DCGAN module. It includes event handling for user inputs, communication with the DCGAN module, and data management tasks.

3. DCGAN Module

This module encapsulates the DCGAN model responsible for generating synthetic images. The model receives input from the application logic layer. The model then processes the requests using the pre-trained model, and returns a set of generated images.

4. Database

The database holds the real image dataset used to train and evaluate the DCGAN. It contributes to the realism and diversity of the generated images.

The Tkinter desktop app serves as the front-end interface, allowing users to interact with the application. The logic layer then manages the user inputs, communicates with the DCGAN module, and handles data operation. DCGAN module, situated in the backend, generates synthetic images based on the input received from the logic layer.

This architecture facilitates a user-friendly desktop application that leverages the ability of DCGAN in generating synthetic images.

4.3 Technical Specification

The section outlines the hardware, software, frameworks, and programming languages that established the foundational elements of the proposed system. This comprehensive overview is essential for understanding the building blocks that support the successful implementation of the project. The specifications detail the computational infrastructure, including the processor, memory, and graphic processing unit (GPU), as well as the software tools selected for the development and training tasks. Frameworks and programming language chosen reflects the decisions made to achieve the project objectives efficiently. This section aims to provide a clear and concise overview of the technical environment, explaining the essential components that contribute to the functionality and robustness of the system.

1. Hardware Specifications

Processor: The system is equipped with an AMD Ryzen 5 3350H processor. This will provide the necessary computational power needed for running complex tasks, including DCGAN training and desktop application execution.

System Type: The architecture operates on a 64-bit system, ensuring compatibility with modern software and taking advantage of enhanced memory addressing capabilities.

Installed RAM: The system is equipped with a substantial 32GB of RAM, facilitating efficient multitasking and handling of large datasets during DCGAN training and application usage.

Graphics Processing Unit (GPU): The system utilizes an NVIDIA GeForce GTX 1650 GPU with GDDR5 memory, featuring a memory bandwidth of 128GB/sec. This powerful GPU is crucial for accelerating deep learning tasks, such as DCGAN training.

2. Software Specifications

Jupyter Notebook: Jupyter Notebook is employed for DCGAN training, offering an interactive and collaborative environment for developing and executing Python code. Its integration allows for a step-by-step exploration of the DCGAN model during training.

Visual Studio Code: VS Code is chosen as the integrated development environment (IDE) for desktop app development using Tkinter. The versatility and extensions of VS Code support efficient coding and debugging.

Draw.io: Draw.io is utilized for creating charts and diagrams, aiding in visualization and documentation of the system architecture. Its user-friendly interface allows for creation of clear and informative visuals.

3. Frameworks

Tensorflow: Tensorflow is employed as the primary framework for implementing the DCGAN model. With its flexibility and scalability, Tensorflow provides a comprehensive ecosystem for deep learning tasks, ensuring efficient DCGAN training.

Tkinter: Tkinter serves as the GUI framework for the desktop application. Leveraging the simplicity and effectiveness of Tkinter facilitates the creation of an interactive and visually appealing user interface

4. Programming Languages

Python: Python is chosen as the primary programming language for both DCGAN implementation and desktop app development. The extensive libraries and frameworks of Python make it possible for both machine learning and graphical user interface development.

This detailed technical specification provides a comprehensive overview of the hardware and software components, frameworks, and programming languages for the successful implementation of proposed system. It provides clarity on the tools and technologies chosen to support the objectives of my project. Table 4 shows the summary of the technical specifications used in the project.

Table 4: Table of Technical Specifications

Category	Specifications
Hardware	
Processor	AMD Ryzen 5 3550H
System Type	64-Bit
Installed RAM	32GB
GPU	NVIDIA GeForce GTX 1650 <ul style="list-style-type: none"> • Memory Type : GDDR5 • Memory Bandwidth : 128GB/sec
Software	
Jupyter Notebook	DCGAN training
Visual Studio Code	Desktop app development using Tkinter
Draw.io	Creating charts and diagrams
Frameworks	
Tensorflow	DCGAN implementation
Tkinter	GUI development for the desktop application
Programming Language	
Python	Primary language for DCGAN and desktop app

4.4 Data Flow Diagram (DFD)

The Data Flow Diagram (DFD) illustrates the flow of information within the system, emphasizing key processes, inputs, outputs, and storage. Maintaining precision and simplicity is essential, using clear symbols and concise labels to facilitate understanding without unnecessary complexity. The DFD of proposed system utilizing DCGAN can be seen in Figure 7.

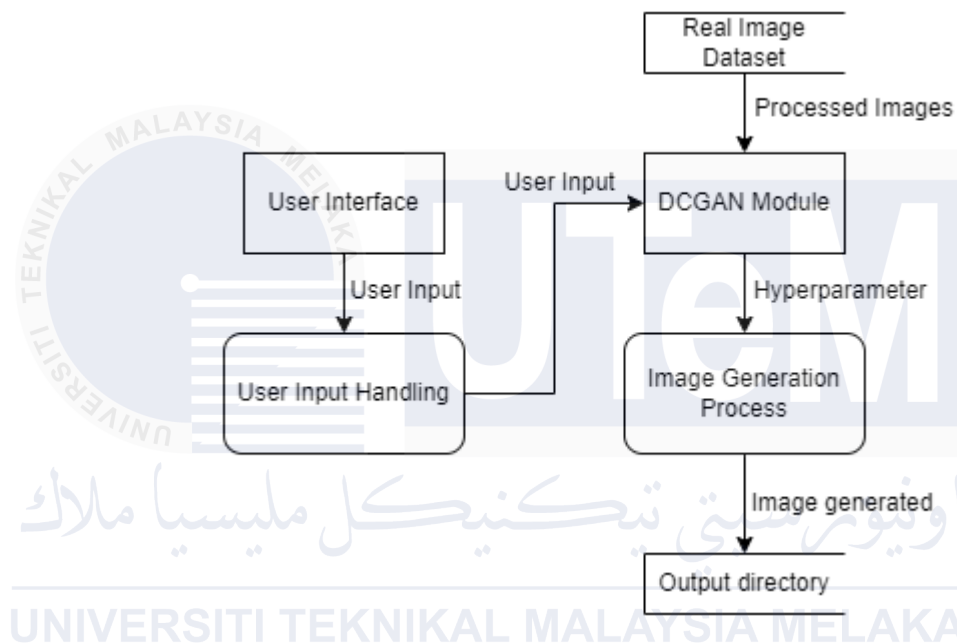


Figure 6: Data Flow Diagram of the Proposed System

1. External Entities

User Interface: Represents the external entity through which users interact with the system.

DCGAN Module: External entity representing the DCGAN responsible for image synthesis.

2. Processes:

Image Generation Process: Represents the core process where the DCGAN generates synthetic images based on user input.

User Input Handling: Process responsible for managing user inputs from the interface and directing them to the appropriate components.

3. Data Flows:

User Input Data Flow: Shows the flow of user input from interface user to the User Input Handling. Flow of user input then continue from User Input Handling to the DCGAN Module for hyperparameter tuning.

DCGAN Training Data Flow: Flow of processed real image data from database to the DCGAN module for training.

Generated Image Output Flow: The flow of synthetic images from the Image Generation Process to the output directory for saving.

This structured DFD provides a visual representation of how information flows within the system. External entities interact with the User Interface and DCGAN Module, contributing to the processes that handle user input and generate synthetic CT scan images. The flow of data between these components and the real image database is clearly illustrated, ensuring a precise and comprehensible depiction of the system's data dynamics.

4.5 User Interface Design

This section presents the exploration of visual and functional elements that shape the user experience. Through mock-up and wireframes, the design of the UI that prioritize user-friendly navigation and accessibility is illustrated.

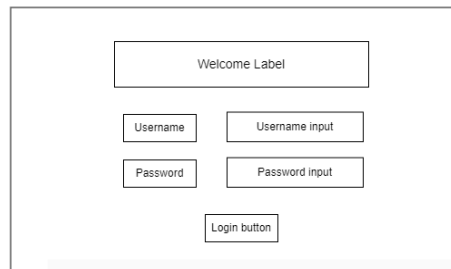


Figure 7: Wireframe of the Login Window

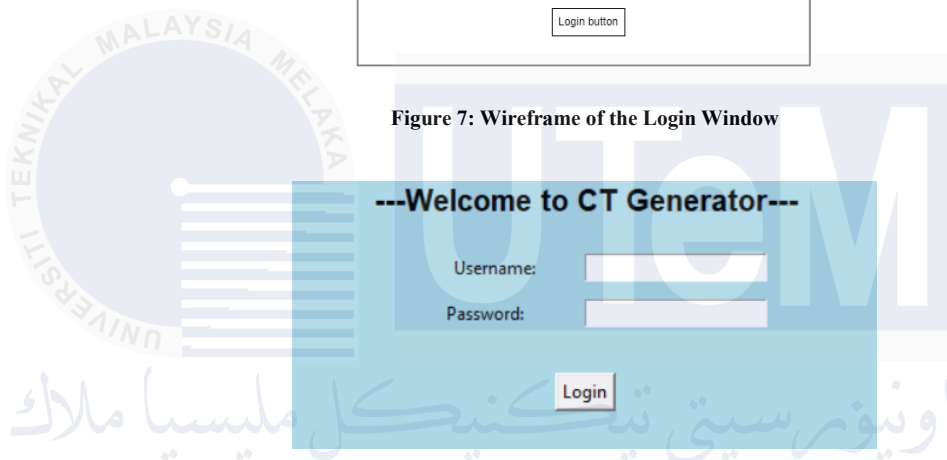


Figure 8: Mockup of the Login Window

Figure 8 and Figure 9 is the side-to-side comparison between the wireframe and mock-up of the login window. The login window serves as the entry point to the desktop application, providing users with a secure and personalized access point. After successfully logging in with the correct credentials, user will be given access to the main window. Wireframe and mock-up of the main window is shown in Figure 10 and Figure 11.

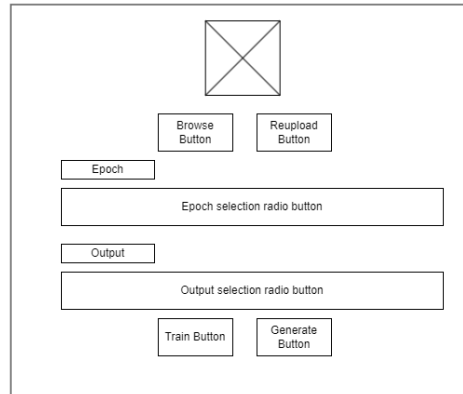


Figure 9: Wireframe of the Main Window

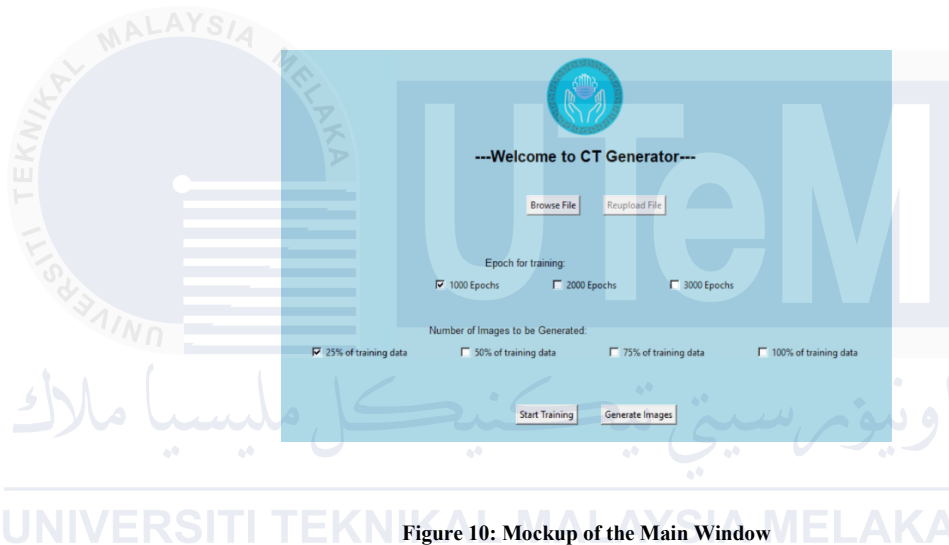


Figure 10: Mockup of the Main Window

The main window is the bridge that connects user interface to the DCGAN module that generate synthetic CT scan images. User can opt to generate images using the default parameter or upload new training data to apply transfer learning and create new variation of lung CT scan.

In this section, the visual and functional aspects of the desktop application has been discussed. Through wireframes and mockups, representation of the design choices that emphasize user experience, accessibility, and aesthetic appeal has been presented. This section sets the stage for a smooth transition into the exploration of the algorithmic design, where principles to generate high quality and diverse image will be applied.

4.6 Algorithmic Design

The chosen algorithm, Deep Convolutional Generative Adversarial Network (DCGAN) takes center stage as a crucial framework in driving image synthesis task within the project. The selection of the DCGAN lies in its generative capabilities, which is particularly relevant to the identified problem of data scarcity. With its ability to generate realistic images, DCGAN becomes an instrumental solution for expanding the dataset used for training and evaluation.

The reason behind opting for DCGAN takes consideration of addressing data scarcity and ethical and privacy concerns of patients' data. By generating synthetic data, the reliance on real dataset is minimized, alleviating ethical considerations tied to data privacy. This strategic use of DCGAN not only increases the available data but also protects patients' data privacy, marking significant advantage in scenarios where genuine data may pose privacy challenges. Figure 10 shows the architecture of the DCGAN used in this project.

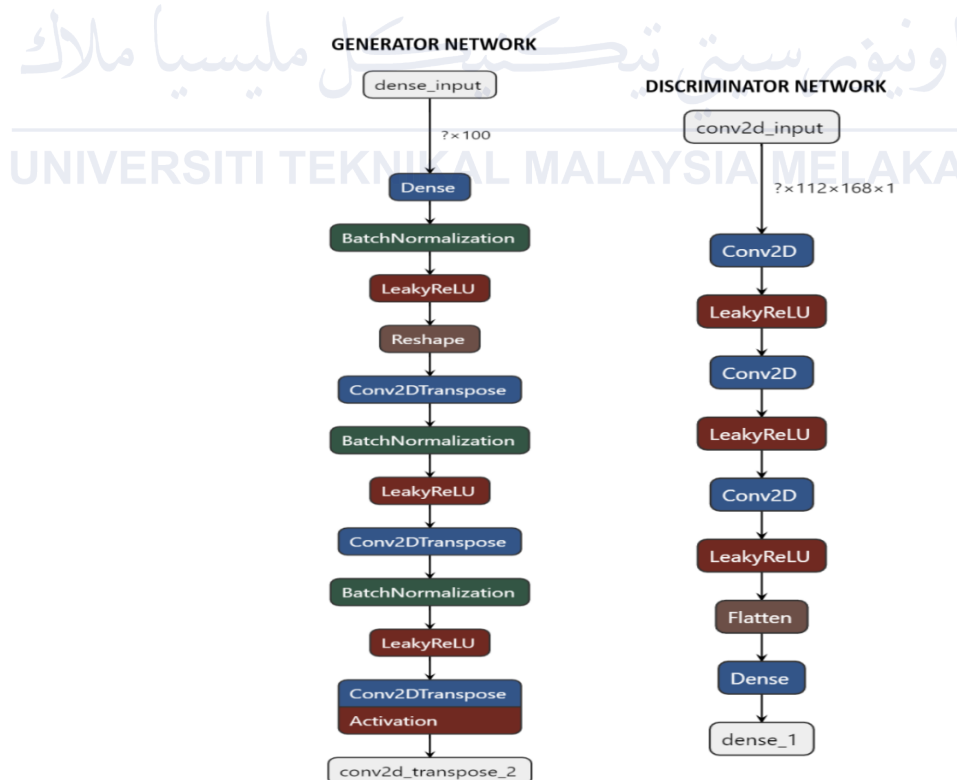


Figure 11: DCGAN Model Architecture

Linking the chosen algorithm to problem-solving, this section provides a high-level overview. It illustrates how DCGAN adeptly addresses the project's key challenges without exploring too much into the technical complexities. The emphasis is on DCGAN ability to overcome data scarcity by generating synthetic images and at the same time solving privacy and ethical concerns.

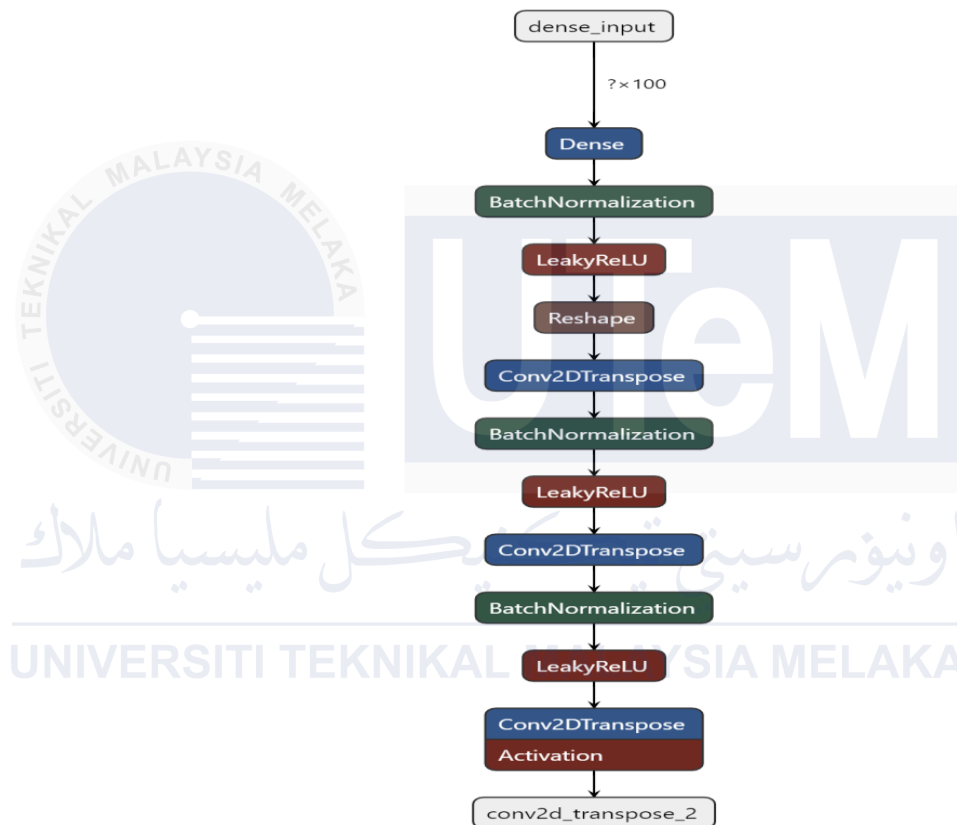


Figure 12: Generator Network of DCGAN

Figure 11 shows the architecture for the DCGAN generator network. The generator will learn to generate synthetic lung CT scan images by analyzing the real data features. The integration of DCGAN with the user interface enhances the overall user experience. The synthesized image can contribute to diverse and realistic visualization, capturing more engaging interaction. Additionally, the potential for integrating DCGAN to provide personalized feedback further strengthens the link between the algorithm design and the user interface, aligning the technical aspects of the project with user-centered goals.

All in all, this section brought forth the comprehensive nature of the solution offered by DCGAN. It addresses the identified problems effectively, balancing technical complexity precisely to ensure a thorough understanding of its relevance in the broader context of the project.

4.7 Conclusion

To conclude, this chapter serves as foundation, which outlines the proposed system and its component, The user interface section presented visually appealing and user-friendly interfaces, emphasizing preciseness, accessibility, and smooth interaction. The inclusion of mock-ups and wireframes illustrated careful consideration of design principles, ensuring good user experience. The incorporation of DCGAN proposed a strategic approach to address challenges defined in Chapter 1. The chosen algorithm was explained at a high level, linking it explicitly to the identified problems and the objectives of this project. As the project progress into subsequent chapters, the defined design in this chapter lays the groundwork for implementation, testing and analysis, and the ultimate realization of the proposed solution.

CHAPTER 5: IMPLEMENTATION

5.1 Introduction

The implementation chapter serves as gate that connects conceptualization and practical realization. This chapter will explore into the execution of the proposed system. This chapter delves into the coding, integration of algorithms, and the translation of designs into functional interfaces. Focus will extend to the integration of algorithms, with DCGAN as the central component. Implementation of user interface, data handling procedures, and overall system architectures will be discussed to explore the process of implemented solution. Challenges encountered during implementation is acknowledged before testing methodologies, optimizations applied, and strategies applied to make sure the system runs correctly and efficiently. This chapter is a testament to the practical realization of theoretical design concepts, reflecting dynamic interplay between creativity and technical prowess.

5.2 Coding and Programming Environment

In this section, chosen programming language, frameworks, and libraries that form the backbone of implementation phase will be given careful consideration. Python has been chosen to be the primary programming language for its unparalleled versatility and readability. The wide choices of libraries aligns with the diverse needs of the project, spanning from algorithm implementation to graphical user interface development. Figure 12 shows the python logo, the programming language used in the project.



Figure 13: Python Logo

Tensorflow, a deep learning framework, fits the role of implementing DCGAN within the project. With its capabilities, particularly in deep learning applications, Tensorflow is chosen to be the main framework in implementing the synthetic image generation task. As a result, optimal foundation for efficient model training and evaluation are established. To develop the GUI of this project, Tkinter is selected as the framework. The simplicity, cross-platform compatibility, and tight integration with Python make Tkinter an easy pick for the GUI development. Tkinter provides the project with a user-friendly interface, enhancing the overall user experience. Figure 13 shows the Tensorflow and Tkinter logo, the deep learning framework and the GUI framework used in the project.



Figure 14: Tensorflow Logo



Figure 15: Tkinter Logo

After that, the project's structure is designed to fit the modular design. Functionalities are divided into distinct modules. This modular approach not only facilitates code organization but also eases collaboration and paves way for future enhancements. Within the project's file structure, hierarchical organization is implemented, which includes modules, datasets, and evaluation metrics. This structure approach will help code navigation, contributing to a well-organized codebase. Strict naming convention is implemented consistently throughout the project, making sure the modules, variables, and functions are equipped with descriptive names. This approach enhances code readability, promoting a standardized coding environment.

Chosen programming languages, frameworks, and libraries, along with project structure and naming conventions, synergize to create a coding environment. This environment is designed to meet the requirements of the project, providing a solid base for a successful implementation phase.

5.3 DCGAN Implementation and Training

To construct and train the Deep Convolutional Generative Adversarial Network (DCGAN), computational capabilities and versatility of Tensorflow framework is utilized. Tensorflow's integration with Python, efficient numerical computation capabilities, and automatic differentiation features made it an ideal choice for this model architecture.

The Generator Network takes a random noise vector as input and employs a series of upsampling layers to generate synthetic images. Input layer which contains 2,842,256 neurons to accommodate the initial noise vector. The network then progresses through a reshape layer that transforms the input into a 3D tensor with dimension (28, 42, 256). Next, three subsequent convolutional transpose layers, each uses batch normalization and LeakyReLU activation function, gradually upsample the feature maps to create final generated image. The final layer utilizes hyperbolic tangent (tanh) activation function to ensure pixel values fall within appropriate range. Figure 14 shows the code snippet which defines the generator network.

Generator Model

```

1 def generator_model():
2     model = tf.keras.Sequential()
3     model.add(layers.Dense(28*42*256, use_bias=False, input_shape=(100,)))
4     model.add(layers.BatchNormalization())
5     model.add(layers.LeakyReLU())
6
7     model.add(layers.Reshape((28,42,256)))
8     assert model.output_shape == (None, 28, 42, 256) #None = Batch Size
9
10    model.add(layers.Conv2DTranspose(128, kernel_size=(5, 5), strides=(1, 1), padding='same', use_bias=False))
11    assert model.output_shape == (None, 28,42,128)
12    model.add(layers.BatchNormalization())
13    model.add(layers.LeakyReLU())
14
15
16    model.add(layers.Conv2DTranspose(64, kernel_size=(5, 5), strides=(2, 2), padding='same', use_bias=False))
17    assert model.output_shape == (None, 56, 84, 64)
18    model.add(layers.BatchNormalization())
19    model.add(layers.LeakyReLU())
20
21    model.add(layers.Conv2DTranspose(1, kernel_size=(5, 5), strides=(2, 2), padding='same', use_bias=False,
22                                   activation='tanh'))
23    assert model.output_shape == (None, 112, 168, 1)
24
25    return model

```

Figure 16: Generator Network Definition

To evaluate the generated images generated by the Generator Network, Discriminator Network serves as evaluator, distinguishing between real and generated images. Starting with a convolutional layer with 64 filters as the input layer, the layer will receive either real or generated images. Additional convolutional layers with increasing filter sizes and LeakyReLU activation extract meaningful features from the input images. Flatten layer transform the feature maps into a one-dimensional vector, which is then processed by a dense layer with a single neuron and sigmoid activation. The network will produce a binary classification output which indicates whether the input is real or fake. The definition of the discriminator network used in the project can be seen in Figure 17.

```

1 def discriminator_model():
2     model = tf.keras.Sequential()
3     model.add(layers.Conv2D(64, kernel_size=(5,5), strides=(2,2), padding='same', input_shape=[112,168,1]))
4
5     model.add(layers.LeakyReLU())
6
7     model.add(layers.Conv2D(128, kernel_size=(5,5), strides=(2,2), padding='same'))
8     model.add(layers.LeakyReLU())
9
10    model.add(layers.Conv2D(256, kernel_size=(5,5), strides=(2,2), padding='same'))
11    model.add(layers.LeakyReLU())
12
13    model.add(layers.Flatten())
14    model.add(layers.Dense(1))
15
16    return model

```

Figure 17: Discriminator Network Definition

In terms of implementation details, Tensorflow is the library and frameworks chosen for DCGAN model development and training. The vanilla DCGAN architecture is employed for this project due to computational resource limitations. This baseline architecture, while computationally efficient, provide a foundation for image generation tasks. The specified architecture and components, along with the deep learning library, defines the implementation strategy, ensuring a balance between computational efficiency and the ability to generate realistic synthetic images.

Before passing the input images into the DCGAN model, the real images need to be loaded into Jupyter Notebook and pre-processed. The provided Python snippet utilize relevant libraries and methodologies, demonstrating a clear pipeline to ensure the input data aligns with the requirements of the adversarial training process. Figure 18 shows the code used to load and pre-process the real image dataset.

```

1 #Image path
2 folder = '/Users/End User/Downloads/PSM/Picture/Train/MALIGNANT'
3
4 pic_file = [f for f in os.listdir(folder) if os.path.isfile(os.path.join(folder, f))]
5 print("Working with {0} images".format(len(pic_file)))
6
7 images = []
8 for pf in pic_file:
9     img = load_img(folder+"/"+ pf, target_size = (112,168)) #This command load the image with a target size of 112*168 pixel
10    img1 = img.convert('L') # This command convert the images in pic_file into grayscale
11    img1 = np.expand_dims(img1, axis=-1) # This command expand the dimension of the image by 1 to create a 3D array with a
12    images.append(img1)

```

Figure 18: Real Image Loading and Pre-processing

The data loading process begins with the utilization of ‘os’ and ‘PIL’ libraries, where os facilitates directory traversal, and PIL is used to load the images. Real images are sourced from the specified directory (‘/Users/End User/Downloads/PSM/Picture/Train/MALIGNANT’). Each image in the dataset is resized to a standardized dimension of (112, 168) pixels using the ‘load_img’ function from the PIL library. In addition to that, images are converted to grayscale through the ‘convert(‘L’)’ command. The images are then expanded along the last axis, accomplish using ‘np.expand_dims’, which is crucial to ensure compatibility with the DCGAN architecture, which requires input data in a specific format.

After data loading process is completed, transformation and augmentation steps are integrated in the data preparation strategy. Normalization of images were employed through the formula $(\text{imgs} - 127.5)/127.5$. This is a critical preprocessing step that centers the pixel value around zero as shown in Figure 19, to make sure stable training process is achieved by both generator and discriminator networks.

```

14 #Converting the images list to a NumPy array before casting each into a 'Float32' data type
15 imgs = np.asarray(images).astype('float32')
16 #Pixel normalization
17 train_images = (imgs - 127.5)/127.5

```

Figure 19: Pixel Normalization Technique

The training process for the DCGAN starts with carefully designed training loop and well-defined hyperparameter settings. The training loop, enclosed within a Tensorflow function annotated with '@tf.function'. Starting with generation of random noise vectors, the loop utilizes separate gradient tape contexts for the generator and discriminator, facilitating efficient gradient computation during a single forward pass. Real and generated images are then evaluated by the discriminator, leading to the calculation of generator and discriminator losses based on binary cross-entropy. Subsequently, the gradients are computed, and model parameters are updated using the Adam optimizer. The entire training process is coordinated by the 'train' function, iterating over a specified number of epochs as shown in Figure 20.

```

1 def train(dataset, epochs):
2     for epoch in range(epochs):
3         start = time.time()
4
5         for image_batch in dataset:
6             train_step(image_batch)
7
8         #Produce images for the GIF while training
9         if (epoch + 1) % 200 == 0:
10            display.clear_output(wait=True)
11            generate_and_save_images(generator,
12                                   epoch + 1,
13                                   seed)
14
15        #Save model every 200 epochs
16        if (epoch + 1) % 200 == 0:
17            checkpoint.save(file_prefix = checkpoint_prefix)
18
19        print ('Time for epoch {} is {}'.format(epoch+1, time.time()-start))
20
21        #generate image after final epoch
22        display.clear_output(wait=True)
23        generate_and_save_images(generator,
24                                epochs,
25                                seed)

```

Figure 20: Function that Defines Training Step of DCGAN

During the iteration based on number of epochs, a checkpoint of the model will be made at every 200 epochs for back tracking purpose. At the same time, the sample image generated by the generator will be saved in the working directory. Figure 21 and Figure 22 shows the sample image generated by the DCGAN generator network.

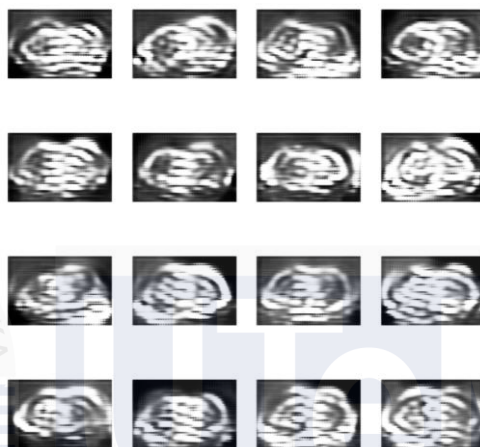


Figure 21: Sample Image Generated at Epoch 200

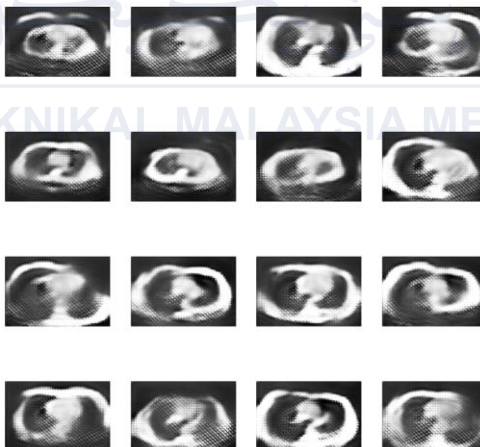


Figure 22: Sample Image Generated at Epoch 400

Hyperparameter settings play an important role in shaping the training dynamis. The binary cross-entropy loss function is employed with ‘**from_logits=True**’, indicating the direct use of model output logits. The discriminator loss utilizes binary-cross entropy losses to distinguish real and generated images, while generator loss is computed using binary cross-entropy with

the goal of generating statistically similar to real world data images. Both the generator and discriminator use the Adam optimizer with learning rate ' $1e-4$ '. The training process is configured to run for 1000 epochs, save model, generate 16 sample images before continuing the training process until 2000 epochs and 3000 epochs.

Evaluation metrics quantify performance of any deep learning model after training is finished. Two key metrics employed to evaluate the DCGAN performance are the Fréchet Inception Distance (FID) and the Inception Score (IS).

FID is a measure of similarity between real and generated images. It calculates the Fréchet distance, a statistical measure, between the feature representation of the images in the generated and real datasets. A lower FID generally indicates a closer match between the distributions of real and generated images. This shows improved image generation fidelity.

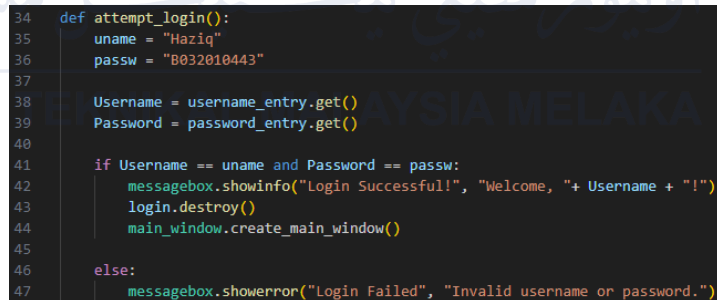
In contrast, Inception Score (IS) assesses the quality and diversity of the generated images. It utilizes the InceptionV3 model's softmax output to evaluate the informativeness and distinctiveness of generated images. A higher IS signifies better image quality and diversity. These metrics collectively provide valuable insights into the performance of the DCGAN, offering quantitative measures to gauge the model's ability to generate realistic and diverse synthetic images. Monitoring these metrics over epochs assists in observing the convergence and effectiveness of the training process, guiding potential adjustments to hyperparameter or architectural components for enhanced image synthesis performance.

5.4 User Interface Implementation

In the user interface implementation, two windows are created using Tkinter for the desktop application. The first window is the login window, where user enter their credentials, the second window is the main interface, which provides various functionalities for the CT scan generator.

5.4.1 Login Window

The login window is designed using Tkinter widgets. It includes a welcome label, username and password entry fields, and a login button. The login credentials are hardcoded for simplicity, with a predefined username (“Haziq”) and password (“B032010443”). When the user clicks the login button, the ‘**attempt_login**’ function is triggered. If the entered credentials match the hardcoded values, a success message is displayed, and the login window is destroyed, transitioning to the main window. Otherwise, an error message is shown. Figure 23 show the error handling of the login function.



```

34 def attempt_login():
35     uname = "Haziq"
36     passw = "B032010443"
37
38     Username = username_entry.get()
39     Password = password_entry.get()
40
41     if Username == uname and Password == passw:
42         messagebox.showinfo("Login Successful!", "Welcome, " + Username + "!")
43         login.destroy()
44         main_window.create_main_window()
45
46     else:
47         messagebox.showerror("Login Failed", "Invalid username or password.")

```

Figure 23: Error Handling for Login Function

Upon successful error handling and function definition, the login window has provided security measure to prevent unidentified personnel from illegal access. Successful login message window can be seen in Figure 24.

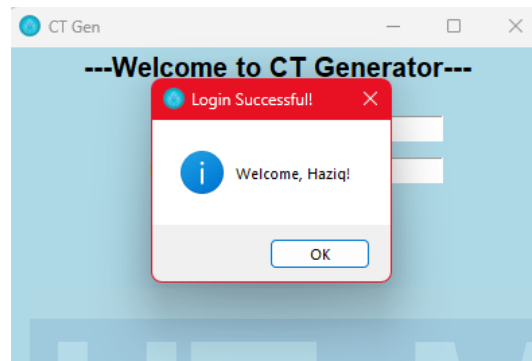


Figure 24: Successful Login Window

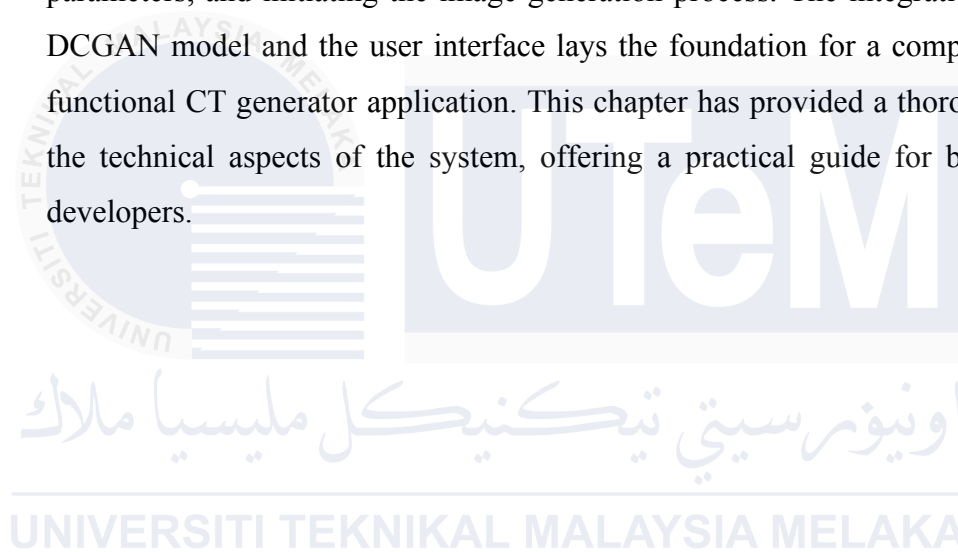
5.4.2 Main Interface Window

The main window offers functionalities for uploading a ZIP file, configuring training parameters (number of epochs), and initiating the training process. It includes buttons for browsing and re-uploading training images, checkboxes for selecting the number of epochs, and checkboxes for specifying the quantity of images to be generated. The **'train_gan_function'** function is called when the "Start Training" button is clicked, initiating the training process. Additionally, the "Generate Images" button triggers the **'creating_gan_progress'** function, which shows a progress bar while generating images.

The code also includes functionality for handling file uploads, displaying a progress bar during image generation. It also handle various checkboxes for configuring the training process. Overall, the implementation aims to provide a user-friendly interface for interacting with the CT generator application.

5.5 Summary

To summarize, the implementation chapter has detailed the practical realization of the proposed CT generator system. The DCGAN architecture, consisting of a generator and discriminator network, has been successfully implemented using Tensorflow and Python. The training process was described, which includes key components such as the training loop and hyperparameter settings. In addition to that, the user interface was implemented using Tkinter, offering a user-friendly interaction for uploading files, configuring training parameters, and initiating the image generation process. The integration of both the DCGAN model and the user interface lays the foundation for a comprehensive and functional CT generator application. This chapter has provided a thorough details of the technical aspects of the system, offering a practical guide for both users and developers.



CHAPTER 6: ANALYSIS

6.1 Introduction

Testing and analysis serve as a critical phase in the development process, which aims to assess and inspect the performance of the implemented DCGAN and the Tkinter desktop application. This chapter investigates the evaluation metrics employed, the robustness of the DCGAN model under various conditions, and the subsequent analysis of the generated CT scans. Through systematic testing and analysis, this chapter seeks to provide valuable insights into the reliability, adaptability, and effectiveness of the developed system. The results obtained will explain potential refinements and optimizations, contributing to the goal of delivering a robust and reliable solution for the synthetic CT scan generation.

6.2 Quantitative Assessment of the Generated Images

6.2.1 Factors affecting IS and FID

This analysis investigates the influence of three critical factors on the effectiveness of DCGANs in generating realistic lung CT scans. One of the factor that affects the DCGAN image generation task is the training parameters. The impact of varying the number of training epochs on the quality and statistical similarity of the generated images. Epochs represent complete passes through the training data, and determining the optimal number is crucial for achieving a balance between model convergence and overfitting.

Another factor that affects the DCGAN performance is the image generation method within the DCGAN framework. Independent generation is one of the methods used to generate images where the generator network creates entirely new images for each desired number of outputs. Another method used in the DCGAN to generate images is progressive generation. The generator builds upon the previous

batch of generated images. This method aims to improve realism and continuity but will limit the variety of outputs.

Finally, the number of images generated will be investigated to see the impact of generating a variety of synthetic lung CT scans. Four cases of image generation will be tested, which is 1) Generating 140 images (25% of number of training data), 2) Generating 280 images (50% of training data), 3) Generating 420 images (75% of number of training data), and 4) Generating 561 images (100% of number of training data). By analyzing the effect of output size on generated image quality and realism, feasibility and efficiency of generating synthetic data using limited resources will be assessed.

Evaluating the interplay between these factors, the optimal training parameters, image generation method and output data size when producing synthetic lung CT scans will be established. Ultimately, this will pave the way for the development of AI-powered model capable of enhancing lung cancer diagnosis, ultimately translating into improved patient care and outcomes.

6.2.2 Test Results

The following section dissects the impact of training epochs, image generation methods, and output data size on the quality of synthetic lung CT scans generated by the DCGAN. Key relationship between these factors and the evaluation metrics will be discussed, ultimately aiming to identify optimal settings for generating high fidelity synthetic data for enhanced lung cancer diagnosis and research.

Impact of Training Epochs

Figure 25 shows the line graph of inception score over different epoch. Method 1 of image generation will be taken as example.

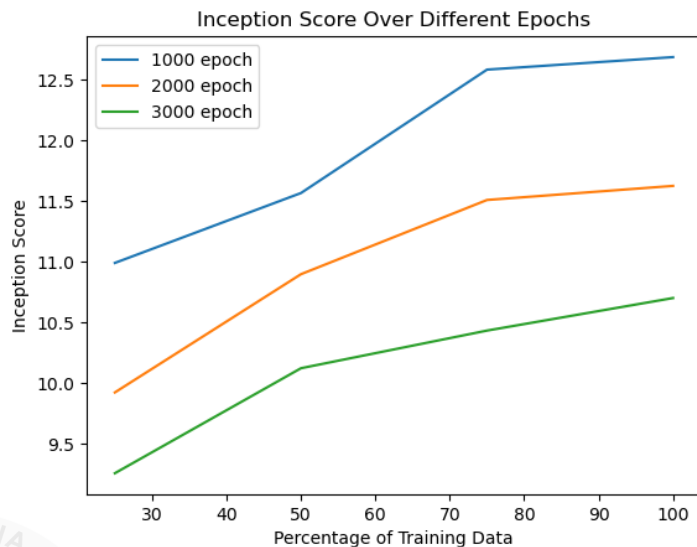


Figure 25: Inception Score over Different Epochs (Method 1)

As shown in Figure 25, Inception Scores (IS) for the DCGAN model were calculated at different epochs (1000, 2000, and 3000) and for varying output size. Notably, the scores decrease with the number of training epochs, suggesting that the image quality and diversity decrease over the course of training. This defies the theory of IS which states that image quality and diversity gets higher with higher IS results. However, the IS results for different proportions of generated images demonstrate that the model can maintain quality and diversity. Figure 26 will show the Fréchet Inception Distance (FID) over different epochs of Method 1.

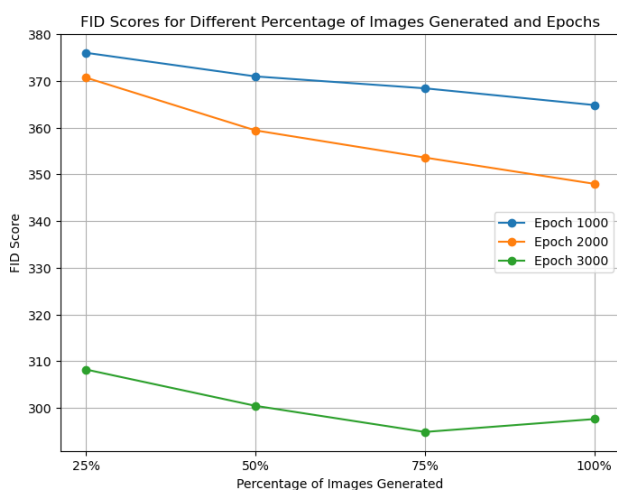


Figure 26: FID over Different Epochs (Method 1)

Based on the output provided in Figure 26, FID results across different epochs (1000, 2000, and 3000), the decreasing trend in FID scores suggests an improvement in the model's ability to generate images that align with the distribution of real CT scans. Lower FID scores indicate reduced divergence between real and generated image distributions. This reflects the result of an enhanced fidelity of the synthetic lung CT scan generated by the DCGAN generator.

Image Generation Method Influences

Another factor that is taken into consideration while analyzing the DCGAN using IS and FID is how the image generation method used to generate the synthetic images have effect on results produced by the two evaluation metrics. The aim of this comparison is to see the limits of images that can be generated using the proposed DCGAN model. Method 1 of the image generation method is independent generation that generate images where the generator network creates entirely new images for each desired number of outputs while Method 2 is progressive generation which builds upon the previous batch of generated images.

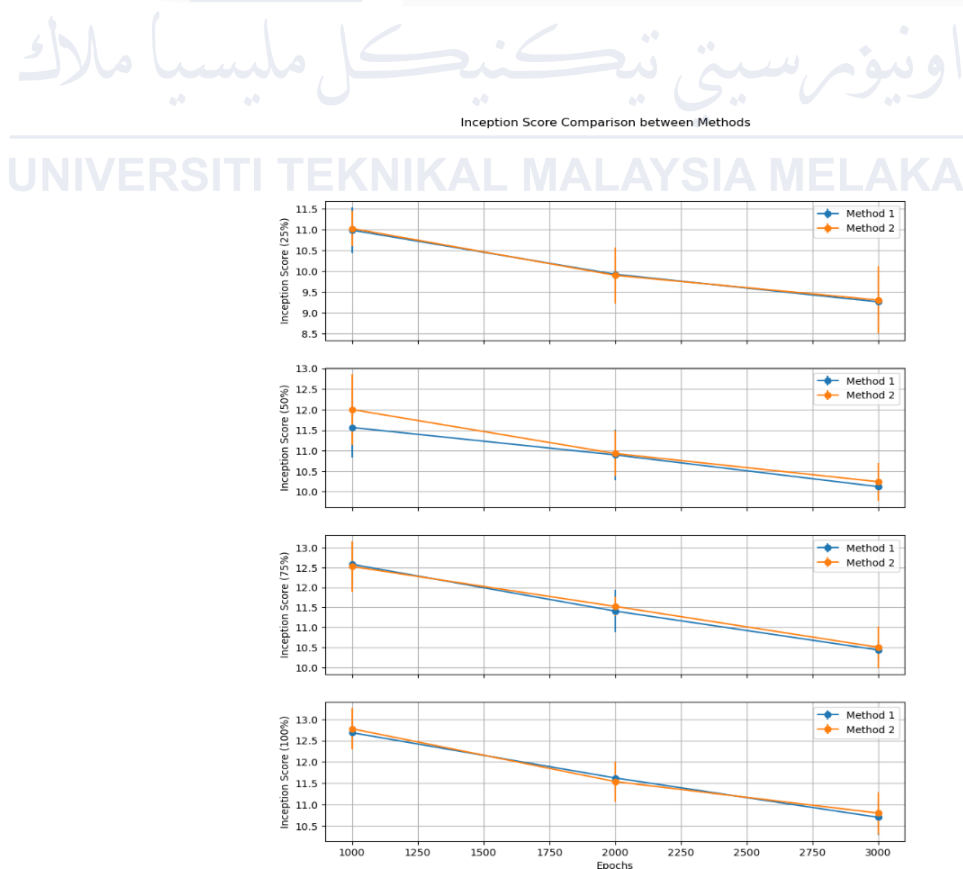


Figure 27: Inception Score Comparison between Method of Image Generation

Based on Figure 27, the IS values obtained from the evaluation of the DCGAN using two different image generation methods provide insights into the model's performance. Both Method 1 and Method 2 demonstrates progressive deterioration in the generated images quality and diversity across epochs and dataset percentages. Even though Method 2 generally producing slightly higher IS scores compared to Method 1, the decreasing trend in IS values over epochs for both method indicates a diminishment in the model's ability to produce realistic images, demonstrating the ineffectiveness of the proposed DCGAN architecture in capturing intricate features and patterns within the real CT scan dataset.

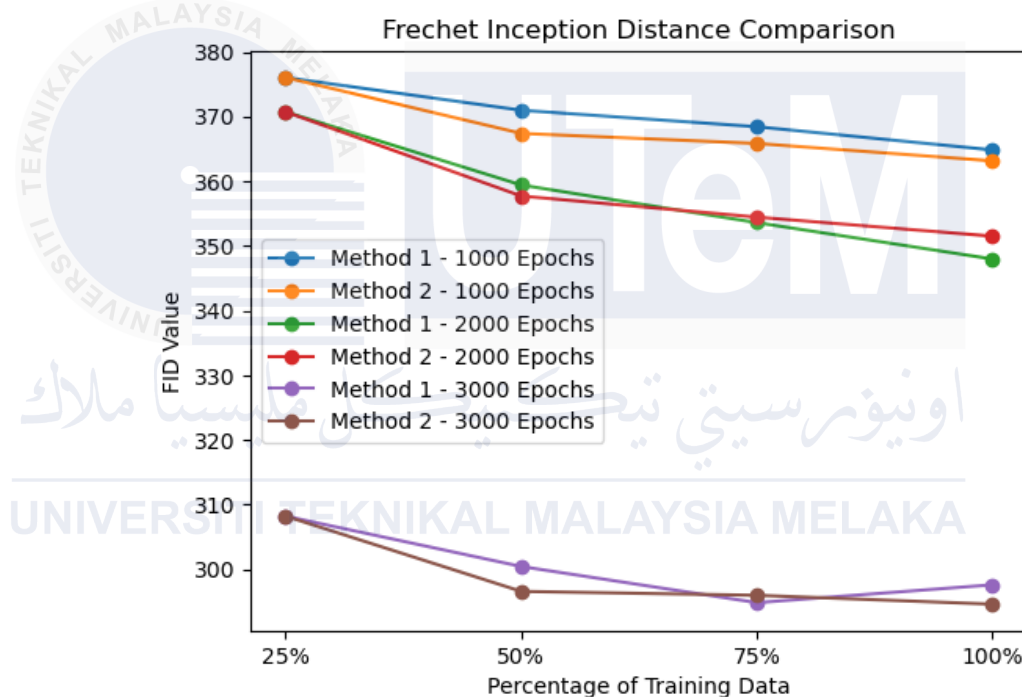


Figure 28: FID comparison Between Method of Image Generation

Figure 28 shows the comparison of FID between the two methods of image generation. The results reveal that, across various epochs and percentages of training data, Method 2 consistently exhibits lower FID scores compared to Method 1. Lower FID scores indicate better similarity between the generated and real images. This suggests that the progressive generation approach employed in Method 2, where the generator refines its output incrementally, leads to more realistic and visually coherent synthetic images. The decreasing trend in FID scores across epochs for both methods indicates an improvement in image quality as the DCGAN model undergoes

further training. These findings emphasize the effectiveness of Method 2 in producing synthetic images that closely resemble the characteristics of the real dataset, aligning with the goal of addressing data scarcity through high-quality data augmentation.

Impact of Number of Images Generated

The impact of the generated images on evaluation metrics is a critical aspect of assessing the performance and quality of the DCGAN. IS and FID used as the evaluation metrics for the proposed model serve as quantitative measures to gauge the realism, diversity, and quality of the synthetic images produced by the model. Understanding how different factors, such as the impact of number images generated on the evaluation metrics output is essential. Figure 29 shows the IS comparison by percentage of images generated.

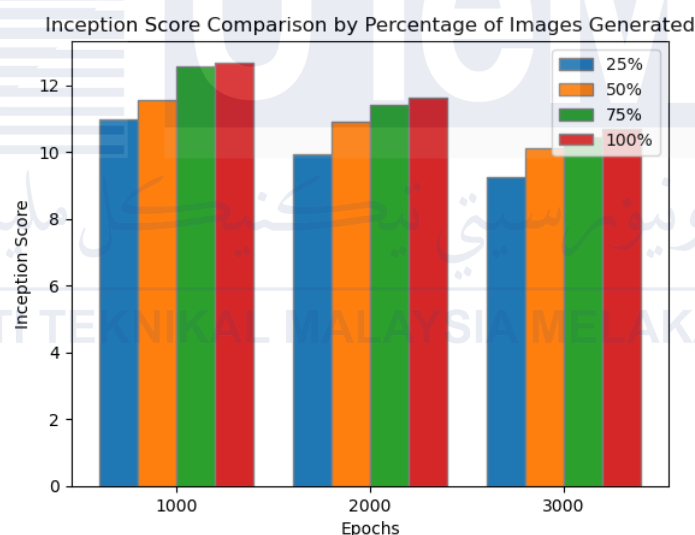


Figure 29: IS of Percentage of Images Generated over Epochs

The Inception Score (IS) results reveal intriguing insights into the quality and diversity of synthetic images generated by the DCGAN at various epochs and percentages of training data. Analyzing the scores across different epochs, it is evident that the IS tends to exhibit a subtle relationship with the proportion of generated images. In the case of 1000-epoch model, the IS tends to increase with a higher percentage of generated images, indicating that the model refines its learning and is improving the quality and diversity of the generated images. However, as the training progresses to 2000 and 3000 epochs, the IS values show more subtle

variations, suggesting a potential saturation in the model's ability to generate substantially more diverse images beyond a certain point. This result emphasizes the need for a balanced approach in optimizing the DCGAN for both training duration and data augmentation effectiveness.

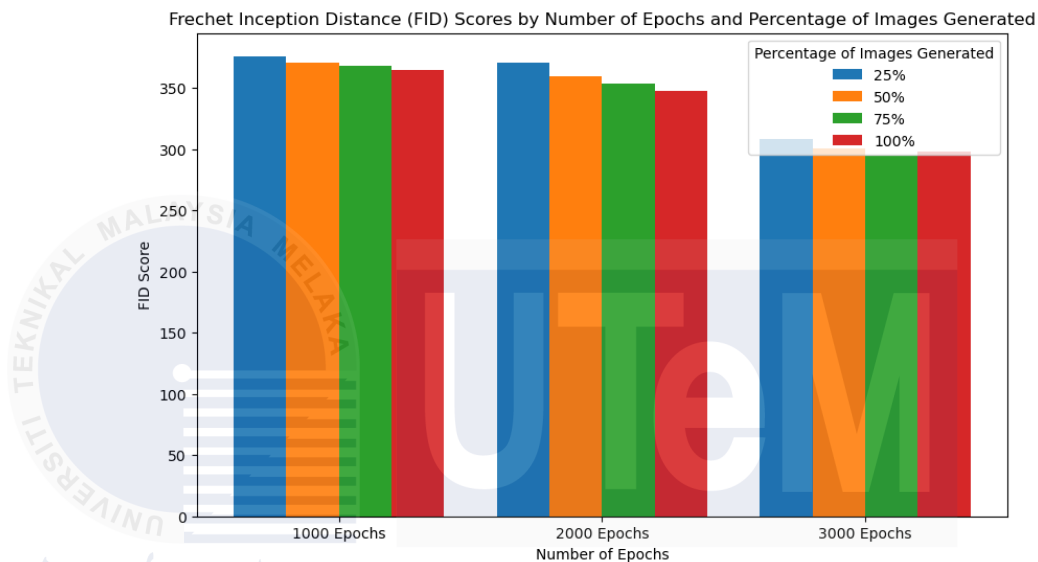


Figure 30: FID Scores by Percentage of Images Generated

Figure 30 shows the FID scores by percentage of images generated for every epoch. A lower FID score indicates better similarity between the distribution of real and generated images. In the presented results, as the percentage of generated images increases, there is a consistent trend of decreasing FID scores across different epochs. This suggests that the DCGAN model performs well in generating synthetic images that closely resemble the distribution of real images. Furthermore, the FID scores tend to decrease as the number of training epochs increases, indicating an improvement in the model's ability to generate realistic and diverse images over extended training periods. The observed FID trends signify the effectiveness of the DCGAN architecture in addressing the data scarcity issue and augmenting the existing dataset by producing high-quality synthetic lung CT scan.

6.3 Summary of Quantitative Assessment

The evaluation of a Deep Convolutional Generative Adversarial Network (DCGAN) for medical image generation involves a comprehensive analysis of key factors that influence performance metrics, particularly Inception Score (IS) and Fréchet Inception Distance (FID). This examination aims to optimize the DCGAN model's ability to generate realistic and diverse images, addressing the data scarcity issue in medical imaging.

Analyzing the impact of training epochs (1000, 2000, and 3000) on IS and FID scores reveals a nuanced relationship. Generally, FID shows improvement with extended training, indicating the model's enhanced capability to generate images that mimic the properties of real images. However, IS results shows that the model are unable to generate diverse and high-quality synthetic lung CT scan with extended training. The findings agree that FID should be lower when epoch increases as the model are learning the complexities of the images over time, but does not agree that IS should be higher because the model are trying to create synthetic images that is more diverse and have high-quality compared to real images to address the data scarcity issue.

A crucial aspect of DCGAN evaluation is the comparison between two image generation methods – independent generation and progressive generation. Both method of generation yields a decreasing trend for IS which indicates a deterioration in the synthetic image quality and diversity. Even though the FID produced align with the theory and objective of the project, the results of IS produced does not align with the objective of the model which is to create a diverse and high-quality dataset in addition to create statistically similar synthetic image to the real world dataset.

The analysis of IS and FID scores concerning the percentage of images generated (25%, 50%, 75%, and 100%) at each epoch provides valuable insights. Higher percentages often lead to improved scores, indicating enhanced image quality and diversity. However, a point of diminishing returns may be reached, emphasizing the need for a balanced approach to resource utilization and image quality. These findings contribute to optimizing the DCGAN model for medical image augmentation, ultimately addressing the challenges posed by limited medical

imaging datasets. Table 5 and Table 6 provide the summary of Inception Score and Fréchet Inception Distance for the images generated by the proposed DCGAN model.

Table 5 : Summary of Inception Score

Method	Epoch	25% Image	50% Image	75% Image	100% Image
Method 1	1000	10.990	11.565	12.581	12.684
	2000	9.924	10.897	11.408	11.624
	3000	9.259	10.123	10.433	10.701
Method 2	1000	11.030	12.003	12.527	12.776
	2000	9.900	10.931	11.525	11.539
	3000	9.302	10.243	10.500	10.800

Table 6: Summary of FID Scores

Method	Epoch	25% Image	50% Image	75% Image	100% Image
Method 1	1000	376.023	370.968	368.420	364.831
	2000	370.712	359.411	353.594	347.969
	3000	308.220	300.442	294.848	297.609
Method 2	1000	376.023	367.389	365.836	363.141
	2000	370.712	357.709	354.448	351.501
	3000	308.220	296.594	295.990	294.617

In conclusion, this multifaceted analysis offers a comprehensive understanding of how training epochs, image generation methods, and the quantity of generated images impact the performance of DCGAN in medical image generation. The insights gained contribute to refining training strategies and optimizing the model to generate realistic and diverse medical images, thus mitigating data scarcity challenges in medical imaging applications. However, based on the results produced, it cannot be concluded whether method 1 or method 2 is the best for generating synthetic images and whether increasing the number of epoch affect the model performance in generating high quality and diverse synthetic images.

6.4 Tkinter Desktop App Testing and Analysis

The Tkinter Desktop App Testing and Analysis section is a focused examination of the application's functional aspects, separate from the main focus on the performance evaluation of the DCGAN model. While the primary goal of this project is to address data scarcity through DCGAN-generated images, it is equally crucial to ascertain the reliability and effectiveness of the accompanying Tkinter desktop application. This section focuses on the primary functions of the app, aiming to test their correct functionality and user-friendliness. This phase of dedicated functionality testing ensures seamless user interaction with the app, emphasizing its practical utility in enhancing existing datasets. This section's rigorous testing scenarios and methodical evaluation contribute to the overall assessment of the entire project, providing insights on the reliability of the Tkinter app's core features.

6.4.1 Objectives and Testing Methodology

The primary objective of app testing is to ensure the seamless and accurate execution of every element within the Tkinter desktop application. This involves a comprehensive examination of the application's various components to verify their proper functioning. Through manual testing, each element, from user interface components to backend functionalities, will be meticulously explored to confirm their reliability. The focus is on validating that users can interact with the app intuitively, and all features contribute to the intended workflow. By employing a manual testing methodology, the goal is to meticulously navigate through the application, simulating user interactions, and systematically assessing the performance of individual elements. This approach allows for a thorough evaluation of the app's overall functionality, providing valuable insights into its usability and ensuring a positive end-user experience.

6.4.2 Functional Testing Scenarios

In this section, we outline a series of functional testing scenarios designed to rigorously evaluate the core functionalities of the Tkinter desktop application. These scenarios have been designed to assess the application's performance in key areas, ensuring that each component operates smoothly. From login functionalities to the generation of synthetic images using the pre-trained DCGAN model, these scenarios aim to validate the reliability and user-friendliness of the application's core features. The execution of these scenarios is essential to guarantee the robustness of the Tkinter app in facilitating the augmentation of medical imaging datasets.

Scenarios and Test Cases:

1. Login Functionality:

- *Scenario:* Verify that the login function works correctly by entering valid credentials.
- *Expected Outcome:* Successful login, granting access to the application's features.

2. File Upload:

- *Scenario:* Attempt to upload a file that is not a zip file.
- *Expected Outcome:* Appropriate error message or restriction, ensuring only zip files are accepted.

3. Training Initiation:

- *Scenario:* Click the "Train" button and observe the initiation of DCGAN training.
- *Expected Outcome:* Confirmation that the DCGAN training process starts without errors.

4. **Checkbox Selection:**

- *Scenario:* Check the checkboxes for specifying the number of epochs and the number of generated images.
- *Expected Outcome:* Successful selection and validation of the specified epoch and image generation parameters.

5. **Generate Images:**

- *Scenario:* Click the "Generate" button after DCGAN training and parameter selection.
- *Expected Outcome:* Successful generation of images based on the specified parameters, leveraging the pre-trained DCGAN model.

6.4.3 **Results and Findings**

In this section, the outcomes of the functionality testing for the Tkinter Desktop App are presented. The testing focused on core functionalities to ensure the proper execution of key elements within the application. Each scenario targeted a specific feature, evaluating the application's behavior against expected outcomes. The results provide insights into the reliability and correctness of the application's functionality, highlighting any issues or unexpected behaviors encountered during the testing process. The detailed findings for each scenario are outlined below, allowing for a comprehensive assessment of the app's performance in terms of its core functionalities.

1. Login Functionality:

- *Scenario:* Verify that the login function works correctly by entering valid credentials.
- *Expected Outcome:* Successful login, granting access to the application's features.
- *Actual Outcome:* Upon entering the correct credentials, login is successful. Login window is destroyed and transitioned to the main window
- *Pass/Fail:* Pass

2. File Upload:

- *Scenario:* Attempt to upload a file.
- *Expected Outcome:* Image is successfully uploaded and stored in training images directory.
- *Actual Outcome:* Image upload successful, message box appear upon successful upload

- *Pass/Fail:* Pass

3. Training Initiation:

- *Scenario:* Click the "Train" button and observe the initiation of DCGAN training.
- *Expected Outcome:* Confirmation that the DCGAN training process starts without errors.
- *Actual Outcome:* DCGAN training process initiates without error, message box appear after training is finished.
- *Pass/Fail:* Pass

4. **Checkbox Selection:**

- *Scenario:* Check the checkboxes for specifying the number of epochs and the number of generated images.
- *Expected Outcome:* Successful selection and validation of the specified epoch and image generation parameters.
- *Actual Outcome:* Selection is successful, user can change selection at will before initiating training process of DCGAN.
- *Pass/Fail:* Pass

5. **Generate Images:**

- *Scenario:* Click the "Generate" button after DCGAN training and parameter selection.
- *Expected Outcome:* Successful generation of images based on the specified parameters, leveraging the pre-trained DCGAN model.
- *Actual Outcome:* Generation of images successful. Progress bar appear while generating images. Image is zipped and stored in output file directory.
- *Pass/Fail:* Pass

The functionality testing for the Tkinter Desktop App revealed positive outcomes across all tested scenarios. Each core functionality, including login, file upload, training initiation, checkbox selection, and image generation, demonstrated successful execution without encountering any issues. The application responded as expected to user inputs, ensuring a seamless user experience. The absence of identified issues during testing indicates the robustness and reliability of the Tkinter Desktop App's core features. The app successfully fulfills its intended functionalities, providing users with a user-friendly interface for interacting with the DCGAN model.

6.4.4 Improvements and Recommendations

To enhance the flexibility and user options, a valuable improvement for the app would be to incorporate a feature allowing users to choose between uploading their own dataset or utilizing the proposed DCGAN model training data. This enhancement empowers users with the freedom to tailor the DCGAN training process to their specific needs, accommodating diverse datasets relevant to their medical imaging requirements. Providing users with the ability to seamlessly integrate their own data ensures the app's adaptability and relevance to a broader user base.

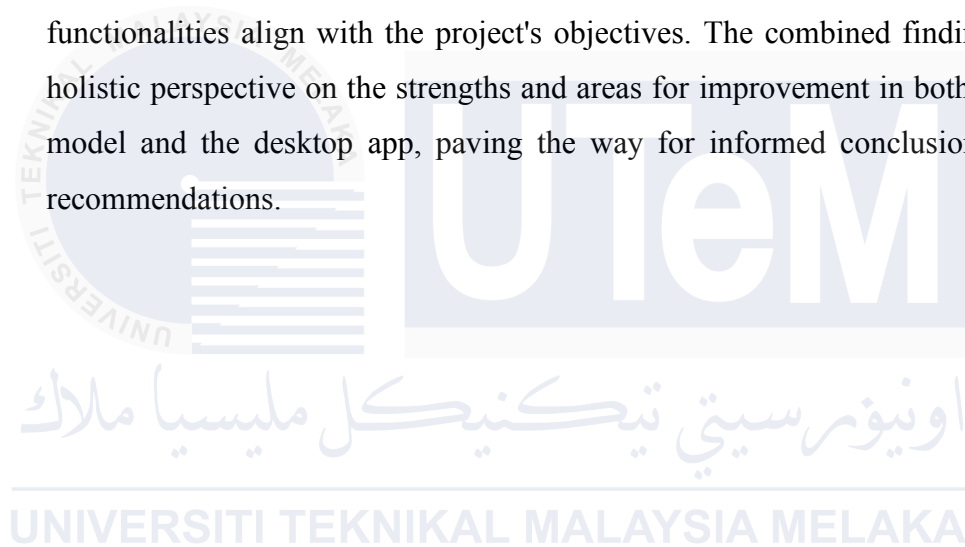
Considering the evolving landscape of technological advancements and accessibility, it is recommended to transition the current Tkinter Desktop App to a web-based application. A web app offers several advantages, including easy accessibility from various devices, improved collaboration, and a wider reach within the medical community. By adopting a web-based approach, the app can transcend platform limitations, allowing medical professionals and researchers to access and utilize the DCGAN model effortlessly. This transition aligns with the contemporary trend of web-based applications, promoting accessibility, collaboration, and scalability in the medical domain.

6.5 Summary

This chapter encompasses a comprehensive analysis of the developed DCGAN model and the Tkinter Desktop App. The DCGAN analysis focused on evaluating the model's performance through key metrics such as Inception Score (IS) and Fréchet Inception Distance (FID). The examination delved into the impact of training epochs, image generation methods, and the number of images generated on these metrics. The findings provided insights into the model's robustness, efficiency, and ability to generate high-quality synthetic medical images.

Simultaneously, the desktop app underwent functionality testing to ensure the correct execution of core features, including login, file upload, DCGAN training initiation, checkbox functionality, and image generation. Each functionality was rigorously tested, and the outcomes demonstrated the successful implementation of these features without encountering any issues.

In summary, this chapter consolidates the outcomes of both DCGAN and desktop app analyses. The DCGAN analysis sheds light on the model's performance under various conditions, contributing to a comprehensive understanding of its capabilities. Meanwhile, the desktop app testing ensures that the user interface and functionalities align with the project's objectives. The combined findings provide a holistic perspective on the strengths and areas for improvement in both the DCGAN model and the desktop app, paving the way for informed conclusions and future recommendations.



CHAPTER 7: CONCLUSION

7.1 Introduction

As this chapter concludes, it encapsulates a comprehensive analysis of the entire project, synthesizing the outcomes of the DCGAN model development and the evaluation of the Tkinter Desktop App. The discussion encompasses a summarization of the key findings, emphasizing the strengths and weaknesses observed during the project's execution. Additionally, insights into potential future improvements will be presented, offering avenues for enhancing both the DCGAN model and the desktop app. The chapter will also acknowledge the contributions made throughout the project, highlighting the novel aspects and advancements achieved. Ultimately, a concise project summary will be crafted, providing a conclusive overview of the undertaken work and its implications.

7.2 Project Summarization

In summary, this project embarked on addressing the critical issue of data scarcity in medical imaging by implementing a Generative Adversarial Network (GAN), specifically a Deep Convolutional GAN (DCGAN), for the generation of synthetic Computed Tomography (CT) scans. The developed DCGAN underwent a thorough analysis, evaluating its performance through metrics such as Inception Score (IS) and Fréchet Inception Distance (FID). Subsequently, the project extended its focus to the development of a Tkinter Desktop App, serving as a user-friendly interface for leveraging the trained DCGAN model to generate synthetic CT scans. The app underwent functionality testing, ensuring the seamless operation of its core features.

Throughout the project, strengths and weaknesses were identified, providing valuable insights for future enhancements. The DCGAN analysis revealed its capability to generate realistic CT scans, but fails to prove that the images generated are diverse and in high-quality. The desktop app's functionality testing demonstrated successful execution of key features, showcasing its user-friendly design. Future improvements could include refining the DCGAN training process for enhanced diversity in generated images and expanding the desktop app's capabilities. The contributions of this project lie in the development of a functional DCGAN model and an accessible desktop app, contributing to the broader exploration of solutions for data augmentation in medical imaging.

In conclusion, this project marks a significant step toward alleviating data scarcity challenges in medical imaging, providing a foundation for further research and development in the field. The successful implementation of the DCGAN model and the functional desktop app sets the stage for continued advancements in generating synthetic medical data, ultimately contributing to improved machine learning models and medical research.

7.3 Project Strengths and Weakness

This project boasts several strengths that underscore its significance in addressing data scarcity issues in medical imaging. The implementation of a Deep Convolutional Generative Adversarial Network (DCGAN) proves to be an effective means of generating synthetic Computed Tomography (CT) scans. Complemented by a user-friendly Tkinter Desktop App, the project offers a comprehensive solution for researchers and practitioners. However, like any undertaking, there are areas where improvements can be made to enhance the overall impact and effectiveness of the solution.

One of the project's notable strengths lies in the successful implementation of the DCGAN model. Demonstrating effectiveness in generating synthetic CT scans, this model contributes significantly to overcoming data scarcity challenges in the realm of medical imaging. The robust Tkinter Desktop App provides users with an intuitive interface, facilitating easy interaction with the trained DCGAN model. Thorough analysis, incorporating metrics such as Inception Score (IS) and Fréchet

Inception Distance (FID), adds depth to the project's contribution, ensuring a solid foundation for assessing model performance. Ultimately, the project makes a valuable contribution to the broader field of medical imaging research.

Despite its strengths, the project does have areas that warrant attention. The DCGAN model, while effective, may exhibit limitations in generating diverse and high quality synthetic CT scans. To enhance the variety and realism of generated images, future efforts could focus on refining the training process. Experimenting with different hyperparameter might improve the model's performance to increase the diversity of the generated images. Furthermore, monitoring the training process with validation function will help researchers to capture signs of instability or mode collapse and early stopping can be considered. Visual inspection of the generated samples by certified medical experts can provide insights into the specific shortcomings of the model. The desktop app, while robust in its core functionalities, has a scope limited to facilitating image generation. Potential enhancements could explore additional features, user customization options, and improved visualization tools. Sensitivity to training parameters may impact the model's performance, suggesting a need for fine-tuning and experimentation. Additionally, considering a transition to a web-based application could broaden accessibility and scalability, especially within the medical community.

In summary, the strengths and weaknesses of this project collectively contribute to its ongoing evolution and potential impact. While the DCGAN model and desktop app represent significant advancements, addressing identified weaknesses in subsequent iterations will ensure a more comprehensive and refined solution. The continuous improvement of this project aligns with the dynamic nature of medical imaging research, promising further advancements and contributions to the field.

7.4 Project Contribution

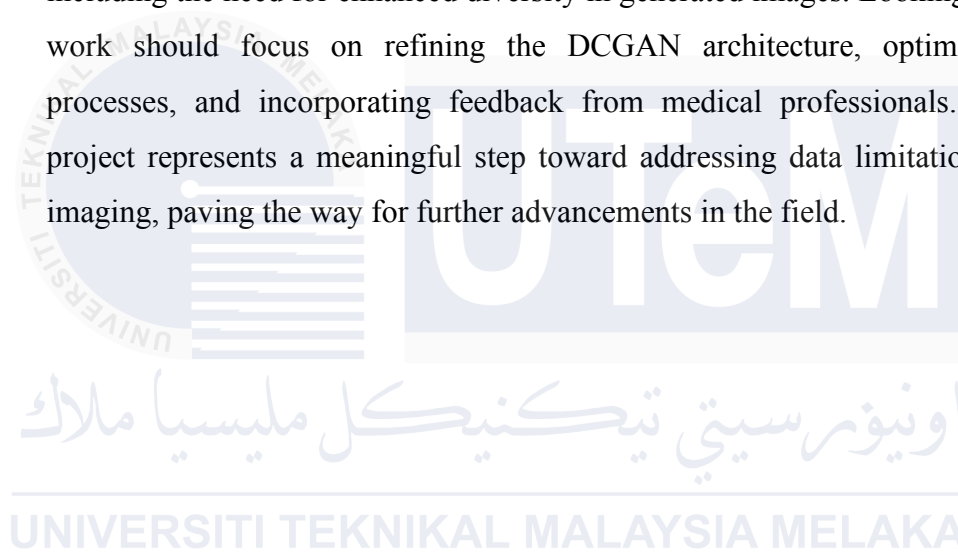
This project makes a substantial contribution to the domain of medical imaging by tackling the critical issue of data scarcity. The implementation of a Deep Convolutional Generative Adversarial Network (DCGAN) serves as a novel and effective approach to generating synthetic Computed Tomography (CT) scans. The project provides a user-friendly Tkinter Desktop App, empowering researchers and practitioners to seamlessly interact with and utilize the trained DCGAN model. The thorough testing and analysis, incorporating metrics such as Inception Score (IS) and Fréchet Inception Distance (FID), offers a robust evaluation framework for assessing the quality of generated images. By providing a practical solution for augmenting existing datasets, this project contributes to advancing research in medical image analysis and addresses the data limitations that often hinder progress in the field.

7.5 Future Work

While this project lays a solid foundation for addressing data scarcity in medical imaging through DCGAN-generated synthetic scans, there is room for future work to enhance its impact. First, exploring more sophisticated variations of GAN architectures or incorporating additional modalities could potentially improve the diversity and quality of synthetic images. Moreover, refining the DCGAN training process by optimizing hyperparameters and leveraging advanced training techniques may further enhance the model's performance. Additionally, extending the application to accommodate various medical imaging datasets and incorporating domain adaptation methods could broaden the scope of its applicability. Lastly, integrating feedback from medical experts and practitioners to fine-tune the generated images based on clinical relevance would be crucial for ensuring the practical utility of the synthetic data. These avenues represent promising directions for future research to continuously improve the effectiveness and applicability of DCGAN-based data augmentation in the medical domain.

7.6 Summary

In conclusion, this project has successfully explored the potential of DCGANs in mitigating data scarcity in medical imaging. Through extensive testing and analysis, the DCGAN model demonstrated its ability to generate realistic CT scan images, contributing to the augmentation of existing datasets. The desktop application, designed for easy integration into medical workflows, showcased robust functionality during testing. While acknowledging the project's strengths, such as successful functionality testing, it is important to note areas for improvement, including the need for enhanced diversity in generated images. Looking ahead, future work should focus on refining the DCGAN architecture, optimizing training processes, and incorporating feedback from medical professionals. Overall, this project represents a meaningful step toward addressing data limitations in medical imaging, paving the way for further advancements in the field.



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APPENDIX

Import Libraries

```

1 import tensorflow as tf
2 from tensorflow import keras
3
4 import glob
5 import imageio
6 import matplotlib.pyplot as plt
7 import numpy as np
8 import os
9 import PIL
10 import time
11
12 from tensorflow.keras import layers
13 from IPython import display
14 from tensorflow.keras.utils import load_img, img_to_array, array_to_img

```

```

1 import tensorflow as tf
2 import matplotlib.pyplot as plt
3 import numpy as np
4 import os
5 import imageio
6
7 from skimage.transform import resize
8
9 from math import floor
10
11 from scipy.stats import entropy
12 from scipy.linalg import sqrtm
13
14 from keras.utils import get_file
15 from keras.models import load_model
16
17 from tensorflow.keras.applications.inception_v3 import InceptionV3, preprocess_input
18 from tensorflow.keras.preprocessing import image
19 from tensorflow.keras.utils import load_img, img_to_array, array_to_img
20 from tensorflow.keras.models import load_model
21 from tensorflow.keras import backend as K
22
23 from numpy.random import randint
24 from numpy.random import shuffle
25 from numpy import cov
26 from numpy import trace
27 from numpy import iscomplexobj
28 from numpy import asarray
29 from numpy import expand_dims
30 from numpy import log
31 from numpy import mean
32 from numpy import exp
33 from numpy import ones
34 from numpy import std

```

DCGAN Setup

```

1 def generator_model():
2     model = tf.keras.Sequential()
3     model.add(layers.Dense(28*42*256, use_bias=False, input_shape=(100,)))
4     model.add(layers.BatchNormalization())
5     model.add(layers.LeakyReLU())
6
7     model.add(layers.Reshape((28,42,256)))
8     assert model.output_shape == (None, 28, 42, 256) #None = Batch Size
9
10    model.add(layers.Conv2DTranspose(128, kernel_size=(5, 5), strides=(1, 1), padding='same', use_bias=False))
11    assert model.output_shape == (None, 28,42,128)
12    model.add(layers.BatchNormalization())
13    model.add(layers.LeakyReLU())
14
15
16    model.add(layers.Conv2DTranspose(64, kernel_size=(5, 5), strides=(2, 2), padding='same', use_bias=False))
17    assert model.output_shape == (None, 56, 84, 64)
18    model.add(layers.BatchNormalization())
19    model.add(layers.LeakyReLU())
20
21    model.add(layers.Conv2DTranspose(1, kernel_size=(5, 5), strides=(2, 2), padding='same', use_bias=False,
22                                   activation='tanh'))
23    assert model.output_shape == (None, 112, 168, 1)
24
25    return model

```

```

1 def discriminator_model():
2     model = tf.keras.Sequential()
3     model.add(layers.Conv2D(64, kernel_size=(5,5), strides=(2,2), padding='same', input_shape=[112,168,1]))
4
5     model.add(layers.LeakyReLU())
6
7     model.add(layers.Conv2D(128, kernel_size=(5,5), strides=(2,2), padding='same'))
8     model.add(layers.LeakyReLU())
9
10    model.add(layers.Conv2D(256, kernel_size=(5,5), strides=(2,2), padding='same'))
11    model.add(layers.LeakyReLU())
12
13    model.add(layers.Flatten())
14    model.add(layers.Dense(1))
15
16    return model

```

```

1 cross_entropy = tf.keras.losses.BinaryCrossentropy(from_logits=True)
2
3 def discriminator_loss(real_output, fake_output):
4     real_loss = cross_entropy(tf.ones_like(real_output), real_output)
5     fake_loss = cross_entropy(tf.zeros_like(fake_output), fake_output)
6     total_loss = real_loss + fake_loss
7     return total_loss

```

```

1 def generator_loss(fake_output):
2     return cross_entropy(tf.ones_like(fake_output), fake_output)

```

```

1 generator_optimizer = tf.keras.optimizers.Adam(1e-4)
2 discriminator_optimizer = tf.keras.optimizers.Adam(1e-4)

```

Training Loop Function

```

1 @tf.function(reduce_retracing=True)
2 def train_step(images):
3     noise = tf.random.normal([BATCH_SIZE, noise_dim])
4
5     with tf.GradientTape() as gen_tape, tf.GradientTape() as disc_tape:
6         generated_images = generator(noise, training=True)
7
8         real_output = discriminator(images, training=True)
9         fake_output = discriminator(generated_images, training=True)
10
11        gen_loss = generator_loss(fake_output)
12        disc_loss = discriminator_loss(real_output, fake_output)
13
14        gradients_of_generator = gen_tape.gradient(gen_loss, generator.trainable_variables)
15        gradients_of_discriminator = disc_tape.gradient(disc_loss, discriminator.trainable_variables)
16
17        generator_optimizer.apply_gradients(zip(gradients_of_generator, generator.trainable_variables))
18        discriminator_optimizer.apply_gradients(zip(gradients_of_discriminator, discriminator.trainable_variables))

```

```

1 def train(dataset, epochs):
2     for epoch in range(epochs):
3         start = time.time()
4
5         for image_batch in dataset:
6             train_step(image_batch)
7
8         #Produce images for the GIF while training
9         if (epoch + 1) % 200 == 0:
10            display.clear_output(wait=True)
11            generate_and_save_images(generator,
12                                   epoch + 1,
13                                   seed)
14
15        #Save model every 200 epochs
16        if (epoch + 1) % 200 == 0:
17            checkpoint.save(file_prefix = checkpoint_prefix)
18
19        print ('Time for epoch {} is {}'.format(epoch+1, time.time()-start))
20
21        #generate image after final epoch
22        display.clear_output(wait=True)
23        generate_and_save_images(generator,
24                                epochs,
25                                seed)

```

```

1 def generate_and_save_images(model, epoch, test_input):
2     #The training is set to false
3     #To make sure all layers run in inference mode (batchnorm).
4     predictions = model(test_input, training = False)
5
6     fig = plt.figure(figsize=(12,12))
7
8     for i in range(predictions.shape[0]):
9         plt.subplot(4,4, i+1)
10        plt.imshow(predictions[i, :, :, 0]*127.5 + 127.5, cmap='gray')
11        plt.axis('off')
12
13        plt.savefig('image_at_epoch_{:04d}.png'.format(epoch))
14        plt.show()

```

```

1 xtime = time.time()
2 print(xtime)
3 train(train_dataset, EPOCHS)
4 print('Training time was {} sec'.format(time.time()-xtime))

```

Interface

```

1 import tkinter as tk
2 from tk import *
3 from tkinter import messagebox
4 import main_window
5
6 #Creating the root window
7 login = tk.Tk()
8 login.geometry("")
9 login.title("CT Gen")
10 login.configure(bg="lightblue")
11 login.geometry("400x250")
12 login.minsize(width=400, height=250)
13 login.maxsize(width=400, height=250)
14 login.iconbitmap(".env/Resources/CTGenLogo.ico")
15
16 #Creating login form elements
17 welcome_label = tk.Label(login, text="---Welcome to CT Generator---", font=('Arial', 15, 'bold'), bg="lightblue")
18 welcome_label.pack()
19
20 #Creating frame to manage grid layout
21 login_frame = tk.Frame(login, bg="lightblue")
22 login_frame.pack(pady=15)
23
24 username_label = tk.Label(login_frame, text="Username:", bg="lightblue")
25 username_label.grid(row=0, column=0, pady=5, padx=30, sticky="w")
26 username_entry = tk.Entry(login_frame)
27 username_entry.grid(row=0, column=1, pady=5, sticky="w")
28
29 password_label = tk.Label(login_frame, text="Password:", bg="lightblue")
30 password_label.grid(row=1, column=0, pady=5, padx=25, sticky="w")
31 password_entry = tk.Entry(login_frame, show="*")
32 password_entry.grid(row=1, column=1, pady=5, sticky="w")
33
34 def attempt_login():
35     uname = "Haziq"
36     passw = "B032010443"
37
38     Username = username_entry.get()
39     Password = password_entry.get()
40
41     if Username == uname and Password == passw:
42         messagebox.showinfo("Login Successful!", "Welcome, " + Username + "!")
43         login.destroy()
44         main_window.create_main_window()
45
46     else:
47         messagebox.showerror("Login Failed", "Invalid username or password.")
48
49 login_button = tk.Button(login, text="Login", command=attempt_login)
50 login_button.pack(pady=10)
51
52
53
54 login.mainloop()

```

```
1  import shutil
2  import tkinter as tk
3  import tkinter.filedialog as filedialog
4  import threading
5  import time
6  import gan
7  import generate_image
8
9  from tk import *
10 from PIL import Image, ImageTk
11 from tkinter import messagebox, ttk
12
13
14 file_uploaded = False # Flag to track upload status
15 filename = "" # Global variable to store filename
16
17 def create_main_window():
18
19     #Creating the main window
20     Main = tk.Tk()
21     Main.geometry("")
22     Main.title("CT Gen")
23     Main.configure(bg="lightblue")
24     Main.geometry("400x250")
25     Main.minsize(width=800, height=600)
26     Main.maxsize(width=800, height=600)
27     Main.iconbitmap(".venv/Resources/CTGenLogo.ico")
28
29     image = Image.open(".venv/Resources/CTGenLogo.png")
30     resized_image = image.resize((100,100))
31     CTLogo = ImageTk.PhotoImage(resized_image)
32
33     def browse_file():
34         global file_uploaded, filename #Access the global variable
35
36         if not file_uploaded:
37             filename = filedialog.askopenfilename(
38                 initialdir="/Users/End User/Documents", #Initial Directory
39                 title="Select a ZIP File",
```



```

40         filetypes=(("ZIP Files","*.zip"),)
41     )
42
43     if filename:
44         try:
45             save_path = ".env/GAN/real_image/" + filename.split("/")[-1]
46             shutil.copy(filename, save_path)
47             messagebox.showinfo("Success!", "ZIP file uploaded successfully.")
48             file_uploaded = True
49             browse_button.config(state="disabled")
50             reupload_button.config(state="normal", command=reupload_file)
51         except Exception as e:
52             messagebox.showerror("Error", "Upload failed: " + str(e))
53
54     filename = ""
55
56     def reupload_file():
57         global file_uploaded
58
59         try:
60             file_uploaded = False
61         except FileNotFoundError:
62             pass # Ignore if file doesn't exist
63
64         browse_file() # Call the browse_file function to initiate a new upload
65
66     logo_label = tk.Label(Main, image=CTLogo, bg="lightblue")
67     logo_label.pack(pady=10)
68
69     def train_gan_function():
70         selected_epoch = epoch_var.get()
71         try:
72             gan.train_gan(int(selected_epoch))
73             messagebox.showinfo("Training Complete", "GAN training has finished successfully!")
74             epoch_1000.config(state="disabled")
75             epoch_2000.config(state="disabled")
76             epoch_3000.config(state="disabled")

```

```

77         quantity_25p.config(state="disabled")
78         quantity_50p.config(state="disabled")
79         quantity_75p.config(state="disabled")
80         quantity_100p.config(state="disabled")
81     except Exception as e:
82         messagebox.showerror("Error", "Training failed: " + str(e))
83
84     def generate_images_with_progress(quantity, progress_var):
85         def progress_callback(progress):
86             progress_var.set(progress)
87
88             generate_image.generate_images(quantity, progress_callback)
89
90     def creating_gan_progress(quantity):
91         start_time = time.time()
92
93
94         gan_progress_window = tk.Toplevel(Main)
95         gan_progress_window.geometry("300x100")
96         gan_progress_window.title("GAN Progress")
97
98         progress_var = tk.DoubleVar()
99         progress_bar = ttk.Progressbar(gan_progress_window, variable=progress_var, length=300, mode="determinate")
100        progress_bar.pack(pady=20)
101
102        # Run the generate_images_with_progress function in a separate thread
103        thread = threading.Thread(target=generate_images_with_progress, args=(int(quantity_var.get()), progress_var))
104        thread.start()
105
106        # Close the progress window when the thread finishes
107    def close_progress_window():
108        gan_progress_window.destroy()
109        end_time=time.time()
110        time_taken = round(end_time - start_time, 2)
111        show_success_message(time_taken)

```

```

112         Main.after(100, check_thread, thread, close_progress_window)
113
114
115     def show_success_message(time_taken):
116         messagebox.showinfo("Success", f"Image generation finished successfully!\nTime taken: {time_taken} seconds")
117
118     def check_thread(thread, callback):
119         if thread.is_alive():
120             Main.after(100, check_thread, thread, callback)
121         else:
122             callback()
123
124     #Creating login form elements
125     welcome_label = tk.Label(Main, text="---Welcome to CT Generator---", font=('Arial', 15, 'bold'), bg="lightblue")
126     welcome_label.pack()
127
128     #Creating frame to manage grid layout
129     file_frame = tk.Frame(Main, bg="lightblue")
130     file_frame.pack(pady=30)
131
132     browse_button = tk.Button(file_frame, text="Browse File", command=browse_file)
133     browse_button.grid(row=0, column=0, pady=5, padx=30, sticky="w")
134
135     reupload_button = tk.Button(file_frame, text="Reupload File", state="disabled")
136     reupload_button.grid(row=0, column=1, pady=5, sticky="w")
137
138     # Create a frame for the checkboxes
139     checkbox_frame1 = tk.Frame(Main, bg="lightblue")
140     checkbox_frame1.pack(pady=15)
141
142     # Create a Checkbutton for GAN constant
143     epoch_var = tk.StringVar(value="1000") # Default value
144
145     epoch_label = tk.Label(checkbox_frame1, text="Epoch for training:", font=('Arial', 10), bg="lightblue")
146     epoch_label.grid(row=0, column=0, columnspan=3)
147

```

```

148     epoch_1000 = tk.Checkbutton(checkbox_frame1, text="1000 Epochs", variable=epoch_var, onvalue="1000", bg="lightblue")
149     epoch_1000.grid(row=1, column=0, pady=5, padx=30, sticky="w")
150
151     epoch_2000 = tk.Checkbutton(checkbox_frame1, text="2000 Epochs", variable=epoch_var, onvalue="2000", bg="lightblue")
152     epoch_2000.grid(row=1, column=2, pady=5, padx=30, sticky="w")
153
154     epoch_3000 = tk.Checkbutton(checkbox_frame1, text="3000 Epochs", variable=epoch_var, onvalue="3000", bg="lightblue")
155     epoch_3000.grid(row=1, column=3, pady=5, padx=30, sticky="w")
156
157     # Create a frame for the checkboxes
158     checkbox_frame2 = tk.Frame(Main, bg="lightblue")
159     checkbox_frame2.pack(pady=15)
160
161     quantity_var = tk.StringVar(value="1") #Default
162
163     quantity_label = tk.Label(checkbox_frame2, text="Number of Images to be Generated:", font=('Arial', 10), bg="lightblue")
164     quantity_label.grid(row=0, column=0, columnspan=4)
165
166     quantity_25p = tk.Checkbutton(checkbox_frame2, text="25% of training data", variable=quantity_var, onvalue="1", bg="lightblue")
167     quantity_25p.grid(row=1, column=1, pady=5, padx=30, sticky="w")
168
169     quantity_50p = tk.Checkbutton(checkbox_frame2, text="50% of training data", variable=quantity_var, onvalue="2", bg="lightblue")
170     quantity_50p.grid(row=1, column=2, pady=5, padx=30, sticky="w")
171
172     quantity_75p = tk.Checkbutton(checkbox_frame2, text="75% of training data", variable=quantity_var, onvalue="3", bg="lightblue")
173     quantity_75p.grid(row=1, column=3, pady=5, padx=30, sticky="w")
174
175     quantity_100p = tk.Checkbutton(checkbox_frame2, text="100% of training data", variable=quantity_var, onvalue="4", bg="lightblue")
176     quantity_100p.grid(row=1, column=4, pady=5, padx=30, sticky="w")
177
178     #Frame for training and generate button
179     ganButton_frame = tk.Frame(Main, bg="lightblue")
180     ganButton_frame.pack(pady=30)

```

```

181
182     train_button = tk.Button(ganButton_frame, text="Start Training", command=train_gan_function)
183     train_button.grid(row=0, column=0, pady=5, padx=30, sticky="w")
184
185     #generate_button = tk.Button(ganButton_frame, text="Generate Images", state="disabled")
186     #generate_button.grid(row=0, column=1, pady=5, sticky="w")
187     generate_button = tk.Button(ganButton_frame, text="Generate Images", state="normal", command=lambda: creating_gan_progress(int(quantity_
188     generate_button.grid(row=0, column=1, pady=5, sticky="w")
189
190     # Enable reupload button if a file has been uploaded
191     if filename:
192         reupload_button.config(state="normal", command=reupload_file)
193
194     Main.mainloop()

```