Investigating the Utility of Synthetic Data in the Detection of Lung Cancer

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Abstract. Artificial Intelligence (AI) is broadly used in healthcare to automate various clinical tasks. However, these models require large medical datasets for training, which are not readily available due to privacy issues. To address this challenge, synthetic data generation can help to increase dataset volume and improve diversity without compromising patient privacy. Therefore, this paper aims to analyse the utility of synthetic data in lung cancer detection, which is one of the most commonly diagnosed cancers. For this purpose, we trained and tested Machine Learning (ML) classifiers on a real dataset, substituting different proportions of real data with synthetic data and then replacing real data with synthetic data. We compared the performance of classifiers using accuracy, precision, recall, F1-score, and Area Under Curve (AUC). The results show that synthetic data can be used in conjunction with real data; however, replacing it completely with synthetic data needs more experiments on a large range of generative models to draw useful insights.

Keywords: GANs, cGAN, lung cancer detection, ML, AI, synthetic data.

1 Introduction

Lung cancer is one of the most frequently diagnosed cancers and the deadliest as well, with 1.82 million deaths and 2.48 million new cases reported in 2022. With a 5-year survival rate of only 20%, the leading cause of lung cancer is smoking, followed by other factors such as air pollution, exposure to carcinogens, and genetic or hereditary factors [5]. Furthermore, it is estimated that one in every 16 individuals will be diagnosed with lung cancer during their lifetime. [1].

Early detection of lung cancer is crucial to reduce the mortality rates. Cancer is generally easier to treat when detected in its early stages, unlike in later stages, when it has spread to other body parts. Early detection can provide access to effective and affordable treatment options without undergoing intensive treatments that cause physical and mental strain on the patients [11].

Due to recent developments in cancer treatment that enable early detection, the cases of lung cancer are declining each year [1]. Specifically, advancements in medical imaging provide invaluable insights into pathological processes that can aid in early diagnosis [26]. The different image modalities include Computed Tomography (CT), radiography, ultrasound, mammography, Magnetic Resonance Imaging (MRI), etc, which are widely used to evaluate abnormalities [22]. These medical images are manually assessed by medical experts, which is time-consuming, and also suspect to human errors.

AI models with their sophisticated computer vision abilities can aid detection of lung cancer in the early stages by identifying subtle signs [9]. These AI detections and diagnoses can serve as a second reader for radiologists and oncologists, which not only saves time but also minimises human error [25].

The increasing development in AI and Deep Learning (DL) models has shown the ability to aid clinicians in the early detection of lung cancer [27]. But these models need large and diverse datasets for training. In healthcare, due to strict privacy concerns, medical data is not easily accessible [23]. Therefore, these models are usually trained on small datasets, which results in low accuracy, less robust and generalised systems [2]. Since AI models require extensive datasets for training, it is essential to build capabilities that can overcome data scarcity and ensure AI systems' predictions remain accurate and effective.

Synthetic data generation can be a potential solution to address these challenges [17]. Synthetic data or artificial data exhibits the same properties as real-world data [18]. GAN is one of the most commonly used image generation techniques [14]. There are various variants of GAN proposed to overcome the issues of traditional GAN [24, 28]. Therefore, this paper investigates the utility of synthetic data by generating images using traditional GAN and Conditional GAN (cGAN).

2 Motivation

Lung cancer is one of the leading causes of death worldwide [16]. Due to the absence of symptoms in the early stages, it is usually diagnosed at advanced stages. Typically, diagnosis is performed by manually examining scans, a process that is both time-consuming and susceptible to human error [26]. Recent progress in the field of AI has opened up various opportunities to build such systems that can help clinicians in the early detection of lung cancer. AI algorithms need a large amount of data for their training. Most of the real-world datasets are small in size and imbalanced [18, 7]. As large and diverse medical datasets are not easily accessible, synthetic data generation provides a potential solution to mitigate imbalance, increase data volume and introduce diversity in the existing datasets [23]. Therefore, this paper explores the utility of synthetic images to detect lung cancer. For this purpose, we used traditional GAN and cGAN to generate synthetic images for the lung cancer dataset. To analyse the utility of synthetic data, we compared the performance of Machine Learning (ML) classifiers trained on only real data, real data in conjunction with synthetic data and only synthetic data. The formulated research question is as follows:

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RQ1: What is the effect on performance of the classifier when synthetic data is used in conjunction with real data or when it is replaced with real data?

3 Related Work

In recent years, synthetic data generation has gained significant importance to address challenges, including inaccessibility, imbalances and bias in real-world medical datasets. GANs are commonly used to generate realistic data, particularly images. GAN architecture consists of two neural networks, i.e., a generator and a discriminator. Both these networks are trained in an adversarial method such that a generator is trained to generate synthetic images and the discriminator is trained to classify fake and real images [6]. Using this technique, high-quality images can be generated [20].

To optimise the performance of GANs, various variants have been proposed in the literature. A study by Skandarani et al. [24] implemented different variants of GANs, such as LSGAN, WGAN, SPADE GAN, and styleGAN, to generate synthetic images for three medical image datasets. For each dataset, 10,000 synthetic images were generated. The results show that SPADE GAN and Style GAN produced images that were very similar to real-world data.

Furthermore, a review Waisberg et al. [28] discussed the use of cGAN in ophthalmology to generate synthetic images of the retinal fundus. These synthetic images were used to train a Deep CNN algorithm to detect exudate in retinal fundus images. The images generated by cGAN were of high quality, and the key structure was preserved in the generated images, which are necessary for the diagnosis.

Another study explores the potential of cGAN for generating synthetic images. Building on cGAN, two new models, Enhancement and Segmentation GAN (ESGAN) and Enhancement GAN (EnhGAN) are proposed. In ESGAN, classifier loss is integrated with adversarial loss to predict input patch labels, while EnhGAN is designed to produce high-contrast images. Both models are tested on the publicly available BraTS 2013 and 2018 datasets containing 3D Brain MRI scans. The findings demonstrate that incorporating synthetic data enhances segmentation performance compared to other state-of-the-art methods [8].

The above discussion shows that GANs have the capability to generate high-quality synthetic images, which can help in cases of limited data availability or imbalances in the real-world datasets. Therefore, this study explores the utility of synthetic data for lung cancer detection using GANs.

4 Methodology

Figure 1 presents the methodology of our study. First, the model takes a lung cancer dataset consisting of CT scans as input, then these original images are used to generate synthetic data for each class using traditional GAN and cGAN. In order to evaluate the quality of generated data, the original dataset is then replaced with synthetic data using four cases: using 100% real data, using 60%

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real and 40% synthetic, 50% real and 50% synthetic, and using 100% synthetic images. The features are then extracted using pre-trained DL models, ResNet50 [10], and Unet [15]. ResNet50 and Unet are selected because of their ability to extract high-level and spatial connectivity features, respectively [19, 4]. It allows the model to learn applicable features without the need for a large task-specific dataset. Different ML classifiers are trained to compare the performance on the test set using Accuracy, Recall, Precision, F1-score, and Area Under Curve (AUC).

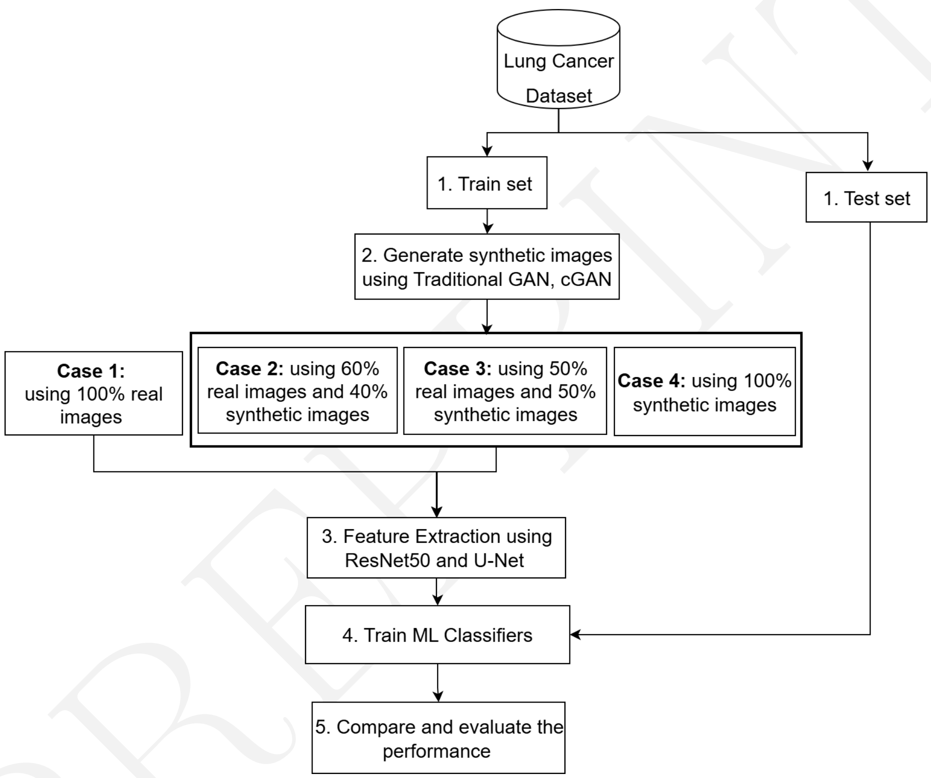

Fig. 1. Methodology diagram to evaluate the utility of synthetic data for lung cancer detection

4.1 Dataset

The study utilises the IQ-OTH/NCCD lung cancer dataset [3], which contains CT scans of 110 cases, with 40 cases diagnosed as malignant, 15 as benign, and 55 as normal. The scans from each case are divided into 3 different classes: normal, benign and malignant, consisting of 416, 120, and 561 scans, respectively.

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Due to computational resource and time constraints, we only used a subset of the dataset, i.e., 50 scans from each class for training and 10 scans for testing.

4.2 Synthetic Image Generation

To generate synthetic data, we start with the very basic architecture of GAN and its variant called cGAN.

Traditional GAN is the basic GAN model that consists of two neural networks, a generator and a discriminator. The generator produces synthetic images starting from random noise, and the discriminator tries to differentiate between real images coming from real datasets and fake images coming from the generator. Over time, this adversarial setup leads to increasingly realistic synthetic images [12].

cGAN is a variant of GAN that is extensively used in image generation. cGAN also consists of two neural networks with a difference that both the generator and the discriminator are conditioned on some information, such as a class label, which helps the model to learn specific features in order to improve the image generation process [13].

Figure 4.2 shows an example of a real image from the dataset and images generated using GAN and cGAN.

(a) (b) (c)

Fig. 2. Real and generated images (a) real image (b) images generated using GAN (c) image generated using cGAN

4.3 Experimental Design

To assess the quality of synthetic image generation, we have divided our experiment into four cases:

Case 1: Using 100% real images to train ML classifiers.

Case 2: Using 60% of real images and 40% synthetic images to train ML classifiers.

Case 3: Using 50% real images and 50% synthetic images to train ML classifiers.

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Case 4: Using 100% synthetic images to train ML classifiers.
The test set consists of real CT scans that remain the same in all cases.

4.4 Feature extraction

In order to train ML classifiers, we extract convolution features from CT scans using pre-trained DL models, including ResNet-50 and U-Net. ResNet-50 extracts hierarchical and semantic features from images [10], whereas U-Net extracts semantic context with fine-grained spatial details [21]. Combining both these features allows for improved performance in tasks such as disease classification.

4.5 Train ML Classifiers

After extracting features, we trained and tested 5 different ML classifiers in order to evaluate the performance in each case. These classifiers include Support Vector Machine (SVM), Logistic Regression (LR), Random Forest (RF), Gradient Boosting (GB), and an Ensemble Voting Classifier (EVC), which is a soft voting classifier applied on all the mentioned classifiers.

5 Results

The performance of each ML classifier is assessed on each of the cases as mentioned in Section 4.2 using Accuracy, Precision, Recall, F1-Score and AUC.

Table 1, Table 2, Table 3, and Table 4 shows the performance of classifiers on each case. The results indicate that classifiers achieve the highest performance when trained on real datasets. A slight decrease in performance is observed when synthetic data is used in conjunction with real-world datasets. The difference in metric scores between cases 2 and 3 (different proportions of synthetic data) is not significant. However, a substantial decline in performance occurs when classifiers are trained solely on synthetic data, compared with real data (case 1) or mixed data (cases 2 and 3).

Table 1. Performance metrics scores for case 1: using 100% real training images

Model	Accuracy	Precision	Recall	F1-Score	AUC
SVM	**0.8667**	0.8928	**0.8667**	0.8573	0.9633
LR	0.8333	0.8498	0.8333	0.8295	0.9750
RF	0.8000	0.8116	0.8000	0.7867	0.9017
GB	0.8333	0.8498	0.8333	0.8295	0.9033
EVC	**0.8667**	**0.9048**	**0.8667**	**0.8611**	**0.9667**

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Table 2. Performance metrics of GAN and cGAN models for Case 2: 60% real and 40% synthetic training images

Method	Model	Accuracy	Precision	Recall	F1-Score	AUC
GAN	SVM	**0.8333**	**0.8387**	**0.8333**	**0.8255**	**0.9433**
	LR	0.7333	0.7235	0.7333	0.7249	0.8983
	RF	0.7667	0.7586	0.7667	0.7613	0.8933
	GB	0.6000	0.5896	0.6000	0.5698	0.8100
	EVC	0.7333	0.7280	0.7333	0.7213	0.9067
cGAN	SVM	**0.8000**	**0.7955**	**0.8000**	**0.7937**	**0.9283**
	LR	0.7000	0.6932	0.7000	0.6931	0.9083
	RF	0.7667	0.7586	0.7667	0.7613	0.8833
	GB	0.7000	0.7033	0.7000	0.6931	0.8317
	EVC	0.7667	0.7586	0.7667	0.7613	0.9050

Table 3. Performance metrics scores of GAN and cGAN models for case 3: 50% real and 50% synthetic training images

Method	Model	Accuracy	Precision	Recall	F1-Score	AUC
GAN	SVM	**0.8000**	**0.7963**	**0.8000**	**0.7943**	**0.9283**
	LR	0.7000	0.6882	0.7000	0.6929	0.8883
	RF	0.7333	0.7356	0.7333	0.7257	0.8800
	GB	0.6667	0.6667	0.6667	0.6667	0.8233
	EVC	0.7667	0.7586	0.7667	0.7613	0.9033
cGAN	SVM	**0.8000**	**0.8059**	**0.8000**	0.7923	**0.9167**
	LR	0.7333	0.7602	0.7333	0.7175	0.8533
	RF	0.7333	0.7253	0.7333	0.7280	0.9033
	GB	0.5667	0.6517	0.5667	0.5766	0.7383
	EVC	**0.8000**	0.8056	**0.8000**	**0.7980**	0.8933

6 Discussion

This section discusses the overall findings of the study in view of our research question, experiment and its results.

RQ1. What is the effect on performance of the classifier when synthetic data is used in conjunction with real data or when it is replaced with real data?

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Table 4. Performance metrics scores of GAN and cGAN models for case 4: using 100% synthetic training data

Method	Model	Accuracy	Precision	Recall	F1-Score	AUC
GAN	SVM	0.4667	0.3418	0.4667	0.3889	0.6800
	LR	**0.5333**	**0.6070**	**0.5333**	0.5228	0.7167
	RF	0.5000	0.5212	0.5000	0.5021	0.6608
	GB	0.5000	0.4948	0.5000	0.4817	0.7150
	EVC	**0.5333**	0.5508	**0.5333**	**0.5410**	**0.7267**
cGAN	SVM	0.4333	0.4294	0.4333	0.4176	0.6717
	LR	0.4667	0.4540	0.4667	0.4500	0.6433
	RF	0.4667	0.4667	0.4667	0.4633	**0.7083**
	GB	**0.5000**	**0.5187**	**0.5000**	**0.5018**	0.6167
	EVC	0.4667	0.4802	0.4667	0.4462	0.6867

The experiment is conducted by using only two generative models that are trained on a relatively small subset of the dataset. However, the performance scores decrease when the proportion of real-world data is replaced with synthetic data. Keeping in view the limitations of the experiment and evaluation metric scores, we can say that the performance of the classifiers in cases 2 and 3 is comparable with case 1 (real-world dataset only). However, we cannot apply statistical tests to identify any significant difference in performance because the dataset was very small. Therefore, we can conclude that synthetic data can be helpful when limited real-world datasets are available. It can be used in conjunction with real-world data. However, the significant drop in metric scores when synthetic data entirely replaces the real-world data set highlights the need for further experiments with more sophisticated generative models and larger datasets before drawing definitive conclusions.

7 Conclusion and future work

In this study, we explored the utility of synthetic data in the detection of lung cancer. For this purpose, we used traditional GAN and cGAN to generate synthetic images. We evaluated the performance of ML classifiers using 4 different cases. These cases involve training the classifiers exclusively on the real dataset, partially substituting the real dataset with synthetic data, and completely replacing the real dataset with synthetic data. The results show that synthetic data can be used in conjunction with real data to address issues like limited data availability. However, the study is limited to only two generative models and a small data subset. Therefore, in future, we plan to extend our experiments to more sophisticated generative techniques trained on larger datasets to provide better insights. Also, we will apply statistical tests to identify any significant differences in the performance of the classifiers in different scenarios.

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