AZERBAIJAN REPUBLIC

MINISTRY OF EDUCATION

KHAZAR UNIVERSITY

SCHOOL OF SCIENCE AND ENGINEERING

Major: Informatics

Master thesis

Generative Adversarial Network Image synthesis method for skin lesion Generation and classification

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Fall 2020

Baku, Azerbaijan

Acknowledgements

On the submission of my Thesis report to fulfill the requirements for the award of master of science in informatics, I wish to extend my gratitude and my sincere thanks to my supervisor Ph.D. Behnam Kiani Kalejahi for his constant motivation and support during the course of my work in the last one year. I really appreciate and value his esteemed guidance and encouragement from the beginning to the end of this thesis.

My heartfelt gratitude goes to the computer science department at Khazar University, for offering valuable support to this academic exercise. Having learned the integral concepts of machine learning in most of my modules in the previous semester now I ought to augment the practical skills out of the sphere of these modules by replicating a research article on unsupervised deep learning.

More importantly, I am grateful to my parents who have always been supportive and understanding. Without them, I wouldn't even have a chance to receive a University education let alone complete one.

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September, 2020

Abstract

Skin cancer is the most commonly diagnosed cancer in today's growing population. One of the common limitations in the treatment of cancer is in the early detection of this disease. Mostly, skin cancer is detected in its later stages, when it has already compromised most of the skin area. Early detection of skin cancer is of utmost importance in increasing the chances for successful treatment, thus reducing mortality and morbidity. Currently, most dermatologists use a special microscope to examine the pattern and the affected area. This method is time-consuming and is prone to human errors, so there is a need for detecting skin cancer automatically. In this study, we investigate the automated classification of skin cancer using the Deep Convolution Generative Adversarial Network(DCGAN).In this work, Deep Convolutional GAN is used to generate realistic synthetic dermoscopic images, in a way that could enhance the classification performance in a large dataset and to evaluate whether the classification accuracy is enhanced or not, by generating a substantial amount of new skin lesion images. The DCGAN is trained using images generated by the Generator and then tweaked using the actual images and allow the Discriminator to make a distinction between fake and real images. The DCGAN might need slightly more fine-tuning to ripe a better return. Hyperparameter optimization can be utilized for selecting the best-performed hyperparameter combinations and several network hyperparameters, namely number of iterations, batch size, and Learning rate can be tweaked, for example in this work we decreased the learning rate from the default 0.001 to 0.0002 and the momentum for Adam optimization algorithm from 0.9 to 0.5, in trying to reduce the instability issues related to GAN models. Moreover, at each iteration in the course of the training process, the weights of the discriminative and generative network are updated to balance the loss between them. This pretraining and fine-tuning process is substantial for the model performance.

Keywords—DCGAN, Dermoscopy, Pretraining, skin lesion

Table of Contents

Chapter 1

Introduction

Skin cancer is a common medical challenge around the globe [1]. Early screening of skin cancer is of paramount importance to curb mortality and increase the possibilities of survival rate in patients. Skin lesion analysis plays an essential role in skin cancer prophylaxis, notably in terms of getting an effective early diagnosis. Having learned the integral concepts of neural networks in the previous semester, the researcher now ought to augment the practical skills out of the sphere of this module by replicating a research article on unsupervised deep learning. Even though an increasing amount of data is becoming available on the Internet, the vast majority of it remain unlabelled. In this context, we leveraged the ready unlimited number of unlabelled images to learn proper machine learning techniques, which can then be utilized on number of unsupervised learning tasks like image classification [2].

Generative models are one of the most prevalent methodologies that are applied for this, as the model has to examine and understand the gist of the training image data before it can generate comparable results itself [3]. “What I cannot create, I do not understand”, stated the renowned physicist Richard Feynman. It can be said that, for models to understand their input, they need to learn to create the data to explore this quote in the circumstance of machine learning.

The most promising approach is to use generative models that learn to discover the quintessence of data and find the best distribution to represent it. Generative Adversarial Network [2] is contemplated as a principal group of models to build satisfactory image depictions and generate " realistic " images. The notion of GAN is to synchronously train two distinct models namely the generative model **G** and the discriminative model **D**. In this case, the generative model produces convincing images that are analogous to a real image data distribution while the chore of the discriminative model is to ascertain whether or not a considered image looks true or not.

To understand a generative modelling technique, it may be comparable to a criminal gang of counterfeiters, attempting to fabricate counterfeit currency and make use of it without getting caught, whereas the discriminative model is similar to law enforcement agents, endeavour to uncover the counterfeit money. In this context, contention pushes onward two of them to enhance their tactics up to a time where they would not be able to discern the counterfeits from authentic currency.

In this study, our objective is to investigate a remarkable situation where the generative network produces specimens by transmitting random noise within a multi-layered perceptron, similarly discriminative model is equally a multi-layered perceptron that utilizes random noise as its input and outputs the ultimate prediction of the discriminator on the produced images [4]. In this instance, we will be able to train these models mutually employing only the enormously successful dropout and backpropagation algorithms [5] as well as an instance that could have come from the generative model after applying only forward propagation. To assist dermatologists in making their diagnostic study, this work seeks to propose an improved cutaneous lesions scrutiny and classification procedure employing DCGAN and assess a set of constraints as well as hyperparameters on this architectural topographic anatomy.

In accession towards this image segmentation approach, dermal lesions are processed by applying effective image filtering and enhancement algorithms to enhance the model feature detection and extraction during training.

1.1 Background

1.1.1 Generative Adversarial Network

Generative paradigms have been the most prevalent methodologies that are implemented for these kinds of situations. The model should be competent enough to examine and comprehend the essence attributed to training data before it can generate similar results [3]. Generative Adversarial Networks (GANs) have turn out to be one of the predominant developments of generative deep learning methodologies since it was established [6]. The generator needs to understand how to generate data in a manner that the discriminator won't be able to discern between fake and real. The discriminator network has the assignment of discerning produced images from true images. The fundamental structure of generative adversarial networks incorporates two multi-layered networks, that trained concurrently, a generative model **G** sublimates random vector **z** adapted from preceding distribution $\boldsymbol{P}_{(\boldsymbol{Z})}$ into image data, furthermore a discriminative model **D** make an attempt to draw a distinction between true images obtained from training images **P** and simulated samples from the generator **G**. An instance of a generative adversarial networks (GAN) framework notably trained upon MINST dataset [7] as indicated in **Fig.1**.

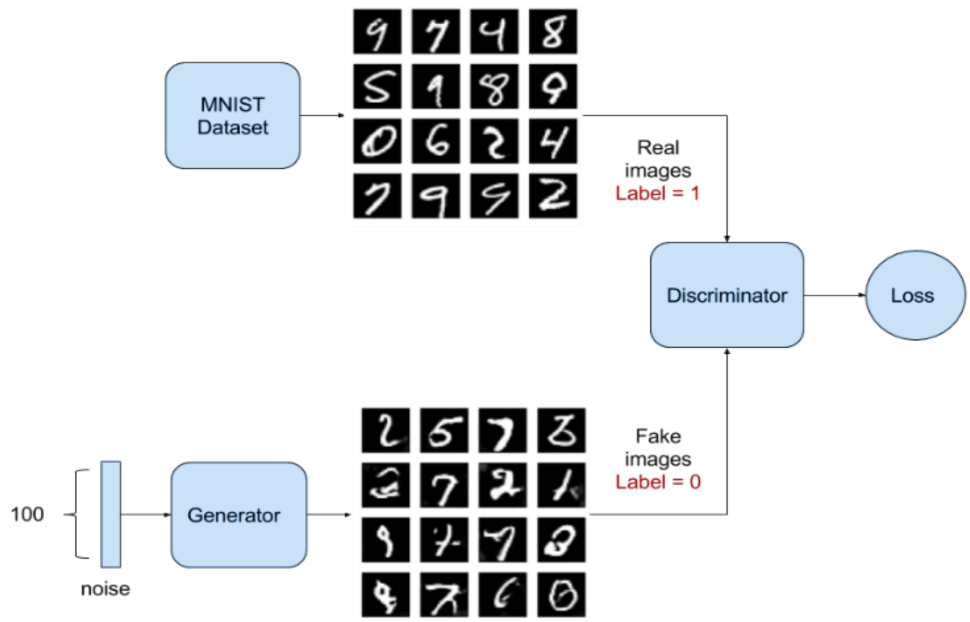

Fig. 1. An illustration of the generative adversarial network (GAN) training upon MNIST dataset. The generator attempts to produce images equivalent to images in MINST dataset thus the discriminator may not tell apart genuine images from generated images [1].

Such networks are tutored conflictingly, in the form of two-player minimax game, until none of them could make additional advancement against one another, either the generator turns to be pretty good that the discriminator may not easily distinguish between true and false. An illustration of the generative adversarial network cognitive function is depicted in the following manner:

$$\min_G \max_D V\,(D,G) = \min_G \max_D [E_{X\sim P_{data}(x)}[\log D(x)] + E_{z\sim p_{z}(z)}[\log(1 - D(G(z)))]$$

x implies the factual training data, **z** signifies latent features aggregated upon the generator, furthermore, ***G(z)*** portrays the sample originating from the generator given a noise vector. ***D(x)*** connotes the discriminator's approximation of the possibility that real image data ***x*** is real, furthermore ***D(x)*** has to be as close as possible to **1**, to perform better. The possibility that the discriminator determines if the samples obtained from generator are true or false is represented by ***D(G(z))***. Taking into account that the target of the generative model is to produce images analogous to the real images, the anticipation of the generator is for the value to be as big as possible. $P_{data^{(x)}}$ and $P_{Z^{(z)}}$ represents the probability density of x and $\mathbf{z}$ accordingly**.** In order to mislead Discriminator ***D, G*** is trained in a manner that it diminishes $\mathbf{log}(\mathbf{1} - \boldsymbol{D}(\boldsymbol{G}(\boldsymbol{z})))$. Contrarily ***D*** is trained so that it can enhance the likelihood that the generated data is authentic, illustrated by **1**, bear in mind **0** constitute a fake. The narrative aforementioned is the underlying principle of the generative adversarial network. The algorithm for this model can be expected to take the following steps:

Algorithm: Minibatch stochastic gradient descent training of generative adversarial net. Here ***k***, is a hyperparameter which represents number of steps to be implemented on the discriminator. We used ***k =1*** because it is a less expensive choice, in our experiment.

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for number of training recurrences do

for *k* steps **do**

- sample minibatch of *m* noise samples $\{z^{(1)}, \ldots\ldots, z^{(m)}\}$from noise prior $\mathbf{P_g}\,(\boldsymbol{z})$
- sample minibatch of *m* examples $\{x^{(1)} \ldots, x^{(m)}\}$ from data generating distribution $\mathbf{P_{data}}^{(x)}$.
- Update the discriminator by ascending its stochastic gradient:

$$\nabla_{\theta_g} \frac{1}{m}\sum_{i=1}^{m}[\log D(x^{(i)}) + \log(1 - D(G(z^{(i)})))]$$

end for

- sample minibatch of *m* noise samples $\{z^{(1)}, \ldots\ldots, z^{(m)}\}$from noise prior $\mathbf{P_g}\,(\boldsymbol{z})$
- Update the generator by descending its stochastic gradient:

$$\nabla_{\theta_g} \frac{1}{m}\sum_{i=1}^{m} \log(1 - D(G(z^{(i)})))$$

end for

Fig. 2: The algorithm of GAN [10]. here ***k*** is the considerable number of iterations carried out on the discriminator (hyperparameter).

In the wake of consequences due to the contest of these two networks, generative adversarial networks (GANs) are well known to have limitations. Initially, there is an issue of model collapse in the generative adversarial networks [8]. Furthermore, due to high degree of autonomy, these networks exhibit some issues, such as non-convergence and instability during execution. On the other hand, it is complex to train a generative adversarial network (GAN) because it does not have a loss function, making it difficult throughout the learning process to determine if it has made some positive developments or not.

To address those issues, Radford and counterparts [4] suggested a group of Convolution Networks named Deep Convolutional GAN, that possess a set of architectural constraints to balance GAN networks [9]. It is a set of broad lines for the establishment of architectures for images. This method is pretty common and in particular, this article has already been cited by many publications in accordance with Google Scholar.

1.1.2 Deep Convolutional Generative Adversarial Network

The principal idea of DCGAN, is to broaden generative adversarial network using Convolution Network architectures. Radford [10]. managed to attain stable results by endorsing certain architectural constraints to DCGAN.
Below principles were introduced in [7]

- Modification of the generator by replacing pooling layers with stride convolutions in discriminator and fractional-strided convolutions.
- The use LeakyReLU activation function in the discriminator over the entire layers.
- Removal of fully connected layers on top of convolutional features and directly linking the outcome to the convolutional layers.
- The use of ReLU activation function in the generator in all layers leaving out the output, which uses tanh activation function.
- Batch Normalization incorporated in either of the two, generator and discriminator

The illustration of model architecture is expressed in **Fig.3.** Not entirely connected or pooling layers are implemented. The input **z** to the model is one hundred-dimensional vector habitually sampled from unvarying distribution.

1.2 Problem Definition

Commonly Melanoma's consideration when it reaches metastasis state is chemotherapy and radiotherapy. These painful procedures are not always successful, in most cases lead to death. Early detection of skin cancer is of utmost importance in increasing the chances of successful treatment. An automated machine learning model is essential to explore for improving the accuracy of skin lesions classification by incorporating some Image processing techniques.

1.3 Research Objectives

The key objective of this study is to establish a fully automatic model that helps Dermatologists as a means of decision-making scheme for skin cancer handling process using the Deep Convolution Generative Adversarial Network (DCGAN) on a ready unlimited number of unlabelled images to improve skin lesion detection and classification.

Moreover, improving the early detection of skin lesions by implementing effective image filtering and enhancement algorithms to enhance the model feature detection and extraction during training.

Specific objectives:

- To develop a model that can extract useful and powerful textural features from image data.
- To establish enhanced algorithms and to broaden the functional capability of the already existing approaches to improve the segmentation procedure of skin lesions
- To establish a paradigm that can precisely categorize skin lesions with high sensitivity and specificity.

Sub-questions

How to enhance the classification process of skin cancer to contend with other variety of sophisticated features present in skin images that may have an impact on the classification exercise?

How to make use of image processing techniques and effectively utilize extracted features for enhancing the classifier performance?

How to coach the classifier efficiently by making use of unlabelled training data in order to improve its generalization performance when small amount of labelled training image data is given?

This study attempts to provide answers to the above-aforementioned questions and endeavor to solve them by enhancing the performance of present algorithms used in similar studies. The results of the proposed method are compared with other algorithms and results are observed.

1.4 Significance of the study

The prevalence of skin cancer has proved to be increasing through time and it has become an underlying reason of the death of large numbers of people around the world. The customary medical practice of melanoma examination is a visual examination by the dermatologist followed by taking a biopsy invasively. nonetheless, this symptomatic approach lacks visualization of morphological features which are not distinguishable by inspecting with a naked eye. furthermore, the substantial costs of inspections and the lack of specialists hinder great deal of patients from receiving effective treatment. By virtue of these challenges, developing computer aided skin cancer classification and detection model becomes vital. This helps to examine a significant number of images in short space of time while reducing the cost and workload of dermatologists. The ultimate decision becomes more objective than observer driven proficiencies. This study is comprised of a powerful medical images analysis that is potentially beneficial in skin lesion classification and detection procedures.

The primary objective is to carry out semantic segmentation on skin lesions by developing a proficient model valuable to enhance the process of generation and classification of cutaneous lesions. This classification model provides spatial intelligence that could be useful in the future for cancer risk prediction. Cancer risk prediction in a relatively new avenue of study that intends to predict the likelihood of developing cancer in the future.

In addition to this, categorization of skin lesion images using high precision neural networks allows automating the detection of anomalies in image data. Also, with strong reliability, it allows a faster and even an enhanced analysis. However, the insufficiency of labelled image data poses some challenging problems in the medical domain as a result of privacy issues, [2]. It is because the accuracy of the classifier is limited by the short amount of image data.

1.5 Project overview

Chapter 2 we debate about the general overview of human skin and existing clinical skin cancer diagnostic techniques. It presents some of the well-known cancer, benign together with malignant skin lesions. Chapter 3 considers the fundamental theories of Computer Aided Diagnosis (CAD) systems and the general detection approach of most CAD schemes like classification of lesion images, feature extraction and pre-processing. Chapter 4 presents some overview of existing models and proposed melanoma skin lesion detection and classification scheme and the steps to be followed. Chapter 5 discusses about the methodologies used and the data sets implemented in the current project. Chapter 6, is about the regularities involved during the training process and those parameters considered to adjust the models for better performance. In addition, Chapter 7 reviews how the model was implemented for assessment and how the performance was measured. Chapter 8 is about the analysis of the produced results given some adjustments made during training. Lastly chapter 9 concludes this work and brings up suggestions for future work.

The fundamental objective of the project is to establish a reliable paradigm that can precisely classify skin lesions with high sensitivity and specificity using deep convolutional generative adversarial networks. In accordance with achieving this goal, a CNN is utilized to organize the images of skin lesions as well as to pull out features that are rendered into a support vector machine (SVM) to handle the segmentation from a different perspective. The project is conducted following an implementation of a deep convolutional GAN using the Python-based deep learning library Keras and it presents series of further experiments conducted during the training process with the comparable outcome and a short discussion in the last chapter.

Chapter 2

Skin Cancer, Human skin And Diagnosis Methods

2.1. Skin Cancer

Cancer is classified among the prime causes of mortality in general population in the world. According to World Health Organization statistics, it is expected that cancer is going to be the principal cause of death by 2030 [11]. However, diagnosis in early stages plays an essential role on saving lives. For a better understanding about early detection and assessment of the skin cancer, it is important to examine human skin and different types of skin cancers. Below, this chapter explains the layers of human skin, various types of skin cancers, and the third part focuses on computer-aided diagnosing techniques in details.

2.2. Structure of the human skin

Skin is by far the largest organ in the human body averaging surface area of 1.5-2.0 square meters. It is responsible for keeping the body safe from ultraviolet radiation (UV) and pathogens, controls evaporation and it also regulates our body temperature. Skin mainly consists of three main layers: hypodermis, epidermis and the dermis. Figure 2.1 shows the anatomy of the human skin.

Epidermis

The epidermis is the uppermost layer of human skin made from multi-layered squamous cells along with basal lamina. This layer contains many special skin cells which are namely melanocytes along with keratinocytes. Keratinocytes are cells that produce a special fat which is responsible for providing the skin with waterproof properties. The actual skin color of humans is affected by many substances, nevertheless, the vital substance that determines the color of human skin is called the melanin. This melanin is produced inside the skin cells called melanocytes. The melanocytes are the ones responsible for determining the color of darker-skinned people. The color of light skin people is mainly determined by the bluish-white connective tissue beneath the dermis and by the hemoglobin moving in the veins of the dermis. More so, the epidermis does not have any blood vessel, and oxygen goes to the cells in the deepest layer as a result of diffusion [12].

Dermis

Dermis is the second layer beneath the epidermis, mainly composed of different cell types that make up sweat glands and blood vessels. This layer protects the body from stress and strain by working like a cushion. A dermis is a thick layer incorporating firm connective tissues.

This layer is further partitioned into two levels; the upper called the papillary layer, and the lower layer called the reticular layer consisting of tissue that is more closely packed. This layer is constructed from a matrix of collagen, elastin and network of capillaries and nerves. This collagen gives the skin its strength, the elastin maintains its elasticity and the capillary network supplies nutrients to the different layers of the skin. In Addition, dermis consists of several specialized cells and structures. These includes: sweat glands, sebaceous glands, hair follicles and nails. It also plays a vital role in controlling our skin temperature and acts as a cushion against mechanical injury.

Hypodermis

Even though the hypodermis is listed as a part of the skin, it is not always considered as a skin layer. It is found below the dermis and connects the skin to the bone and muscles. The hypodermis contains connective and fat (adipose) tissue. The hypodermis consists of 50% of our body’s fat that assists by insulating the body from heat and cold, providing protective padding, and serving as an energy storage area.

Melanocytes

Melanocytes are pigment cells that are situated in the basal layer of the epidermis and they produce a protein called melanin, a brown pigment which is in charge of the skin coloration as well as shielding the skin against the harmful effects of ultraviolet (UV) light by absorbing some potentially dangerous UV radiation. Nonetheless, it also comprises of DNA that are responsible for repairing enzymes that reverse UV damage. Melanocytes can convey melanin to diverse skin cells like keratinocytes through dendrites when stimulated by exposure to UV radiation and these cells help to strengthen the hair, nails, and the skin itself. Melanin production increases when the skin is exposed to the sun. This condition produces a tan a body's natural defence mechanism against sunburn.

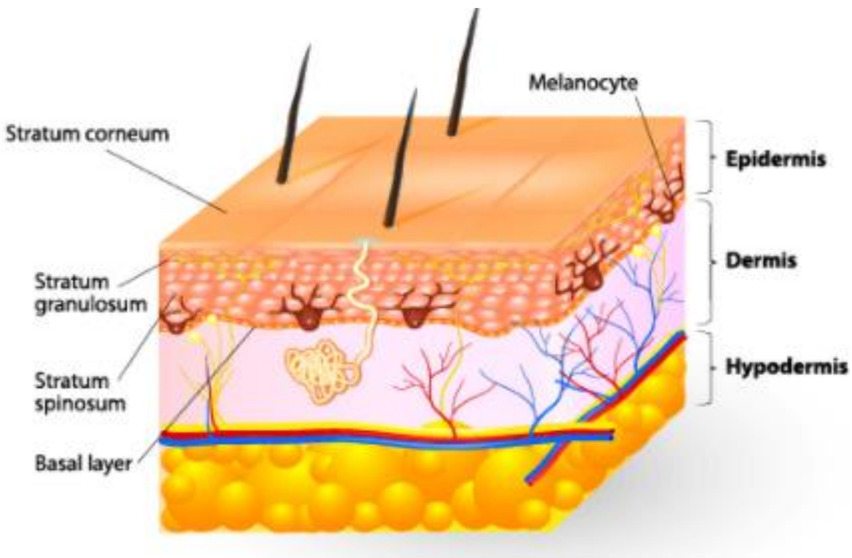


Fig 2. Layers of skin

2.3 The Skin Lesion

2.3.1 Benign skin lesion

Benign skin lesions may have non-melanocytic origins. Proliferation of melanocytes may lead to acquired benign melanocytic naevi. Melanocytic lesion can be cancerous or noncancerous which are primarily described by the words malignant and benign respectively. Also, Seborrhoeic keratosis and dermatofinroma are the most common benign non melanocytic lesions [13]].

2.2.2 Skin cancer

Melanoma is the prevalent type of all cancers, particularly in people with light colored skin who are mostly vulnerable to the sun. Based on the origin, skin cancer can be categorized into melanocytic and non-melanocytic. Basal cell carcinoma

(BCC) and squamous cell carcinoma (SCC) are the most common non-melanocytic skin cancers. The most common malignant melanocytic skin cancer is melanoma [28]. These skin cancer types are named after the skin cell in which the cancer develops. This duo, Basal as well as squamous cell carcinomas are often grouped together and often called common skin cancers.

Melanoma

Melanoma can become life-threatening within six weeks and can grow very quickly. This cancer can appear on that part of skin which is not normally exposed to the sun and it may be brown, black, blue, red or grey in color [32].This one is usually found under the fingernails and toenails, on the palms of the hands, and on the soles of the feet ,furthermore it is rare in people with dark skin. Melanoma is a malignant melanocytic lesion that can disseminate other areas of the body if untreated. It is life-threatening because of its metastasis behavior [13].

The dark pigment, melanin, which is responsible for the color of skin is made by melanocytes. It is less frequent but aggressive in contrast to non-melanocytic skin cancers like BCC, SCC and rare soft tissue sarcomas. Too much exposure to solar UV-B radiation is probably the major cause for the widespread increase in the incidence of melanomas of the skin. No other environmental factors show a consistent association with melanoma of the skin apart from exposure to solar radiation, Melanoma can come up in or near to a mole, but can also appear on skin that looks quite normal. They develop when the skin pigment cells (melanocytes) become cancerous and multiply in an uncontrolled way. Melanoma can appear on any part of the skin but they are most common in the body of men, and on the legs of women.

Melanoma is malignant tumor of melanocytes, there are specific patterns which may represent melanomas globally or even locally. A typical pigmented network, irregular streaks, and regression structures are local features that show the highest association with melanoma, followed by irregular blotches, blue-whitish veil and irregular dots. The local features represent grouped characteristics that appear in the lesion. Multicomponent pattern is a global feature that is most predictive for the diagnosis of melanoma, whereas the homogeneous, globular, starburst patterns and cobblestone are most predictive for the diagnosis of benign melanocytic lesions. On the contrary, typical pigmented network, regular blotches, regular dots and regular streaks are mostly associated with benign melanocytic lesions. This type of cancer can originate in any part of the body that contains melanocytes. These cells predominantly occur in skin, but are also found in other parts of the body, including the bowel and the eye.

2.4 Existing clinical skin cancer diagnostic methods

If skin cancer is diagnosed in its early stages, skin cancer is 90% treatable compared to 50% in late stages [47]. Due to the development of high-resolution and non-invasive imaging techniques, the accuracy of in-situ diagnosis of skin lesions has increased. The most common imaging techniques currently used for diagnosis of skin cancers are reflectance confocal microscopy, optical coherence tomography, ultrasound, and dermoscopy. Clinically in the past, most physicians checked the skin moles by naked eyes and clinical experience. False positive diagnosis is the major contributor of excessive treatment cost increases due to leading to excise an unnecessarily high number of benign lesions for biopsy and pathological examination. Biopsy is recommended if something suspicious is found while diagnosis. Especially, the lower diagnostic accuracy for melanoma is the major reason for over treatment or under treatment. However, high-resolution imaging techniques have great potential to improve diagnostic specificity, and thus, these techniques introduce a possibility of inducing a reduction in unnecessary excisions and related costs. Dermoscope could help dermatologists to assess and extract much more information from the skin lesion. Pattern analysis was the first dermoscopic procedure introduced for diagnosis of pigmented skin lesions and it has been later amended and polished by the International Dermoscopy Society (IDS). ABCD rule, the 7-point checklist (7PCL) and Menzies method are some methods that have been utilized previously. These methods endeavour to simplify the pattern investigation procedure by examining only a small subset of dermoscopic structures and produce a scoring system and this lowers their accuracy from the full system pattern analysis.

Reflectance confocal microscopy (RCM)

Confocal microscopy is a non-invasive imaging method that utilises a laser focused on a specific point on the skin and visualizes the cellular details of the skin in-vivo. Because cellular structures (cells, melanin, hemoglobin, etc.) have different refraction indexes, RCM can easily differentiate reflected light from the skin. However, RCM is the costliest among other skin imaging techniques.

Optical Coherence Tomography (OCT)

OCT can be used to image microscopic structures in-vivo and can distinguish healthy tissue from cancerous tissue. However, the OCT is incapable to visualize the subcellular elements as well as the membrane: it cannot detect the tumor in early stages. Additionally, without histological confirmation, the OCT cannot fully determine the diagnosis of melanoma. Thus, the OCT is not an advantageous way of melanoma diagnosis process.

Ultrasound

Ultrasound is one of the most common non-invasive procedures as it is versatile, pain-free, and has low risk. In this procedure, the skin morphology can be visualized by the ultrasound waves that return from the tissue. Even though ultrasound waves can reach to the deep skin layers and evaluate the tumor, the low resolution does not allow to distinguish skin lesions histomorphologically. Also, it does not catch tumors at early stages.

Dermoscopy

Dermoscopy, also known as epilumence microscopy (EM), is a non-invasive and inlive method that is very practical for early detection of malignant melanoma and other pigmented lesions. It allows users to capture the colors as well as subsurface structures of the skin to detect melanoma in early stages. According to the statistics of the literature, using dermoscopy can increase the accuracy of diagnosis between 5% and 30% depending on the type of skin lesion.

2.5 Diagnosis Methods of Skin Cancer

Visualizing skin lesions by any abovementioned imaging technique is not enough to distinguish malignant melanoma from benign melanoma. There is a need for reproducible diagnosis techniques that can be used by clinicians to understand the skin cancer types. There are four commonly accepted reproducible methods for the diagnosis of skin cancers especially melanoma. These are:

i) ABCD-E rule
ii) 7-point checklist
iii) Pattern analysis

Pattern Analysis

Pattern analysis is another method that is used to detect melanocytic lesions and to distinguish benign melanocytic lesions from malignant melanoma. This method is used to identify specific patterns of skin lesions that can be either global or local. Any diagnosis based on pattern analysis needs critical assessment of the dermoscopic structures (features) that are seen in a pigmented skin lesion, since many patterns have dermoscopic structures. The first thing to do is check if there is a pigmented structure or not. This analysis method is used to recognize specific patterns of skin lesions that can be either global or local. The local patterns are pigment network, dots, streaks, blue-whitish veil, regression structures, hypopigmentation, blotches, and vascular structures, which are also refer to benign melanocytic lesions. Also,some of the global patterns are reticular, globular, cobblestone, homogeneous, starburst, parallel, multicomponent, and nonspecific, which refer to benign melanocytic lesions.

ABCD rule

ABCD rule: This method was introduced in 1994 by Stolz et. al [35]. ABCDE stands for asymmetry, border, color, diameter, and evolving by time which are five dermoscopic criteria for semi-quantitative assessment of skin lesions. Melanomas are typically asymmetric with jagged edges and bigger than 6 mm. They usually have mixed colors along with changing size, color, shape, and bleeding. These criteria (except E) have their possible scores based on the look of the skin lesion (Table 1). These scores are multiplied by associated weight factors to yield a total dermoscopy score (TDS). It is a common feature extraction method, which helps dermatologists to recognize melanoma in its early stages. ABCD describes the clinical features of melanoma using parameters A (standing for Asymmetry), B (Border irregularity), C (Color) and D (Diameter) and these are stated as follows:

ABCD-E Rule:

Criteria	Possible Score	Description	Weight factor
Asymmetry	0-2	Asses contour, color and structures	1.3
Border	0-8	Abrupt ending of pigment pattern	0.1
Color	1-6	Presence of max colors (w-white, r-red, lb-lightbrown, db-dark-brown,bg-blue-gray, b-black)	0.5
Dermoscopic Structures	1-5	Presence of network, Structureless areas and dots	0.5

Asymmetry: In the event that a lesion is symmetric (value 0) then it is benign (non-cancerous). Also, for cancerous cases asymmetry in zero (value 1), or two orthogonal axes (value 2) are considered.

Border irregularity: The irregularity of a lesion indicates the existence of a cancer. To calculate the border, the lesion is divided into eight sections and the sharpest pattern will get the score of 1, its value ranges from 0 to 8 for the minimum and the maximum irregular borders respectively.

Colors: Most common cancerous skin lesion's pigmentations are not evenly distributed. There exist up to six known colors that could be easily be detected: black, dark brown, slate blue, red, light brown and white. Its value ranges from 0 to 6, a score of 1 for the presence of each of these colors.

Diameter: The diameter that is greater than 6mm are most likely to be melanoma than the small ones.

At the end, the Total Dermoscopy Score (TDS) based on the above four parameters, is computed as follows:

$$\text{TDS} = (1.3 * A) + (0.1 * B) + (0.5 * C) + (0.5 * D)$$

If the score is less than 4.75, then the lesion is benign, if it is between 4.75 and 5.45, then it's suspicious to melanoma and if the TDS is greater than 5.45, then it is considered to be melanoma.

7-point Checklist

The 7-point checklist assigns points to specific dermoscopic structures as per the checklist. It comprises of 3 most important features: gray-blue areas, atypical vascular pattern, a typical pigment network as well as 4 minor criteria: blotches, regression patterns, irregular dots and globules and streaks. When any of the most important features is detected in a melanocytic lesion, immediate help from health professionals is recommended. When there are minor features, it is advised to be monitored regularly. The minor criteria are worth 1 point each whereas the major is worth two. Finally, a total score is computed by summing the point value based on the presence of each criterion and if the score is greater than 3, then the lesion is classified as melanoma.

Chapter 3

Computer Aided Diagnosis system

Introduction

Computer aided diagnosis (CAD) system is basically a clinical decision support system, which assists doctors in the interpretation of medical images. CAD is utilized as a means of providing additional information to clinicians, who then come up with final decision as to the diagnosis of a patient. Its primary goal is to enhance the accuracy and consistency of clinician's diagnosis by reducing the false negative rate due to observational oversight, inter-observer and intra-observer variation. in CAD systems two types of general approaches are employed. The first one is to find the location of the lesions and the second is to quantify the features of an image of normal and/or abnormal patterns.

In general, the CAD system includes three basic components. The first is image processing which helps to enhance and extract the lesions by picking up the initial candidates of the lesions and suspicious patterns. The second is the quantification of image features such as the size, contrast, and shape of the candidates selected in the first step. Here it is important to find unique features that can distinguish reliably between a lesion and other normal anatomical structures. The third component is data processing which distinguishes between normal and abnormal patterns, based on the features obtained in the second step.

In overall CAD schemes described above, one of the main techniques is to extract the lesion region from the background and thus it has attracted a lot of efforts. The proposed method can process skin cancer images with blurred and irregular edges well and can achieve a better performance with blurred and irregular edges as compared with other state of the art segmentation methods.

Chapter 4

Related Work

4.1 Introduction

An automated system for detection and classification of Melanoma. There is a certain feature of these types of skin cancers, which can be extracted using the proper feature extraction algorithm [9]. Various algorithms such as segmentation and characterization are used for the classification of chaotic skin jungle from a macroscopic image. Segmentation of the skin lesion of the surrounding skin in dermoscopic images using the segmentation algorithm of the neural network. Various segmentation approaches were used to the dermoscopic images to segment the skin lesions and calculated with 3 different metrics, such as sensitivity, accuracy and border error. Segmentation performance shows that Neural Network based lesion segmentation has high sensitivity, accuracy and less border error.

A study on past and present technology for skin cancer detection are given in detail with their relevant tools. Then it goes on discussing briefly about features, advantages or disadvantages of each of them, discussed the mathematics initial required to process the image of skin cancer lesion using the proposed scheme. An automated method for melanoma diagnosis is applied on a set of dermoscopy images. Multilayer perceptron classifier to classify based on the extracted characteristics, the melanocytic navigator and the malignant melanoma [14].

4.2 Deep Learning

Deep learning is an intuitive process whose complexity of learning increases with the increase in the number of layers. Due to its high performance, it is regarded as a mature application for medical diagnostics [21]. In recent times, deep learning has contributed significantly for skin lesion classification problems [22-25]. However, limited data set creates tougher environment for the potential ground-breaking research in medical diagnostics with deep learning. One reason is dependency of the deep learning algorithm on training data size as it requires millions of parameters and profusion of labelled data to learn [26]. When deep learning model uses limited data to train, it uses large amount of its resources to train the model, creating overfitting issues. Overfitting issue refer to model's incapability to generalize on unseen data. A large number of researches has been done to overcome challenges imposed by limited data on the training of deep learning models. It includes techniques like augmentation [27], transfer learning [26] and ensemble of classifiers [28]. The following sections provide an overview of existing techniques and related works done in field of skin lesion classification

4.3 Generative models

In the recent times, generative algorithms involve variational autoencoders, networks able to map from image space to latent space and back, or autoregressive models, which take actions from the previous step as input to deliberate on the value of the next step. However, the application of adversarial training into generative modelling occasioned a considerable step towards a more powerful method of synthesizing new data.

Goodfellow et al., 2014 [10] introduced generative adversarial networks as a system of two neural networks, a generator and a discriminator, opposing one another. The former synthesizes images that match the data distribution which are then classified by the latter as either true or false. As the discriminator gets better at distinguishing the authenticity of the images, the generator is forced to enhance itself to be able to fool the discriminator, thus, slowly learning the structure of the data that passes through the network. Initially, both of them will show low effectiveness, the images generated will be essentially noise and the loss of the discriminator will be high. As the training advances, the results will start to resemble the data until the discriminator can no longer recognize real from fake. Given this mechanism of image generation, the set of available data can be further expanded, making the design and training of generative models for data augmentation a plausible choice. Moreover, in practice, increases in accuracy have been seen in several learning systems [15]

4.4 Generative Adversarial Networks

A generative adversarial network (GAN) is a machine learning architecture that incorporates two models, a generator and a discriminator, working against one another. As the names imply, the generative contribution lies on the former, whose purpose is to capture the data distribution, being then able to map from latent space to image space with the characteristics provided during the training process. The latter is responsible for estimating the probability that a sample came from training data rather than synthetic data. Therefore, since this framework corresponds to a zero-sum game, the generator intends to maximize the expectation of the discriminator making a mistake, thus being forced to slowly learn the distribution of the data as its counterpart acquires the capability of distinguishing fake samples from real ones.

An automated system for detection and classification of one of the skin three types of skin cancerous proposed here: Melanoma, Basal cell carcinoma, Squamous cell carcinoma. There is a certain feature of these types of skin cancers, which can be extracted using the proper feature extraction algorithm [16]. Various algorithms such as segmentation and characterization are used for the classification of chaotic skin jungle from a macroscopic image. A new system for characterizing digital images of skin lesions has been presented [17]. A scheme for automated detection of skin diseases by analysing the texture recognition approaches based on gray level co-occurrence matrix (GLCM) is discussed here. The characteristic features of the test and the reference images and analysed the skin diseases using texture analysis are extracted. Texture analysis is one of the fundamental aspects of human vision by which we differentiate between surfaces and objects [16].

Classification of Melanoma using the segmentation algorithm of the neural network. different segmentation techniques were used to the dermoscopic images to segment the skin lesions and calculated with 3 different metrics, such as sensitivity, border error and accuracy. Classification performance shows that Neural Network based lesion segmentation has high less border error, sensitivity and accuracy [18].

A study on past and present technology for skin cancer detection are given in detail with their relevant tools. Also, goes on to discuss briefly about features, advantages or disadvantages of each of them, explore the mathematics initial required to process the image of skin cancer lesion using the proposed scheme [19].An automated method for skin cancer diagnosis is applied on a set of dermoscopy images. Multilayer perceptron classifier to classify based on the extracted characteristics or to classify the gray-level co-occurrences matrix (GLCM) and the melanocytic navigator and the malignant melanoma [6].

4.4. Foundations of GANs: Adversarial training

Formally, the Generator and the Discriminator are represented by differentiable functions, such as neural networks, each with its own cost function. The two networks are trained by backpropagation by using the Discriminator's loss. The Discriminator strives to minimize the loss for both the real and the fake examples, while the Generator tries to maximize the Discriminator's loss for the fake examples it produces.

Importantly, the training dataset determines the kind of examples the Generator will learn to emulate. If, for instance, our goal is to produce realistic-looking images of cats, we would supply our GAN with a dataset of cat images [20].In more technical terms, the Generator's goal is to produce examples that capture the data distribution of the training dataset [21]. Recall that to a computer, an image is just a matrix of values: two-dimensional for grayscale and three-dimensional for color (RGB) images. When rendered onscreen, the pixel values within these matrices manifest all the visual elements of an image lines, edges, contours, and so forth. These values follow a complex distribution across each image in a dataset; after all, if no distribution is followed, an image will be no more than random noise. Object recognition models learn the patterns in images to discern an image's content. The Generator can be thought of as the reverse of the process: rather than recognizing these patterns, it learns to synthesize them.

4.5. Brief history of the DCGAN

Introduced in 2016 by Alec Radford, Luke Metz, and Soumith Chintala, DCGAN marked one of the most important early innovations in GANs since the technique's inception two years earlier. [10]This was not the first time a group of researchers tried harnessing ConvNets for use in GANs, but it was the first time they succeeded at incorporating ConvNets directly into a full-scale GAN model.

The use of ConvNets exacerbates many of the difficulties plaguing GAN training, including instability and gradient saturation. Indeed, these challenges proved so daunting that some researchers resorted to alternative approaches, such as the LAPGAN, which uses a cascade of convolutional networks within a Laplacian pyramid, with a separate ConvNet being trained at each level using the GAN framework.[2] If none of this makes sense to you, don't worry. Superseded by superior methods, LAPGAN has been largely relegated to the dustbin of history, so it is not important to understand its internals.

Although inelegant, complex, and computationally taxing, LAPGAN yielded the highest-quality images to date at the time of its publication, with fourfold improvement over the original GAN (40% versus 10% of generated images mistaken for real by human evaluators). As such, LAPGAN demonstrated the enormous potential of marrying GANs with ConvNets.

With DCGAN, Radford and his collaborators introduced techniques and optimizations that allowed ConvNets to scale up to the full GAN framework without the need to modify the underlying GAN architecture and without reducing GAN to a subroutine of a more complex model framework, like LAPGAN. One of the key techniques Radford et al. used is batch normalization, which helps stabilize the training process by normalizing inputs at each layer where it is applied. Let's take a closer look at what batch normalization is and how it works.
In the previous chapter, we implemented a GAN whose Generator and Discriminator were simple feed-forward neural networks with a single hidden layer. Despite this simplicity, many of the images of handwritten digits that the GAN's Generator produced after being fully trained were remarkably convincing. Even the ones that were not recognizable as human-written numerals had many of the hallmarks of handwritten symbols, such as discernible line edges and shapes especially when compared to the random noise used as the Generator's raw input.

Imagine what we could accomplish with more powerful network architecture. In this chapter, we will do just that: instead of simple two-layer feed-forward networks, both our Generator and Discriminator will be implemented as convolutional neural networks (CNNs, or ConvNets). The resulting GAN architecture is known as Deep Convolutional GAN.

Chapter 5

METHOD

5.1 Introduction

In this chapter, the datasets implemented to train and test the network are introduced. This is succeeded by a concise description of the architecture of the network, the training process, and an inspiration for the parameters utilized. In conclusion the discussion of measurements used to assess the network's performance.

5.2 Dataset

We have trained our Deep Convolutional Generative Adversarial Networks (DCGAN) framework on skin cancer dataset 3,597 images from Kaggle [21].Also, before training our model, we incorporated some image processing techniques. The primary objective of processing images is usually to enhance the common image characteristics like picture quality and features and thereby suppressing undesired distortions and accommodating extra examination.

5.2.1 Image processing

The initial step towards designing an effective image segmentation approach is image acquisition. In most cases, after this image acquisition process, the model will contain noisy images that might not be good enough for image analysis and segmentation. Thus, enhancing the brightness and contrast of the acquired images becomes more essential in improving the overall performance of our model. The main objective of our skin lesion segmentation technique is to locate lesions and their boundaries in the image dataset and classify them. Also, after the extraction of each segment, the next operation will be to extract a category of substantial features such as shape, color, and texture. Ultimately, each segmented lesion after training is then classified into one of the categories of significant classes under the set of those extracted features [18].

The pre-processing stage is responsible for detecting and reducing the number of artifacts from images, with the purpose of enhancing their quality. Therefore, this step is mandatory, since as aforementioned that the dermoscopic images contain several types of noise (hairs and reflection artifacts), which is covering most of the lesion areas. Incorrect segmentation of pigmented lesions can be obtained if hairs covering the images and lightening reflection are not detected and removed. Therefore, we used the same algorithm presented in Chapter 3. Section 3.3.1 to eliminate all these issues and obtain clearer images.

5.2.2 Image Enhancement

Medical images occurred in most radiological applications are visually examined by a physician. The purpose of image enhancement methods is to process a picked image for better contrast and visibility of features of interest for visual examination as well as subsequent computer-aided analysis and diagnoses. As described in [236] different medical imaging modalities provide specific characteristics information about internal organs or biological skins. Image contrast and visibility of the features of interest depend on the imaging modality as well as the anatomical regions. Image enhancement is one of the steps in our image processing techniques to make the result of our images appealing and clear for feature extraction. The essential parts of our application constitute:

- Highlighting edges.
- Sharpening an out-of-focus image.
- Eliminating noise.
- Improving image contrast.

in this study, we have used a bilateral filter to enhance our skin lesion images [18].Commonly Gaussian Blur technique [18] is exploited to reduce the amount of noise in an image. Nevertheless, this method presupposes pixels nearest to the middle pixel would have to be closest to the true value of that pixel, so they will sway the averaged value of the centre pixel greater than pixels further away, which tend to blur edges. In this work, we want the edges for the benefit of the model to get the circumference of the lesion to perform better. We suggested the exploitation of a bilateral filter that is highly efficient at removing noise whilst conserving the edges.

In addition, we have employed gamma-correction under the name of the Power Law Transform [9] to transform our image data to the desired texture. Primarily, the intensities of our image pixels need to be adjusted from the pixel range of 0 - 255 to 0 - 1.0. Furthermore, to get the result of the corrected image we implement succeeding formula:

$$\boldsymbol{O} = \boldsymbol{I}^{(\mathbf{1}/\boldsymbol{G})}$$

In this formula, **I** represent our input image and ***G*** denotes the gamma value to be adjusted. In addition to that, **O** represent our resulting image and after gamma corrections it is then restored to the range **0 - 255.** In this instance, we tried ***G* = 1.0** first, and then later implemented ***G* = 1.5** and then our image data started to illuminate up and we witnessed more detail, which is enough value to attain a decent looking corrected image as the following.

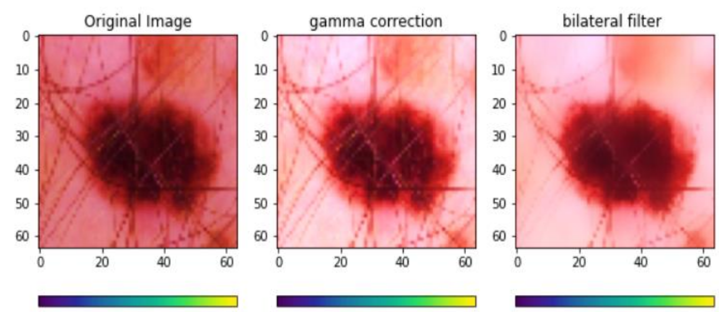


Fig. 5: Example of images enhanced using gamma correction and bilateral filter. We further cropped the images into 64 × 64 pixels.

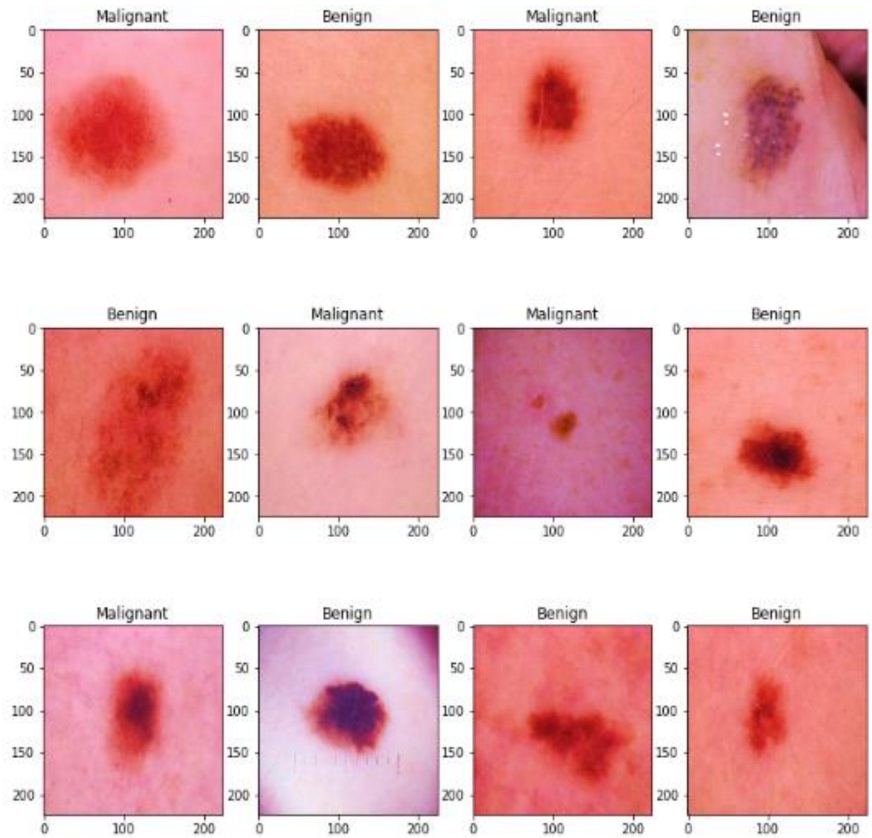


Fig. 6: Example of images from the skin cancer dataset.

5.2.3 Data argumentation

Considering that our dataset is not that big, data augmentation is quite handy to increase our dataset. Data argumentation is also one way to fight overfitting given the fact that our samples are most likely to be correlated when the dataset is small, which leads to overfitting. Overfitting [5] takes place when a model is exposed to a too-small set of data and understands patterns that do not necessarily generalize to a new set of data. Our principal objective for fighting overfitting is the entropic capacity of our model, for this reason, we incorporated this method to increase the size of our dataset by transforming existing images into a new form of the dataset using some transformation methods, such as rotation, shear, and flip as indicated in **Fig.6**.

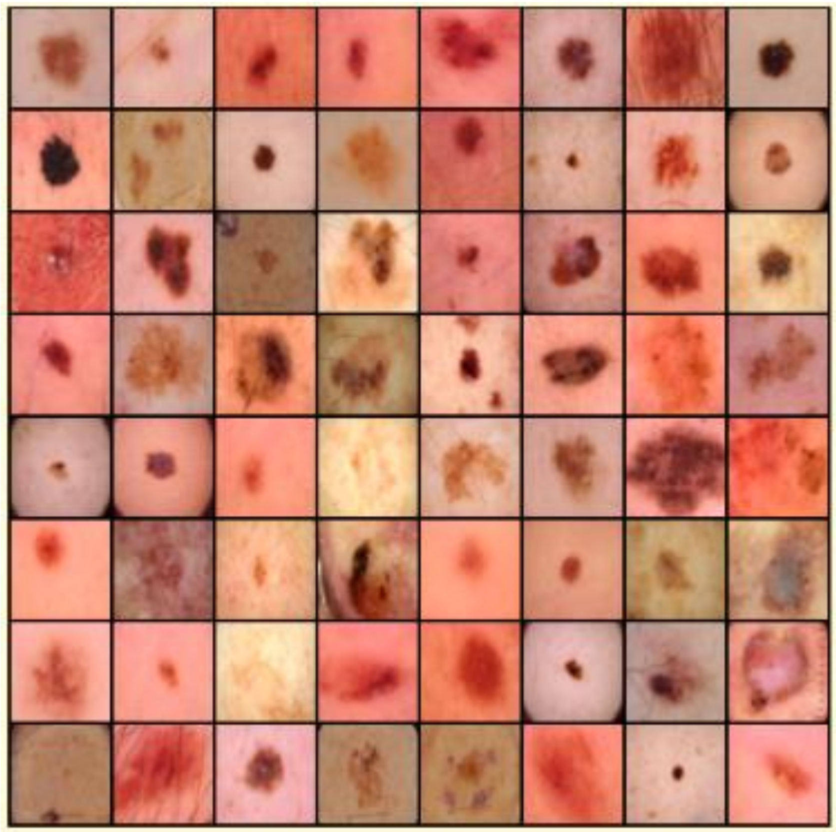


Fig. 6: Example of images from skin cancer dataset after argumentation.

5.3. Image classification

The classification of images by computer has been making strides since the first algorithms produced aimed at managing this classification problem. Neural networks surpassed the previous designs and, lately, with the recent schemes in the field of DL, the examination of image data has in recent times experienced major improvements in proficiencies and methodologies applied to different cases. The different areas of supervised learning have been approaching problems considering these breakthroughs. There are various methods used on increasing the quantity of data available to use, some of which consist on modifying the already accessible data. However, with some these techniques one can only produce a limited set of alternative data. In some cases, especially in critical areas such as medicine, acquiring as much data as possible is a primary objective, as the accuracy of the classifier is of crucial concern, seeing that mistakes in the field can induce severe consequences. Here is when the use of generative models can be convenient.

DCGAN

A DCGAN is a direct extension of the GAN described above, except that it explicitly uses convolutional and convolutional-transpose layers in the discriminator and generator, respectively. It was first described by Radford et. al. in the paper Unsupervised Representation Learning with Deep Convolutional Generative Adversarial Networks [4]. The discriminator is made up of strided convolution layers, batch norm layers, and LeakyReLU activations. The input is a 3x64x64 input image and the output is a scalar probability that the input is from the real data distribution. The generator is comprised of convolutional-transpose layers, batch norm layers, and ReLU activations. The input is a latent vector, z, that is drawn from a standard normal distribution and the output is a 3x64x64 RGB image. The strided conv-transpose layers allow the latent vector to be transformed into a volume with the same shape as an image. In the paper, the authors also give some tips about how to setup the optimizers, how to calculate the loss functions, and how to initialize the model weights, all of which will be explained in the coming sections.

5.4 DCGAN specifications

DCGAN implemented with TensorFlow, was used during the experimentation. The discriminator had two convolutional layers succeeded by twin fully connected layers. Batch normalization was used in the second and third layer. Furthermore, the activation was LeakyReLU on all layers except the last one which was Sigmoid. The generator had twin fully connected layers followed by twin "deconvolution" layers, here deconvolution means the transpose of 2-D convolution. Batch normalization was used in all layers expect the last one. The first three layers used ReLU activation while the fourth layer used sigmoid. Both the discriminator and the generator had a 5x5 filters with a stride of 2. Weights in convolutional layers were initialized with a truncated normal distribution initializer with a standard deviation of 0.02, all other layers used a random normal initializer with a standard deviation of 0.02. All biases were initialized to 0.1 The decay for the moving average for the batch normalizations was set to 0.9, the epsilon was set to 10.5. Every network used ADAM optimizer with the momentum term 1 set to 0.5 and the learning set to 0.0002. Additionally, the loss functions were the sigmoid cross entropy with logits. The slope of the leak was set to 0.2, in the LeakyReLU activation, Lastly, the training process was balanced by making two training steps for the generator for each training step made for the discriminator. Most of the configurations were adopted both from the DCGAN paper and from implementations of DCGANs by its authors found in GitHub [20].

5.5 Details of DCGAN architecture

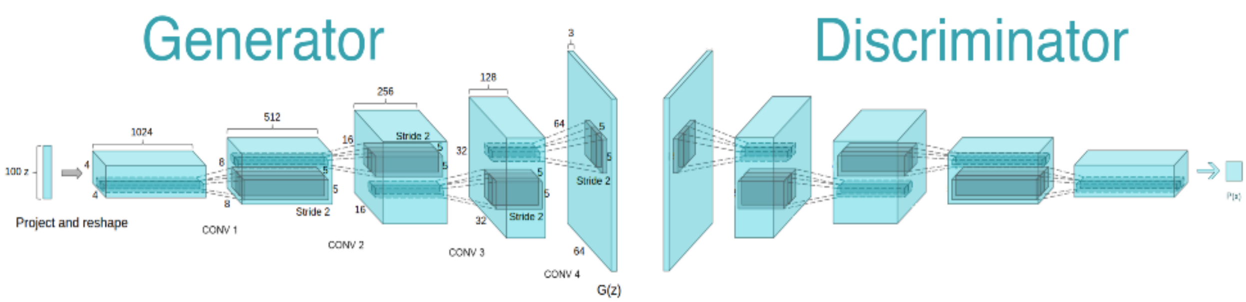


Fig. 3: DCGAN framework employed on LSUN scene simulation [4].

Deep Convolutional GAN training process is built by the recurrence of the following efforts:

1) A collection of image data *x* is exploited to train network ***D*, **the Discriminator**.**
2) The generative network produces satisfactory image depictions or " realistic " images.

Eventually, the discriminator ***D*** is refreshed in accordance with produced images. The goal of this procedure is for the generator ***G*** to produce images that are gradually more indistinguishable from the real images by incorporating a backpropagation and dropout algorithms [17] after repeated iterations, as Illustrated by **Fig 4**.

The design of DCGAN in this work is in reference to the code from a publicly accessible repository [20]. This code was scripted to train a DCGAN model on the CIFAR-10 dataset [7].We have amended this code to accomplish much resemblance as possible to the DCGAN framework stated within the preceding paragraph.

This necessitated building the appropriate code for our input size as well as modifying several appropriate filters present in the convolutional layers. The trained model design is indicated in **Fig. 3.**We have ensured that we employ deconvolutions alas transposed convolutions in generator and stridden convolutions in discriminator. Notably Batch Normalization was applied and ReLU/LeakyReLU activation functions were brought into play as suggested in the guidelines.

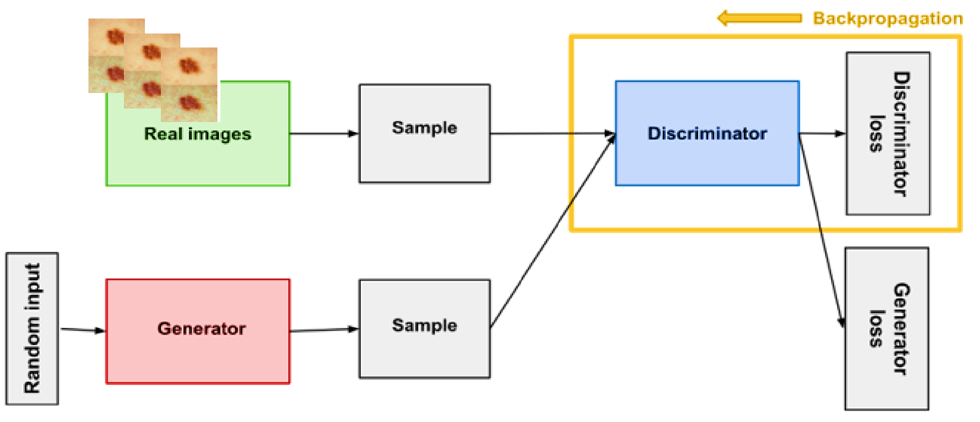


Fig. 4: Illustration of backpropagation implemented on Discriminator ***D*.**

In a similar case of the Deep Convolutional GAN article [9], solely transformation process of the images was just resizing them to range of tanh activation function [−1, 1]. This design was trained using mini-batch size 128. Additionally, Adam optimizing algorithm was incorporated applying 0.0002 as the learning rate and 0.2 as the momentum $\boldsymbol{\beta_1}$. The incline of the leak in the LeakyReLU was fixed to 0.2. The entire weights were initialized by default settings. In the present case, the noise $\mathbf{z}$ was taken from a standard normal distribution. The realization of this undertaking is performed using Keras in python anaconda development application software.

5.5.1 Generator definition

In this work, the deconvolution neural network of our generator is put into operation by invoking conv2d_transpose method from the TensorFlow library to carry out weight multiplication as well as executing bias addition using the bias_add method. Furthermore, in order to carry out weight multiplication as well as executing bias addition, the convolution neural network in the discriminator also invoked the conv2d method in the TensorFlow library to accomplish these two functions.

We constructed our generator addressing the needs of the DCGAN framework, additionally we have fixed our OUTPUT_SIZE to 64 since our ultimate outcome is expected to be 64 × 64. The step of movement of the deconvolution is set to 2, and among all, each output augments fourfold than the input, so that we can get the output size of each layer were 32 ×32, 16 × 16,8 × 8 and 4× 4 accordingly.

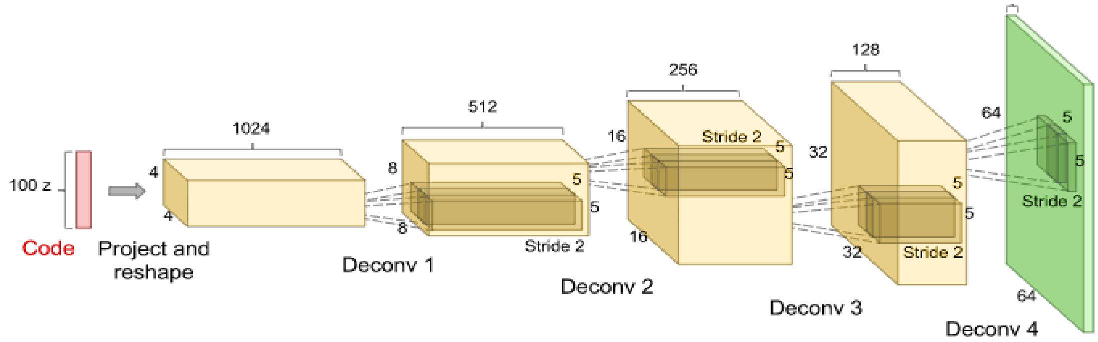


Fig. 7. Generator, here the input is a random normal vector that passes through deconvolution stacks and outputs an image.

The BATCH_SIZE and GF is set to 64 respectively, additionally the number of feature maps is set to 512, 256, 128, 64 accordingly. Lastly, the structure of the generator is portrayed in **Fig. 7**.

5.5.2 Discriminator definition

The discriminator is a feed-forward neural network with five layers, including an input and an output layer, and three dense layers, and in this architecture, spatial pooling layers are absent. We plugged the input into the convolution layer. More so, the moving step of the convolution kernel is set to 2, furthermore the output reduces to a quarter of the original ones after processing of convolution. With reference to that, the convolution layer output size becomes 32 ×32, 16 × 16, 8 × 8, 4× 4 respectively and also the number of feature maps were 64, 128, 256, 512 respectively as well. The final structure of the discriminator is illustrated in **Fig. 8.**

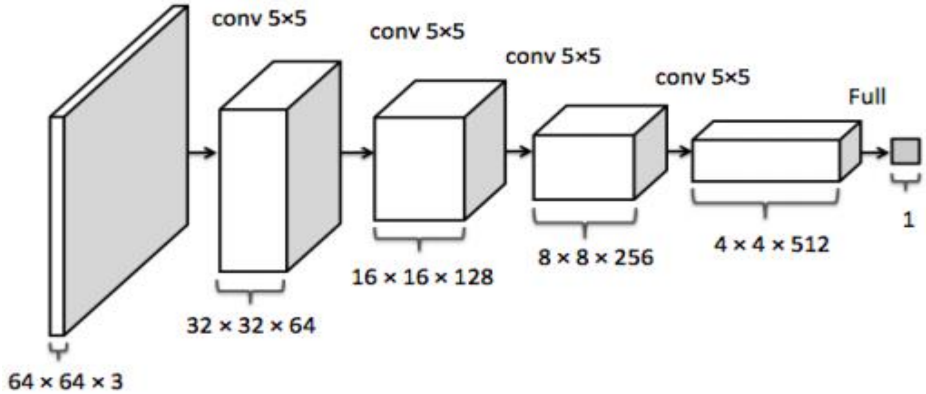


Fig. 8 Discriminator

5.6 Model building

Building an ML algorithm or model during the training phase is typically approached in the same manner: data are fed to the model; a cost function is established and the model will adapt by changing its internal parameters to optimize the cost. Often, the aim is to the maximize the likelihood that the established model gives rise to the presented data (unsupervised) or the likelihood of the model mapping the given inputs towards the target outputs (supervised). In regard to supervised learning, this can be translated into a minimization of the negative log-likelihood as cost function. Alternatively, another popular optimization procedure is the least-mean square rule, which targets the minimization of the sum of squared errors between model outputs and targets.

5.7 Definition of training

After data collection and image preprocessing, we pass the dataset into our model for training after data argumentation. In this work, we called up our generative neural network to produce data during training process and we have also defined our activation and optimization functions. In this study, we have incorporated the sigmoid activation function.

Furthermore, we managed to compute the loss value by invoking the tf.nn.sigmoid_cross_entropy_with_logits() from TensorFlow library during training. With regard to discriminators, the anticipation is that real input needs to be close to **1** moreover the outcome preceding from the generative model is expected to be **0**. With regard to the generator network, the discriminator should produce a prediction of **1** for its generated images. The **d_loss_real** denotes the cross-entropy resulting from the discriminator's real data input and the expected result. Furthermore, **1**.**D_loss_fake** represents the cross entropy arising from the difference between the originated data from the generator, the discriminator and the expected result. **0**.**D_loss** connotes to the sum of **d_loss_real** and **d_loss_fake**. Moreso,**G_loss** refers to the cross-entropy arising from the difference between the result of generated data of the generator input the discriminator.Furthermore,The elected optimization algorithm in this situation is the Adam Optimizer [22], which accommodates the non-convex optimization characteristics suitable for modern deep learning. With reference to that, there is no need to manually modify the learning rate and additional hyperparameters. The discriminator employs a cross-entropy loss function based on number of inputs that were accurately classified as real and number of inputs precisely categorized as generated during training.

5.7.1 Training plan

The training of a generative adversarial network proceeds typically accordance with the following arrangements:

1.A group of indiscriminate inputs is sampled from a predetermined latent space, for example, regular distribution, and seeded to the generator, who generates an image for each input.

2.A sample images from the real dataset is channelled to the discriminator, succeeded by the batch of synthetic images. These images are labelled as true and false, accordingly.

3.Backpropagation is applied such that it refreshes the parameters of the network of the discriminator, with the generator fixed.

4.The discriminator is fixed and the generator is trained by feeding synthetic images labelled as real to the network.

5.The training is stopped if completed, otherwise back to step 1.
As training make headway, if it is stable, both the generator and the discriminator should become more powerful, helping one another improve until the discriminator can no longer tell real from fake.

5.7.2 Major complexities of the training process

The major complexities when training GAN networks spring from the fact that they are a complex system composed of two entities competing against each other. For that reason, it is certain that regulating the training of generative models requires certain carefulness.

Since there are two models involved in a GAN, this practice is not only more complex in a directly proportional manner, but also there needs to be balance between both networks .In the training process of an elementary classification model the major exercise, fundamentally, is to design the architecture of the network and to proceed with the tuning of the hyperparameters and the optimization applied.

The instability in the training of a generative model is usually caused by one network overpowering the other. If the discriminator is learning significantly faster than its counterpart is, it will begin to classify all generated samples as fake due to the slightest differences, thus, the generator can't learn as the discriminator error is too small. Contrarily, if the generator is too strong it will persistently exploit weaknesses in the discriminator that lead to false positives, therefore, not improving in representing the distribution of the real data. It is due to this fact that having a similar number of parameters in both networks helps the stability of the training process. If the generator is trained extensively, it will converge to find the optimal images that fool the discriminator the most.

5.7.3 Conflicting objectives

The Discriminator's goal is to be as accurate as possible. For the real examples x, D(x) seeks to be as close as possible to 1 (label for the positive class). For fake examples x, D(x) strives to be as close as possible to 0 (label for the negative class).

The Generator's goal is the opposite. It seeks to fool the Discriminator by producing fake examples x that are indistinguishable from the real data in the training dataset. Mathematically, the Generator strives to produce fake examples x such that D(x) is as close to 1 as possible.

Chapter 6

Regularization

6.1 Introduction

To prevent overfitting, one path of action lies in controlling the complexity of the model. This is done by extending the cost function (E) used to optimize the model to include a penalty term for model complexity. The amount of regularization in the modified cost-function is determined by a hyperparameters. Typical choices for the regularization term may target the mapping function y(x) through a penalization of e.g. high curvature, or the weights themselves, by controlling the L1 or L2 norm of the weights. The latter approach is motivated by the tendency of weights to increase as the model starts to overfit.

6.2 Overfitting and underfitting

The aim of learning is to build a model on the training set that also performs well on the test set. The extent to which a trained model performs well on unseen data is known as the generalization capability of the model. Given that the model parameters are fitted on a training set of limited size, two challenges can occur. If the model complexity is too high, the problem is likely underdefined, leading to a model that is perfectly fitted to the training data, but does not capture the necessary trends to extend to new test data, known as overfitting. Contrarily, in the case of underfitting, the model capacity might be too low to perform well on even the training set. Thus, for appropriate model design, a trade-off is required between model bias (underfitting leads to a high bias) and model variance (overfitting results in high variance) [16]. This aims for a model that is complex enough to capture underlying trends in the training data, but does not fit to noise and specifics of this data.

6.3 Prevent overfitting

In light of the large amounts of weight parameters that characterize a feedforward neural network with a considerable number of concealed units, it seems clear that preventing a feedforward neural network from overfitting is a critical factor. The most obvious way to prevent overfitting, is to gather more data or otherwise opt for the simplest model that is capable of capturing trends in the available data (i.e. Occam's razor), which will generally entail a reduction in the number of hidden units. Furthermore, regularization, as applied in many machine learning applications, can be used to accomplish this, e.g. through penalizing the L1- or L2-norm of the weights. Another option is to exploit the iterative training process of the neural network. By evaluating the network on a validation set after each training iteration, the start of overfitting can be visualized as the point where validation error starts to increase regardless of a continuing decreasing training error. The training process can thus be halted at the critical point with lowest validation error. Overfitting can also be delayed through data augmentation, which performs operations on the data (e.g. translations, rotations, color modification, noise addition) to simulate a larger dataset. Yet another path forward targets the complexity of this model's architecture. Throughout this training operation of this network, the weights of the respective hidden units are optimized to reduce the output error in light of what the other units are doing. This can consequently lead to co-adaptation of the units, where they will rely on the activities of one another to optimize performance. It is natural that this optimization will not extend to the test set. The technique of dropout [14] aims to reduce or avoid as much as possible co-adaptation by making the presence of other units unreliable. This is achieved through stochastically dropping some hidden units at each iteration and training the net as such. It is important to remark that these are merely some of the most popular techniques in the battle against overfitting. For more information on the many other mechanisms, we refer to [14].

6.4 Feedforward neural networks for object recognition

Feedforward neural networks may be regarded as concise worldwide function approximators: architectures with satisfactory concealed units can be trained via gradient descent/backpropagation to approximate any function among the input and output layers. Applying such deep learning techniques to object recognition aims to eliminate the challenging feature-engineering task of machine learning.

There are however limitations to the performance of feedforward neural networks for object recognition on images.

The primary concern is the ignorance of feedforward neural networks to the character of images, which contain locally-grouped 2D information and recurring patterns at different locations. Furthermore, the sensitivity of the feedforward neural nets to translations, scaling and local distortions of the input requires the need for strong pre-processing to standardize the inputs. Both aspects thus stress the importance of incorporating this prior knowledge about the nature of object recognition in the algorithms. A final concern is the dimensionality of an input image, which generally contains a high number of pixels. Applying a first fully-connected layer of a feedforward neural network to all pixels would result in a high number of weights at this layer, thus resulting in a high-dimensional problem.

6.5 Batch Normalization

Batch Normalization is an approach that alleviates the impact of unsteady gradients within deep neural networks. Batch Normalization present an additional layer to the neural network that carry out some operations on the inputs from the preceding layer. This approach has a profitable effect on the gradient flow through the network, by diminishing the dependence of gradients on the scale of the parameters. Furthermore, this makes it possible for the use of much higher learning rates without the risk of divergence. Sometimes weight initialisation might be difficult, particularly when establishing deeper networks. Batch normalisation helps diminish the sensitivity to the initial starting weights. Another measure is Inception score, proposed by Salimans et al. [15], based on the assumption that a good generative model should be able to generate meaningful objects. Batch normalisation adds a little noise to your network, and in some cases, (e.g. Inception modules) it has been shown to work as well as dropout.

Chapter 7

Implementation

7.1 Introduction

The primary objective of this study is to design and implement a DCGAN network which is able to sustain a stable training and to synthesize peculiar images with comparable quality to original ones.

7.2 Programming language and framework

Python is used as programming language throughout this work. For the implementation of the neural networks, the Keras library [19] is used because it is highly suitable for handling neural models. The Keras backend is chosen to be TensorFlow [149], which offers the high-performance numerical computations. The entirety can run on either CPU or GPU and is rapidly becoming a favourite in industry and research.

7.3 Experiments and hardware

The pretrained neural networks were loaded from the Keras Applications library and all experiments concerning finetuning and training of neural networks are run on windows 10 GeForce GTX 770 GPU (with 3.64 GiB of free memory).

2.4 Hyperparameters

significant degree of the hyperparameters were fixed to their default values. The exceptional situations where: the batch size, training batch size, testing percentage, learning rate, and validation. The learning rate was set from the default 0.001 to 0.0002 and the momentum for Adam optimization algorithm from 0.9 to 0.5, in trying to reduce the instability issues related to GAN models. Moreover, at each iteration in the course of the training process, the weights of the discriminative and generative network are updated to balance the loss between them. We set the training batch size to its default 100 in the second stage of training, nonetheless, in the initial stage it was fixed to 10 given that there were only a small number of training images. ultimately, the validation batch size was set to include all images in the validation set.

Chapter 8

Results

8.1 Produced images

The adversarial network utilizes random noise as its input and outputs the ultimate prediction of the discriminator on the produced images. By adjusting the noise vector, we can get some profound knowledge of how the generator operates and discerns which noise vector results in our desired class. In this case, we discover by trying multiple noise vectors. The more we tried the output was getting only better at producing more abstract and distinct background colours with no white spaces. However, in some projects it was not certainly the case, for example, the sample produced from CIFAR-10 [8] produced more white spaces which affected the quality of the generated images.

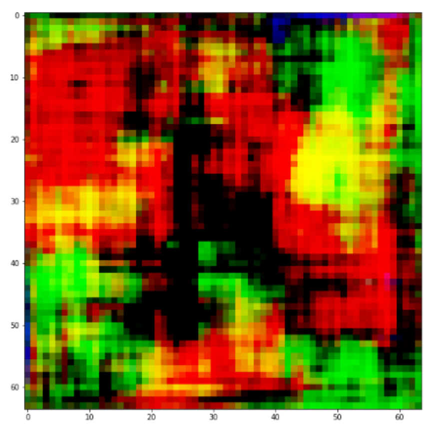
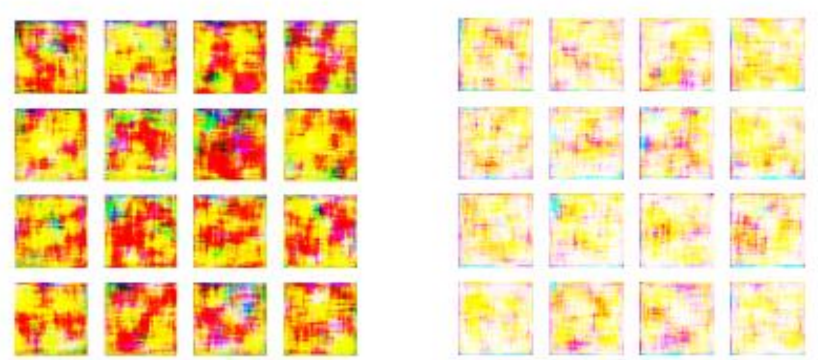


Fig .9. Random noise vector sample as input to the generator.

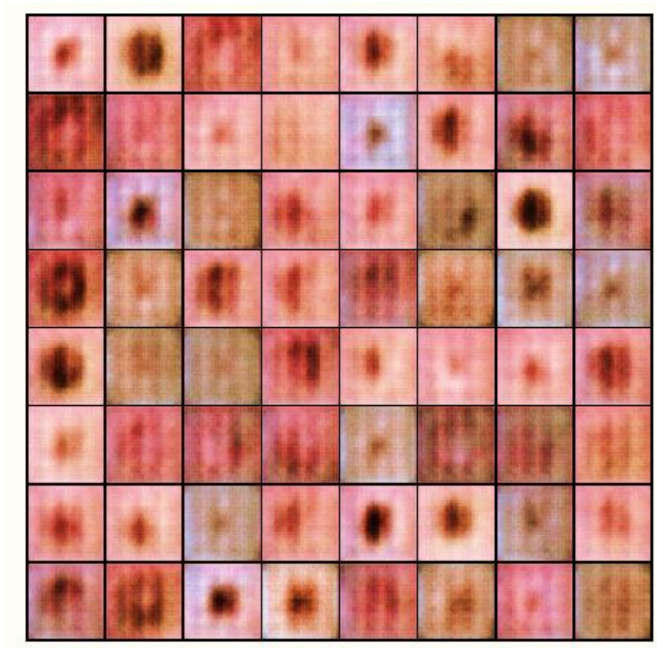
The following suggests different depictions of generations from the generator at different loop variations. In coming up with the results we have incorporated a great deal of tuning to get it running. We tried numerous and different setups and observing the results while tweaking different components such as the hyperparameters, loss calculators, optimizers, learning rate, and activators. It was the best way to enhance our understanding of the algorithm parameters before we got the desirable results.

The examples of images produced after several iterations of training are exhibited in **Fig. 10**. It is significant to look at plots of these generated images at each point to enable us to see the progression in our generated images. At an early stage of the training, the generative model images are of low quality with a great deal of noise, and we can see that the generator has learned to generate a few delicate features in brown texture. The model begins to generate very conceivable lesions with repeated noise textures after 100 epochs. The generated images after 200 epochs are not significantly different, but we can visibly start to detect lesion edges. We observe that in each step there is a smooth transition in resolution, the image quality is enhanced, permitting the model to fill in more structure and detail to depict the lesion of our desired class.

The majority of generative adversarial network (GAN) architectures use 100 as their input shapes, so initially, we had used the same but when we later amended it to 128 and it made some improvements to our results. We have utilized the trained generator to create authentic images based on the random sample noise depicted in **Fig.9**.



```
[93/100][0/21]  Loss_D: 0.5317  Loss_G: 3.1113  D(x): 0.7060   D(G(z)): 0.1308 / 0.0579
[94/100][0/21]  Loss_D: 0.7066  Loss_G: 1.9544  D(x): 0.7119   D(G(z)): 0.2684 / 0.1825
[95/100][0/21]  Loss_D: 1.3299  Loss_G: 1.1414  D(x): 0.3269   D(G(z)): 0.0627 / 0.3752
[96/100][0/21]  Loss_D: 0.9890  Loss_G: 4.1595  D(x): 0.9531   D(G(z)): 0.5581 / 0.0237
[97/100][0/21]  Loss_D: 1.6369  Loss_G: 3.6667  D(x): 0.9295   D(G(z)): 0.7531 / 0.0439
[98/100][0/21]  Loss_D: 1.1217  Loss_G: 1.0361  D(x): 0.4049   D(G(z)): 0.0678 / 0.4618
```



```
[0/200][0/21]   Loss_D: 1.9786  Loss_G: 5.5815  D(x): 0.6111    D(G(z)): 0.6765 / 0.0075
[1/200][0/21]   Loss_D: 0.2901  Loss_G: 17.7125 D(x): 0.8354    D(G(z)): 0.0000 / 0.0000
[2/200][0/21]   Loss_D: 2.1784  Loss_G: 24.1102 D(x): 0.9959    D(G(z)): 0.8479 / 0.0000
[3/200][0/21]   Loss_D: 2.8125  Loss_G: 3.3857  D(x): 0.1649    D(G(z)): 0.0005 / 0.1066
[4/200][0/21]   Loss_D: 0.2417  Loss_G: 5.6802  D(x): 0.8284    D(G(z)): 0.0091 / 0.0040
[5/200][0/21]   Loss_D: 0.0910  Loss_G: 6.7097  D(x): 0.9292    D(G(z)): 0.0097 / 0.0020
```

Fig. 10: Generated skin cancer images after 200 epochs of training.

Fig. 11: Generated skin cancer images after 1000 epochs of training.

Our proposed model was knowledgeable to produce images that are closely similar to synthetic pigmented lesions. The samples produced after several iterations of training are exhibited in **Fig. 11**. Moreover, it is interesting to note the model was able to give a fairly reasonable deconvolution performance that is even better than those of models trained with labels such as in MNIST [9].

We demonstrated that an unsupervised deep convolution GAN coached on a enormous skin lesion dataset can also learn a considerable number of characteristics that are interesting. We have employed a bilateral filter to enhance our image data and it retained more details to improve the quality of rendered images to achievable classification accuracies. However, after examining closely into the results of the resolution of our images, we observe that the completed images are not highly accurate compared with the pictures. This is in reference to the fact that the initial images have very few pixels in the initial phase. This suggests that if we were to train our model on higher resolution images it would have achieved a better performance. Data augmentation contribute to classification optimizations mostly, however not in a coherent manner. Furthermore, if a model can perform reliably on augmented data, it can be a sign of efficiency, if we are to compare with the training images of MNIST, for example, digit ‘9’ after augmentation may yield to a different classification result

8.2 Loss in Training

Below is the plot of the training losses for the Generator **G** and Discriminator **D** put on record after each iteration. Preferably, the generator should receive enormous random noise as its input sooner in the training because it needs to learn how to generate authentic data. The discriminator on the contrary does not always acquire large samples early on, because it may easily distinguish real and fake images. In addition, during training, the generator and discriminator also may face the risk of overpowering each other. It has been observed in fig 12 that if the generator becomes too accurate, it will tenaciously harness shortcomings in the discriminator which then leads to undesirable results, whereas if the discriminator becomes too accurate, it will return values that are close to 0 or 1.

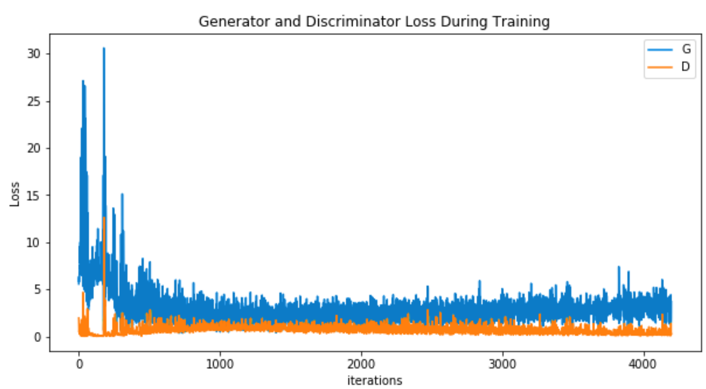


Fig 12. Training loss

To train correctly, we had to make sure that the generator and discriminator are on a similar level throughout the training process. During the experiments, it can be noticed from the figure 12, that while the discriminator continues to have a lower loss, the generator managed to overwhelm the discriminator and produced a fair result. Our generator was proficient enough to trick the discriminator thus proving that the discriminator was not able to extract the finer detail features in the skin lesion image data during the training process. This can entail the need to increase our dataset to allow our discriminator to learn more during the training process.

8.3 Difficulties and Shortcomings

The motivation behind this work is to assess the potential of deep learning Techniques in skin cancer classification. Nevertheless, it is not easy to draw overall conclusions concerning the performance of these deep learning techniques. The magnitude of this Thesis is only confined to evaluating the feasibility of using such deep learning technique, and not its actual implementation as an optimized and practical solution.

Moreover, the DCGAN might need slightly more fine-tuning to ripe a better return. Therefore, a more exhaustive hyper-parameter tuning can be utilized for selecting the best-performed hyperparameter combinations and several network hyperparameters.

Despite, the improvements of the GAN models in recent years, there are still some difficulties involved, such as the accurate segmentation of lesions and instability issues during the classification process of these lesions into malignant and benign. Also, the extraction of the most distinctive set of features portraying the relevant features separating the lesions into benign and malignant skin cancer.

The constraints with this study was mainly to build a proper Deep Convolutional Generative Adversarial Network (DCGAN) and make it generate high quality images that are much like to the synthetic real samples. Generally, deep learning models have great deal of model parameters as well as a plenty of hyper-parameters to be adjusted and we had to be very careful in tuning these hyper-parameters. Moreover, due to the constraints in GPU power, we were unable to generate a perfect sample based on the previous original image data.

The challenges with this study was mainly to build decent DCGANs and make them generate high quality samples that are similar to the ground truth samples. Generally, deep learning models have a lot of model parameters as well as a plenty of hyper-parameters to be tuned. Not only do appropriate layers with relevant number of nodes, type of activations for each layer, the optimizer etc. all affects the performance of a DL model, a DCGAN contains two DL models which further complicates the already complicated training process of a DL model. While the researcher followed the recommendations from the DCGAN paper [15], different datasets may require different settings. This made the fine tuning of a DL model very time consuming due to the many tests that needed to be performed. Speaking of time, the time required for each training session was the foremost limitation to this study. One training session for skin lesion dataset could require 1 hour while for other photos datasets, the time could rise up to 40 hours per session. The extremely time-consuming training sessions took up most of the time dedicated for this study. This further complicated the fine-tuning of the DCGAN on the dataset. Another challenge was the data pre-processing, the datasets needed to be resized, sliced, merged and transformed to an appropriate format. The process_images.py script made it straightforward to process the datasets but the implementation of it took time.

Chapter 9

Conclusion and Recommendations

Introduction

In this section, closing remarks drawn out of the research as well as possible proposals for future work are presented. Section 9.1 gives the conclusions while section 9.2 proposes future work.

9.1. Conclusion

In this endeavor, we have built a DCGAN framework on a skin cancer dataset and this paradigm was knowledgeable to produce images that are closely similar to malignant, although, not quite clearly. Moreover, additional essential aspect to highlight is that the data pre-processing plays a role on a DCGAN performance. For the purpose of this investigation, the acquired images were transformed using some image enhancement techniques to eliminate the cumulative noise whilst reserving as much as possible the important lesion features. The method responded to the primary aim of adaptive segmentation. Nonetheless, it is not fully automatic by virtue of the manually fixed parameters from the original method. In this research, the problem of not having sufficient datasets was tackled using GANs to generate synthetic images in order to expand datasets. The lesson learned is that DCGANs are highly capable of generating synthetic samples which are equivalent to the ground truth. In some cases, the produced samples are even indistinguishable from the ground truth. At the same time DCGANs may require, depending on the dataset, a large quantity of training examples in order to be that good. This does not completely solve the initial problem of not having adequate datasets. For that, a GAN that require a small quantity of examples and at the same time generates high quality synthetic samples similar to the ground truth is needed. However, DCGANs are fully capable of expanding datasets and can be used to complement existing datasets. Another important aspect to point out is that the data pre-processing plays a big roll on a DCGANs performance, as for almost any ML algorithm. Finally, our results uncovered the simple fact that data augmentation strategy based only on available real training images do have a positive influence on classification, but to lesser extent.

The drawbacks of a DCGAN are all related to the training process. First of all, DCGANs contains two models which complicates an already complicated situation since the two models must be trained simultaneously. Secondly, the training process is very sensitive and problems can easily occur if the training process is not balanced between the discriminator and the generator. The discriminator can overpower the generator if it classifies synthetic data with absolute certainty. And the generator can overpower the discriminator if it discovers some weakness in the discriminator. Thirdly, DL models performs massive amounts of computations during the training process, a DCGAN contains two models which means that even more computations are performed so large computational power is required. And even with large computational power the training process will be very time-consuming. This makes it difficult to fine-tune a model.

9.2 Recommendations

In the future work, firstly, we consider that models carry out enormous amounts of computations during the training process. DCGAN contains two models which means that even more computations are performed so large computational power is required to reduce the instability issues related to GAN models. The principal contribution of the suggested course of work is hypothetical, and it can be implemented to other kinds of images as well. Consequently, it clarifies the generalization of the model for different more cases than the original model. Probably using a larger training set or training the model a little longer may attain the desired results. While many different adaptions, tests and experiments have been performed, there is still room for changes in the future. Especially the fine-tuning of the DCGAN on medical photos or other similar but less noisy datasets is interesting since there were no time left for the researcher to continue. Also finding other ML tasks than classification where the accuracy is very dependent to the number of examples available in order to investigate how synthetic examples generated by a GAN affects the accuracy. The author suggests that before a dataset or a task is selected, one should examine if the accuracy is highly dependent on the number of training examples. Another proposal is to investigate whether a DCGAN can be trained to generate noisy samples in order to prevent overfitting.

Furthermore, Additional investigations into the internal structure of the network to manipulate the generator representation might be the next steps in this study. In addition to that, widening this work would be very interesting by exploring images in their grey level and binary state to extract the desired lesion or separating them from the background of the image upon inspection.

Irregular shapes of skin lesions, different types of colors on each skin, and determining the region of interest on each dermoscopy image are just a few challenges in skin cancer detection. Detecting minute changes on the skin requires expertise in this field. However, the human eye may not always catch these tiny changes. Helping doctors with the computer vision and deep learning techniques can save many lives. With this motivation, we studied skin cancer malignancy detection to classify skin lesions and identify malignant cases. Pre-training settings and post-training measurements of all experiments showed that the skin cancer malignancy detection is a difficult task and generalizing a model for all cases requires some image pre-processing techniques to apply before feeding into any deep learning algorithm. We did many experiments and tried various techniques to solve the complexity of skin lesions classes. Finally, we were able to classify skin lesions with 94% average f1-score. Also, the malignant class skin classification f1-score (95%) was higher than benign class f1-score. This result is a good indicator for the potential of such a technology to reduce false-negative and false-positive predictions and eventually help physicians increase their diagnostic prediction power.

Glossary

DCGAN	Deep Convolutional Generative Adversarial Network
MNIST	Modified National Institute of Standards and Technology database
GPU	Graphics Processing Unit
CNN	Convolutional Neural network
DL	Deep Learning
CIFAR-10	Canadian Institute For Advanced Research
ML	Machine Learning
UV	ultraviolet
GAN	Generative Adversarial Network

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