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TITLE

Integrating GANs for Enhanced Data Augmentation in AI-Driven Mobile Skin Cancer Detection

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إهداء و شكر

قال الله تعالى "وآخر دعواهم ان الحمد لله رب العالمين"

لقد كان الطريق طويلا وصعبا و كان الحصول على قدر المشقة مهيبا وعظيما اللهم إني سعيت وإنك أحسنت لي الجزاء وما كنت فعلت لولا الله مكنني فالحمد لله عند البدء وعند الختام

وبعد شكر المولى عزوجل اريد شكر والدي الذي بنعمة دعائهم ومساندتهم المعنويةو المادية جاءت لذة الوصول لتزول مشقة السنين .

كان الفضل الكبير عائد للمشرفة عن مشروع التخرج "الدكتورة بلعلى عبير" ومساعد المشرفة "الدكتور عبد المؤمن زراري" على حسن التسيير والمعاملة الطيبة.

الشكر لإخوتي خاصة أميرة كانت أكبر داعم خلال مشواري ولعائلتي الكبيرة ويليها الشكر لمن كانو رفقاء المشوار هونو عليا الطريق صديقاتي

شكرا للزميل المصري ابراهيم هارون عمران على مساعدته لنا ومشاركته بخبرته معنا

أماني ماريا نعمان

شكر

" يَرْفَعِ اللَّهُ الَّذِينَ آمَنُوا مِنْكُمْ وَالَّذِينَ أُوتُوا الْعِلْمَ دَرَجَاتٍ "

يُبدأُ الشكر منه جل جلاله ، ما كان عمل ولا تم خير إلا و سبقت إرادته و حَفَّه فَضلُه، فالحمد لله حتى يبلغ الحمد منتهاه..

والدتي ، صديقة قلبي و شَجَاعته في بذل الحياة ، إن مِلتُ قَوّمت و رَبّتَت حتى أستقيم ، ولا تسع أن تفيها كل حروف اللغة..

أبي - شفاه الله و دعواتكم - رجل عظيم أمسك بيدي طيلة الخمس سنوات، مهد الطريق ليشقى هو فأرتاح أنا، أبي رجل لا يمل إن مس الأمر رِفعتِي في مجالس العلم. جزء من انطلاقتي في هذا العمل أن لا يشقى أحد بخبث هذا المرض كما أتعب والدي..

رجائي أن يليق العمل بتضحياتهما ،

إخوتي أدامكم الله ، و إن كنت أكبركم ، لا يُخافُ من ضِيقٍ و أياديكم تحيطني..

خالي محافظ الحسابات السيد جودي عبد الرحمان، على خير يد عون قدمها في عمل يرضينا..،

و عائلتي الكبيرة، خير عائلة حضيت بها.. بارك الله في كل فرد فيهم أعان و أحب و تلطف حين استحكمت الحلقات ، شكرا لكم سرور قلبي.

دكتورتنا المشرفة بلعلى عبير، و أستاذنا الفاضل زراري عبد المؤمن، لا يفيهما الشكرو التقدير، و يشهد الله أن أحسنا في التوجيه و الإشراف و منحا من وقتهما فأجادا في إخراج العمل على شاكلته هذه إتقانا و إحسانا ، أحسن الله إليكما و جزاكما عنا خيرا.

طاهري آية الرحمان

إهداء وشكر

وفي مقدمة هذه الرسالة نحمد الله الذي وفقنا وأعطانا القوة والصبر والعزيمة خلال هذه السنوات من الدراسة. بفضل الله، استطعنا تجاوز كل التحديات والعقبات، وكانت توفيقه هو النور الذي أضاء طريقنا وأرشدنا إلى تحقيق هذا الإنجاز.

بداية، أود أن أعبر عن مشاعر الشكر والامتنان العميقين لوالديّ الحبيبين. لقد كنتم النور الذي أضاء طريقي والدافع الذي حفزني للاستمرار. شكراً لكما على الدعم اللامحدود، وعلى تحفيز كما الدائم لي، وعلى كل التضحيات التي بذلتموها من أجلي. كنتم دائمًا الملاذ الآمن والكتف الذي استند عليه في أوقات المحن والصعوبات، وبدونهما لم أكن لأصل إلى هذا الإنجاز.

كما أتقدم بخالص الشكر والامتنان لعائلتي العزيزة، إخوتي وأخواتي، الذين كانوا دومًا مصدر إلهامي وقوتي. لقد كانت محبتكم ودعمكم اللامشروط لي هو السند الذي أعانني على تخطي العقبات وتحقيق النجاح. شكراً لكم على كل كلمة طيبة وكل لحظة فرح وكل لمسة حب واهتمام.

وفي ذات السياق، نود أن نتقدم بخالص الشكر والتقدير إلى الأستاذة الفاضلة "بلعلى عبير" التي كان لها الدور البارز في إشرافنا وتوجيهنا خلال هذا المشروع. إن إرشاداتها الحكيمة وتوجيهاتها السديدة ونصائحها الثمينة كانت بمثابة منارة أضاءت طريقنا وساعدتنا في تجاوز التحديات والصعوبات. نعبر عن امتناننا العميق لها على الثقة الكبيرة التي منحتنا إياها، وعلى دعمها المستمر وتشجيعها لنا. لم تكن ملاحظاتها البناءة مجرد توجيهات، بل كانت دافعًا لنا لتحسين عملنا والارتقاء به إلى أعلى المستويات. كل الشكر والامتنان لها على
تفانيها وإخلاصها في دعمنا طوال فترة المشروع.

نود أن نوجه أسمى عبارات الشكر والتقدير إلى الأستاذ الفاضل "زراري عبد المؤمن"، الذي كان له دور محوري في إتمام إنجاز هذا المشروع. إن جهوده الجبارة وتفانيه اللامحدود كان لهما الأثر الكبير في تحقيق هذا النجاح. لقد كان دعمه المستمر وتوجيهاته القيمة مصدر إلهام لنا،شكراً له على كل دقيقة من وقته الثمين، وعلى كل نصيحة قدمها لنا.

ولا يسعني إلا أن أتوجه بالشكر الجزيل لأساتذتي الكرام في قسم علوم الحاسوب على مدار هذه السنوات. شكراً لكم على ما بذلتموه من جهد وتفان في تعليمنا وتوجيهنا، وعلى كل نصيحة قيمة قدمتموها لنا. لقد كنتم لنا مثالًا يحتذى به في العلم والأخلاق، وأثرت فينا حب التعلم والاستمرار في السعي نحو التفوق.

وأخيراً، أشكر من أعماق قلبي كل من ساهم بشكل مباشر أو غير مباشر في إنجاز هذا التقرير المتواضع. لكم مني كل التقدير والاحترام.

هناء بلعلى

Abstract

Skin cancer represents a critical global health issue, with millions of new cases diagnosed annually. Early detection and accurate classification of skin lesions are essential for effective treatment and improved patient outcomes. Traditional diagnostic methods rely heavily on clinical expertise and invasive biopsies, which can be subjective and time-consuming. This thesis explores the development of an advanced, AI-driven diagnostic tool aimed at the rapid and accurate classification of eight types of skin lesions using dermoscopic and standard images.

Leveraging the ISIC2019 dataset and advanced data augmentation techniques, notably Pix2Pix Generative Adversarial Networks (GAN) technology, we address the common challenge of data imbalance. This enables the creation of a more representative and robust training dataset. Our model employs state-of-the-art transformer technology, specifically Vision Transformers (ViT), to capture long-range dependencies and contextual information in images, surpassing the capabilities of traditional convolutional neural networks (CNNs). This thesis details the entire development process, from data collection and augmentation to model training and evaluation. We present the design and implementation of a mobile application that facilitates remote and early skin cancer detection, aiming to improve accessibility and reduce the burden on clinical workflows. The AI model demonstrates high accuracy, precision, recall, and F1-score across multiple skin lesion types, showcasing its potential to enhance diagnostic accuracy and efficiency.

Keywords: Skin cancer, Computer Aided Diagnosis , AI, medical imaging, Pix2Pix, DieT transformer, ISIC2019, mobile application, Generative Adversarial Networks (GANs)

Résumé

Le cancer de la peau représente un problème de santé mondiale critique, avec des millions de nouveaux cas diagnostiqués chaque année. La détection précoce et la classification précise des lésions cutanées sont essentielles pour un traitement efficace et une amélioration des résultats pour les patients. Les méthodes de diagnostic traditionnelles reposent fortement sur l'expertise clinique et les biopsies invasives, qui peuvent être subjectives et chronophages. Cette thèse explore le développement d'un outil de diagnostic avancé, piloté par l'IA, visant à la classification rapide et précise de huit types de lésions cutanées en utilisant des images dermoscopiques et standards.

En tirant parti du jeu de données ISIC2019 et des techniques avancées d'augmentation des données, notamment la technologie Pix2Pix des réseaux antagonistes génératifs (GAN), nous abordons le défi commun du déséquilibre des données. Cela permet de créer un ensemble de données d'entraînement plus représentatif et robuste. Notre modèle utilise une technologie de pointe basée sur les transformateurs, en particulier les Vision Transformers (ViT), pour capturer les dépendances à long terme et les informations contextuelles dans les images, surpassant les capacités des réseaux neuronaux convolutionnels traditionnels (CNN).

Cette thèse détaille l'ensemble du processus de développement, de la collecte et de l'augmentation des données à l'entraînement et à l'évaluation du modèle. Nous présentons la conception et la mise en œuvre d'une application mobile qui facilite la détection précoce et à distance du cancer de la peau, visant à améliorer l'accessibilité et à réduire la charge sur les flux de travail cliniques. Le modèle IA démontre une haute précision, une grande sensibilité, un bon rappel et un score F1 élevé sur plusieurs types de lésions cutanées, montrant son potentiel à améliorer la précision et l'efficacité du diagnostic.

Mots-clés : Cancer de la peau, diagnostic assisté par ordinateur, IA, imagerie médicale, Pix2Pix,

transformateur ViT, ISIC2019, application mobile, réseaux antagonistes génératifs (GANs).

الملخص

يمثل سرطان الجلد مشكلة صحية عالمية حرجة، حيث يتم تشخيص الملايين من الحالات الجديدة سنوياً. يُعد الاكتشاف المبكر والتصنيف الدقيق للآفات الجلدية أمرين أساسيين للعلاج الفعال وتحسين نتائج المرضى. تعتمد الطرق التشخيصية التقليدية بشكل كبير على الخبرة السريرية والخزعات الجراحية، والتي يمكن أن تعتمد بشكل كبير على خبرة الأطباء و التفسيرات الشخصية وتستغرق وقتاً طويلاً. يستكشف هذا البحث تطوير أداة تشخيص متقدمة تعتمد على الذكاء الاصطناعي بهدف التصنيف السريع والدقيق لثمانية أنواع من الآفات الجلدية باستخدام صور ديرموسكوبية وصور قياسية.

من خلال الاستفادة من مجموعة بيانات ISIC2019 وتقنيات تعزيز البيانات المتقدمة، وخاصة تقنية Pix2Pix Generative Adversarial Networks (GAN)، نواجه التحدي الشائع المتمثل في توازن البيانات. يمكن ذلك من إنشاء مجموعة تدريب أكثر تمثيلاً وقوة. يستخدم نموذجنا تقنية المحولات المتقدمة، تحديداً Vision Transformers (ViT)، لالتقاط التبعيات طويلة المدى والمعلومات السياقية في الصور، متجاوزةً قدرات الشبكات العصبية التقليدية (CNNs) يتناول هذا البحث عملية التطوير بأكملها، بدءاً من جمع البيانات وتعزيزها إلى تدريب النموذج وتقييمه.

نقدم تصميم وتنفيذ تطبيق هاتف نقال يسهل الكشف المبكر والبعيد لسرطان الجلد، بهدف تحسين الوصول وتقليل العبء على سير العمل السريري. يُظهر نموذج الذكاء الاصطناعي دقة عالية، وموثوقية، وفعالية، ونسبة F1 عالية عبر أنواع متعددة من الآفات الجلدية، مما يعرض إمكانياته لتعزيز دقة وكفاءة التشخيص. يشمل العمل المستقبلي تحسين النموذج أكثر، ودمجه في الإعدادات السريرية، وتوسيع قدراته لتغطية نطاق أوسع من الحالات الجلدية. يؤسس هذا البحث أساساً متيناً للتشخيص المساعد بالذكاء الاصطناعي لسرطان الجلد، مع تداعيات كبيرة على الصحة العامة والممارسة السريرية.

الكلمات المفتاحية: سرطان الجلد، التشخيص بمساعدة الحاسوب، الذكاء الاصطناعي، التصوير الطبي، Pix2Pix، محولاتDieT ، ISIC2019، تطبيق هاتف نقال، الشبكات التنافسية التوليدية(GANs)

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General Introduction

Context

Skin cancer poses a major global health challenge, with over 5 million cases reported annually in the United States alone. Worldwide, non-melanoma skin cancers (NMSC) account for 2 to 3 million cases, and melanoma adds another 132,000 cases each year. This highlights the substantial strain on public health systems and emphasizes the critical need for early detection and effective treatment. The three main types of skin cancer are Basal Cell Carcinoma (BCC), Squamous Cell Carcinoma (SCC), and Melanoma, each presenting distinct challenges. Melanoma is the most aggressive and lethal form, known for its rapid spread. Factors such as ultraviolet (UV) exposure and an aging population are driving the global increase in skin cancer cases. According to the World Health Organization (WHO), skin cancer constitutes one in every three cancer diagnoses. Addressing this public health issue requires a strong focus on prevention, raising risk awareness, and advancing treatment and diagnostic methods.

Traditionally, the diagnosis of skin cancer has relied heavily on clinical examination and the expertise of dermatologists. Dermoscopic images are analyzed visually, and suspicious lesions are often subjected to biopsy for histopathological examination. However, this process can be subjective and time-consuming, and it's important to note that biopsies themselves can carry risks. Biopsies, while crucial for definitive diagnosis, can sometimes inadvertently damage the skin cancer site further, leading to potential complications and altering the appearance of the lesion.

Artificial Intelligence (AI) has revolutionized various fields of medicine, including dermatology. AI models, particularly those leveraging deep learning, have shown great promise in the early detection and diagnosis of skin lesions. By analyzing images of skin lesions, AI can assist dermatologists in identifying malignancies with high accuracy, often comparable to human experts. The deployment of AI in this domain can potentially bridge the gap in regions with limited access to dermatological services and improve diagnostic consistency and accuracy.

Problem statement

Despite the potential of AI in skin cancer diagnosis, its application faces several significant challenges:

- **Lack of Data:** Insufficient large, diverse datasets for robust model training.
- **Imbalanced Datasets:** Underrepresented classes leading to biased models.
- **High Similarity in Skin Lesions:** Difficulty in distinguishing between benign and malignant lesions due to their visual similarities.
- **Existence of Artifacts:** Interference from hairs, shadows, air bubbles, reflections, blur, or other distortions that may obscure or complicate the visualization of the lesion). Also, skin lesions can look wildly different due to factors like skin type, size, shape, color, and texture, making things even more difficult.

Proposed solution

To address these challenges, our research proposes a novel approach that leverages Conditional Generative Adversarial Networks (cGANs), specifically the Pix2Pix model, to generate synthetic images for minority classes in the ISIC2019 dataset. By augmenting the dataset with these high-quality synthetic images, we aim to mitigate the class imbalance issue.Our diagnostic model is based on the Vision Transformer (DeiT), which has shown promising performance in image classification tasks. By integrating these synthetic images into the training process, we enhance the model's ability to accurately diagnose skin lesions across all classes.

Furthermore, we are developing a mobile application that integrates our AI model. This application will allow users to take pictures of their skin lesions and receive instant diagnostic feedback. To combine AI expertise with human expertise, the app will also provide the option to contact dermatologists for further diagnosis and advice. This feature ensures that users can get professional medical opinions and follow-up care when needed.

Thesis structure

In this thesis, we thoroughly examine both the theory and practical steps involved in creating a mobile app for diagnosing skin cancer from dermoscopic images. Our work is organized as follows:

- **Chapter One :** We cover skin cancer types and diagnosis methods, explore artificial intelligence with a focus on machine learning and deep learning, highlight key deep learning models like CNNs and GANs, and introduce Vision Transformers as a cutting-edge approach to computer vision.

- **Chapter Two:** We review previous research on dermoscopic image analysis, including dataset usage and AI techniques, describe our contributions to AI model development for skin cancer diagnosis, and evaluate existing mobile apps for skin lesion diagnosis in terms of various functionalities.
- **Chapter Three:** We define the application's purpose, functional requirements, and detail non-functional needs. We also present use case diagrams, and outline the system's design including : sequence diagrams, database structure, and navigation model.
- **Chapter Four:** We detail the data augmentation process, describe the implementation of transformer technology, discuss the development of the mobile app including the programming language and tools used, and provide insights into the testing procedures conducted to validate the effectiveness and functionality of the implemented components.

Chapter 1

Preliminaries and basic concepts

Introduction

This chapter briefly introduces two basic concepts related to our work. In Section1, we introduce skin cancer disease by citing its different types and stages. We emphasize on the diagnosis ways used of skin cancer such as: ABCDE rules, dermoscopy, and biopsy. In section 2, we define the artificial intelligence domain by its two main axes: Machine learning and deep learning and the new technique for image classification called vision transformers.

1 Skin Cancer

Skin cancer is the abnormal growth of cells located in the skin that frequently develop on the sun-exposed (i.e., UV light) regions of the skin (See Figure 1.1). However, skin regions that are not regularly exposed to sunlight may develop cancer. Around the world, skin cancer is the most prevalent cancer type.[1].

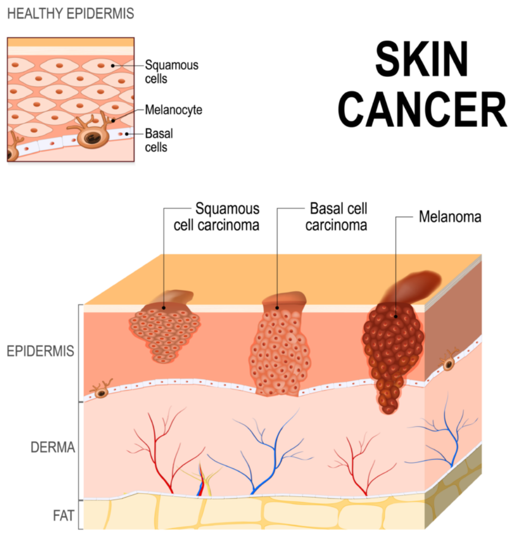

Figure 1.1. skin-cancer.
[2]

1.1 Types of Skin Cancer

Skin cancer is commonly categorized as malignant melanoma and NMSC (non melanoma skin cancer), the latter including basal cell carcinoma (BCC) and squamous cell carcinoma (SCC) as the major subtypes.[3]

We mention here that there are many more types of skin cancer, reaching more than ten , as we can count “Merkel cell carcinoma, Sebaceous carcinoma,DFSP..” but they are not mentioned due to their rarity, meaning that they are not counted globally or considered an important number nationally. Figure 1.2 describes the forms of some types of skin cancer .

The following subsections define the common types of skin cancer:

1.1.1 Melanoma

Melanoma arises from the occurrence of genetic mutations in melanocytes, the pigment producing cells, which can be found in the skin, eye, inner ear, andleptomeninges. Although melanoma accounts for about 1tumors, cutaneous malignant melanoma represents the most aggressive and the deadliest form of skin cancer. Therefore, early identification of this cancer iscrucial for the success of patient treatment.[4]

1.1.2 Non melanoma skin cancer

- **Basal cell carcinoma**

  Basal cell carcinoma is a type of skin cancer. it begins in the basal cells a type of cell within the skin that produces new skin cells as old ones die off. it often appears as a slightly transparent bump on the skin, though it can take other forms. it occurs most often on areas of the skin that are exposed to the sun, such as your head and neck. Most basal cell carcinomas are thought to be caused by long-term exposure to ultraviolet (UV) radiation from sunlight. Avoiding the sun and using sunscreen may help protect against basal cell carcinoma.[5]

- **Squamous cell carcinoma**

  Squamous cell carcinoma of the skin is a type of cancer that starts as a growth of cells on the skin. It starts in cells called squamous cells. The squamous cells make up the middle and outer layers of the skin. And it is a common type of skin cancer.

  Squamous cell carcinoma of the skin is usually not life-threatening. But if its not treated, squamous cell carcinoma of the skin can grow large or spread to other parts of the body. The growth of the cancer can cause serious complications.[6]

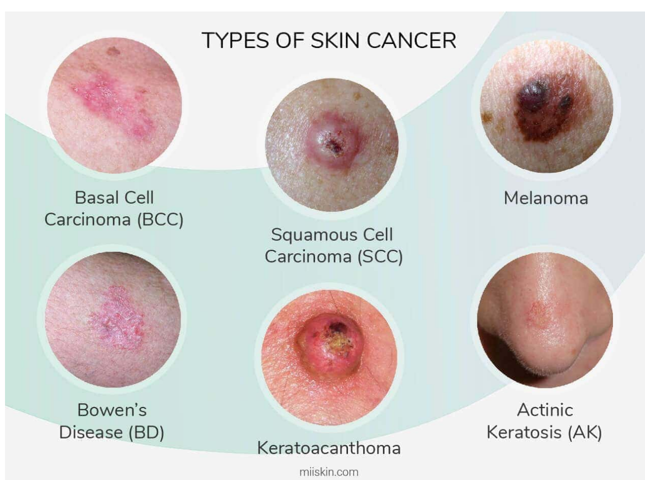

Figure 1.2. Types of skin cancer.
[7]

1.2 Diagnosis of skin cancer

Many methods have been found to diagnose skin cancers over the ages, which we can classify them into two main categories, before and after the intervention of computer science.

1.2.1 Traditional Diagnostic Methods

- **The ABCD rule:(Special for detecting melanoma)**

ABCD rule, a semiquantitative score system, introduced by Stolz and coworkers is based on four criteria In accordance with Figure 1.3.

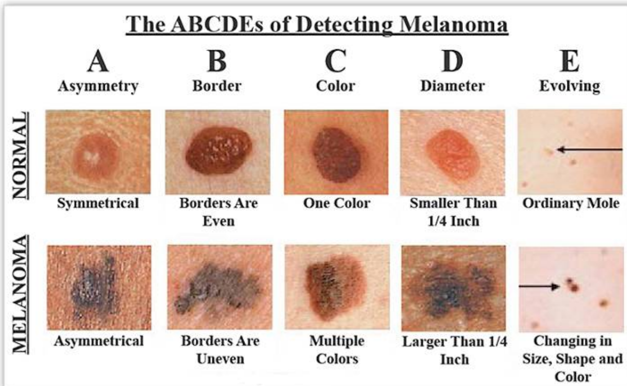

Figure 1.3. The ABCD rule.
[8]

A for Asymmetry (of colors and structures) - in 0, 1 or 2 axes (score 0-2). [9]

B for Border – abrupt ending of pigment pattern at the periphery in 0-8 segments (score 0-8). [9]

C for Color – presence of up to 6 colors - white, red, light brown, dark brown,blue-gray and black (score 0- 6). [9]

D for Dermoscopic structures (Diameter)– presence of network, homogenous areas, branched streaks, dots and globules (score 0-5).[9]

- **Dermoscopy**

Dermoscopy is a non-invasive examination technique based on the use of incident light and oil immersion to make possible the visual examination of sub surface structures of the skin..[10]

- **Skin biopsy**

biopsies are diagnostic techniques , which utilize a representative sample of tissue taken from a disease process for the purpose of histopathologic analysis . in the skin and subcutaneous soft tissues , these procedures are among the most important diagnostic techniques available to guide the surgical and medical management of inflammatory and neoplastic conditions testing.[11] As demonstrated in Figure 1.4.

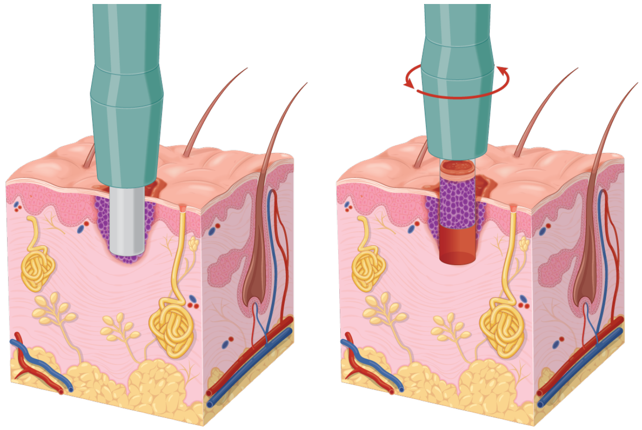

Figure 1.4. Skin biopsy (Punch method).
[12]

1.2.2 Computational Diagnostic Advances

With the intervention of computer science, skin diagnosis has undergone a transformative evolution, revolutionizing the field with advanced algorithms and data-driven insights. Through sophisticated image analysis techniques such as machine learning and computer vision, dermatologists can now achieve more accurate and efficient diagnoses. By harnessing vast datasets and leveraging artificial intelligence, these systems can detect subtle patterns, lesions, and anomalies that might escape the human eye, leading to earlier detection of skin conditions and more personalized treatment plans.[13]

This convergence of technology and dermatology not only enhances diagnostic precision but also holds the promise of democratizing healthcare, empowering both patients and practitioners with innovative tools for better skin health management.[14]

in the next section we going to explain in depth this AI techniques and their architectures.

2 Artificial Intelligence

Artificial Intelligence (AI) represents a multifaceted domain within computer science that encompasses various subfields, including machine learning, deep learning, and vision transformers. At its core, AI aims to develop systems and algorithms that can mimic human intelligence, enabling computers to perform tasks that traditionally require human cognitive abilities.[15]

the subsections will explain each branch with its utilizations

2.1 Machine Learning (ML)

Machine learning is an evolving branch of computational algorithms that are designed to emulate human intelligence by learning from the surrounding environment.[16]

Machine learning algorithms can identify patterns, extract insights, and make predictions or decisions by analyzing large amounts of data. These algorithms are used in various applications, including but not limited to, image recognition, natural language processing, recommendation systems, autonomous vehicles, and medical diagnosis.[17] As displayed in Figure 1.5.

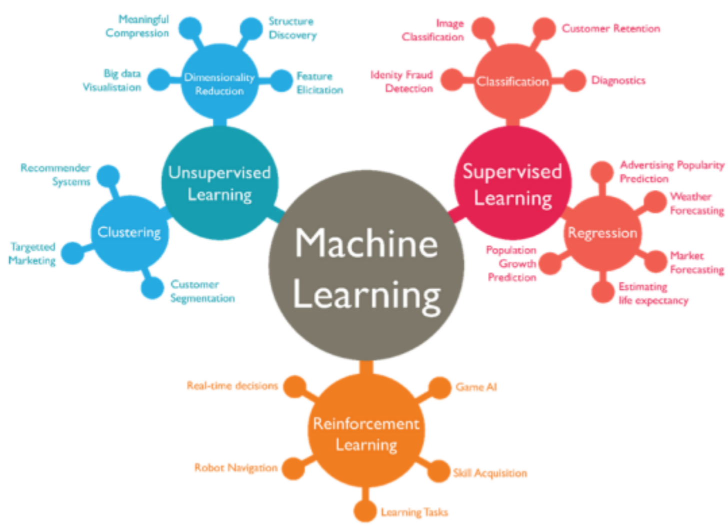

Figure 1.5. Learning Paradigms in Machine Learning
[18]

2.1.1 Types of Machine Learning Algorithms

Machine learning, the bedrock of artificial intelligence, encompasses a diverse array of algorithms tailored for various tasks and datasets. Broadly speaking, these algorithms fall into four main categories:

- **Supervised learning**

  Supervised learning is typically the task of machine learning to learn a function that maps an input to an output based on sample input-output pairs . It uses labeled training data and a collection of training examples to infer a function. Supervised learning is carried out when certain goals are identified to be accomplished from a certain set of inputs , i.e., a task-driven approach. The most common supervised tasks are "classification" that separates the data, and "regression" that fits the data. For instance, predicting the class label or sentiment of a piece of text, like a tweet or a product review, i.e., text classification, is an example of supervised learning.[19]As revealed in Figure 1.6.

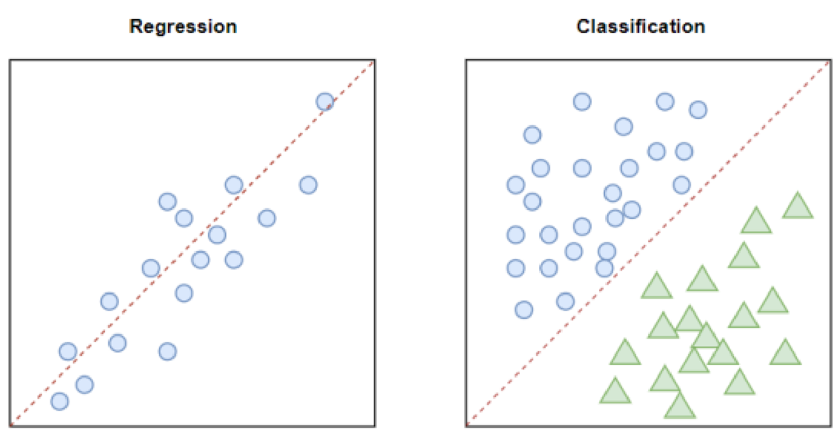

Figure 1.6. Supervised learning.
[18]

- **Unsupervised Learning**

  Unsupervised learning analyzes unlabeled datasets without the need for human interference, i.e., a data-driven process. This is widely used for extracting generative features, identifying meaningful trends and structures, groupings in results, and exploratory purposes. The most common unsupervised learning tasks are clustering (see Figure 1.7), density estimation, feature learning, dimensionality reduction, finding association rules, anomaly detection, etc.[19].

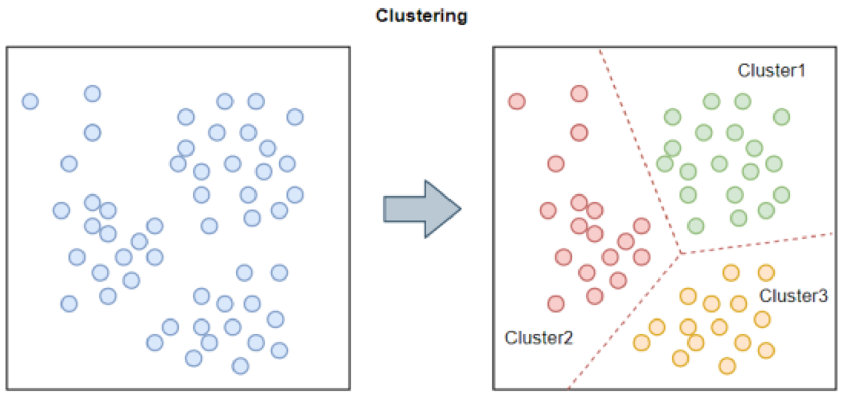

Figure 1.7. Unsupervised Learning.
[18]

- **Semi-supervised Learning**

Semi-supervised learning can be defined as a hybridization of the above-mentioned supervised and unsupervised methods, as it operates on both labeled and unlabeled data . Thus, it falls between learning “without supervision” and learning “with supervision”. In the real world, labeled data could be rare in several contexts, and unlabeled data are numerous, where semi-supervised learning is useful . The ultimate goal of a semi-supervised learning model is to provide a better outcome for prediction than that produced using the labeled data alone from the model. Some application areas where semi-supervised learning is used include machine translation, fraud detection, labeling data and text classification.[19]

- **Reinforcement learning**

Reinforcement learning is a type of machine learning algorithm that enables software agents and machines to automatically evaluate the optimal behavior in a particular context or environment to improve its efficiency , i.e., an environment-driven approach. This type of learning is based on reward or penalty, and its ultimate goal is to use insights obtained from environmental activists to take action to increase the reward or minimize the risk As outlined in Figure 1.8 . It is a powerful tool for training AI models that can help increase automation or optimize the operational efficiency of sophisticated systems such as robotics, autonomous driving tasks, manufacturing and supply chain logistics, however, not preferable to use it for solving the basic or straightforward problems. [19].

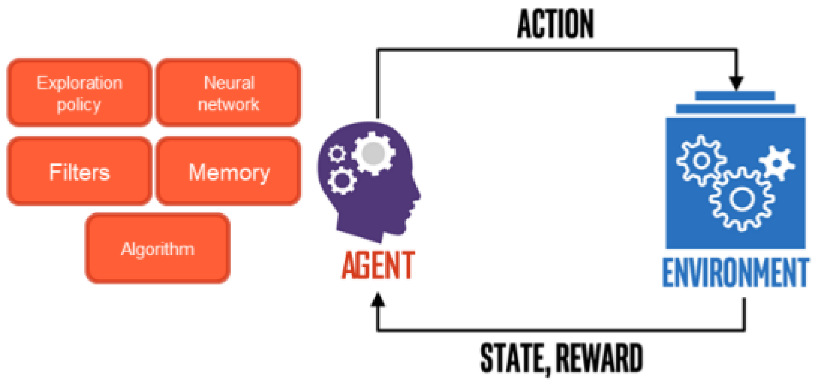

Figure 1.8. Reinforcement learning.
[18]

2.2 Deep learning (DL)

Deep learning is a class of machine learning techniques that use artificial neural networks with multiple layers of representation. Each layer learns to transform its input data into a slightly more abstract and composite representation. This hierarchical organization of the representation allows deep learning models to learn complex patterns in large amounts of data. Deep learning has shown exceptional performance in various domains, including computer vision, natural language processing, and speech recognition.[20]As represented in Figure 1.9.

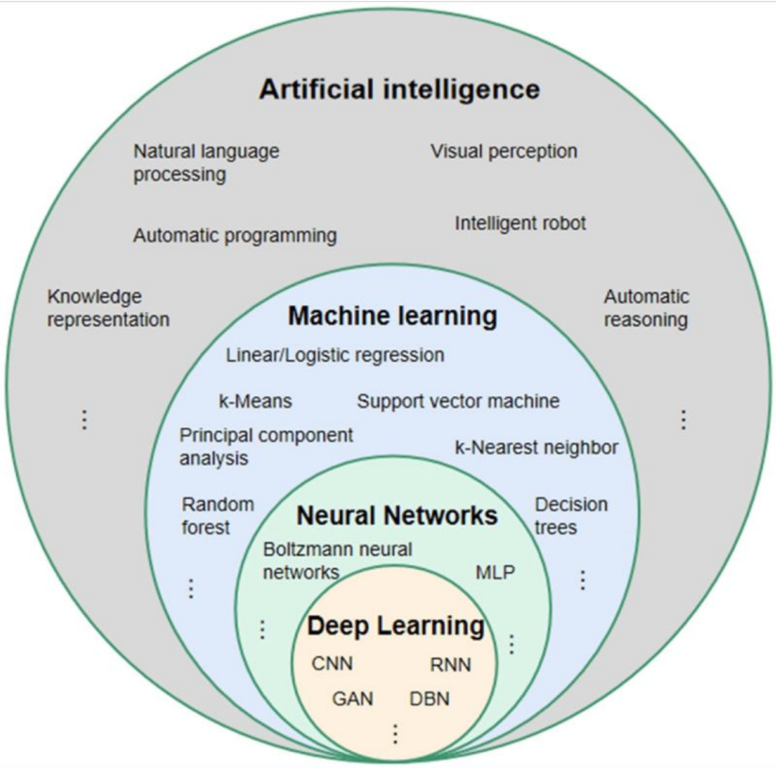

Figure 1.9. deep learning.
[21]

2.2.1 Deep learning process

Deep learning is a subset of machine learning that deals with algorithms inspired by the structure and function of the human brain's neural networks. It's characterized by the use of deep neural networks, which are composed of many layers of interconnected nodes (neurons). These networks are trained on large amounts of data to learn representations of the data through a hierarchical feature extraction process.[20]

The deep learning process typically involves the following steps As presented in Figure 1.10.

Figure 1.10. Deep learning process.
[22]

- Data Collection: Gathering relevant data that the model will be trained on. This can include images, text, audio, or any other type of data depending on the task.[20]

- Data Preprocessing: Preparing the data for training by cleaning, normalizing, and possibly augmenting it to improve the model's performance.[20]
- Model Architecture Design: Designing the architecture of the neural network, including the number of layers, types of layers (e.g., convolutional, recurrent), and the connections between them.[20]
- Training: Using an optimization algorithm (such as stochastic gradient descent) to adjust the weights of the neural network based on the training data. This involves feeding the training data through the network, computing the loss (error), and updating the weights to minimize this loss.[20]
- Validation: Evaluating the model's performance on a separate validation dataset to ensure that it generalizes well to new, unseen data. This step helps prevent overfitting, where the model performs well on the training data but poorly on new data. Hyperparameter Tuning: Adjusting the hyperparameters of the model (e.g., learning rate, batch size) to optimize its performance.[20]
- Testing: Finally, testing the trained model on a separate test dataset to assess its performance in real-world scenarios.[20]

2.2.2 Types of deep learning

- **Convolutional neural networks(CNNs)**

  Convolutional Neural Networks (CNNs) are a type of deep learning algorithm specifically designed for processing structured grid data, such as images. They are characterized by their ability to automatically learn hierarchical patterns and features directly from raw data, without the need for handcrafted feature extraction.[20]

  CNNs leverage a unique architecture composed of layers that perform operations like convolution, pooling, and non-linear activation.[20]

  The convolutional layers apply filters to the input data, enabling the network to detect features at different spatial scales. [20]

  Pooling layers downsample the feature maps, reducing the computational complexity and aiding in translational invariance.[20]

  Additionally, non-linear activation functions introduce non-linearity into the network, enabling it to learn complex relationships in the data.[20]

CNNs have demonstrated remarkable success in various computer vision tasks, including image classification, object detection, and semantic segmentation. Their hierarchical feature learning capabilities make them well-suited for tasks where the input data exhibits spatial structure or locality.[20] As illustrated in the following Figure 1.11:

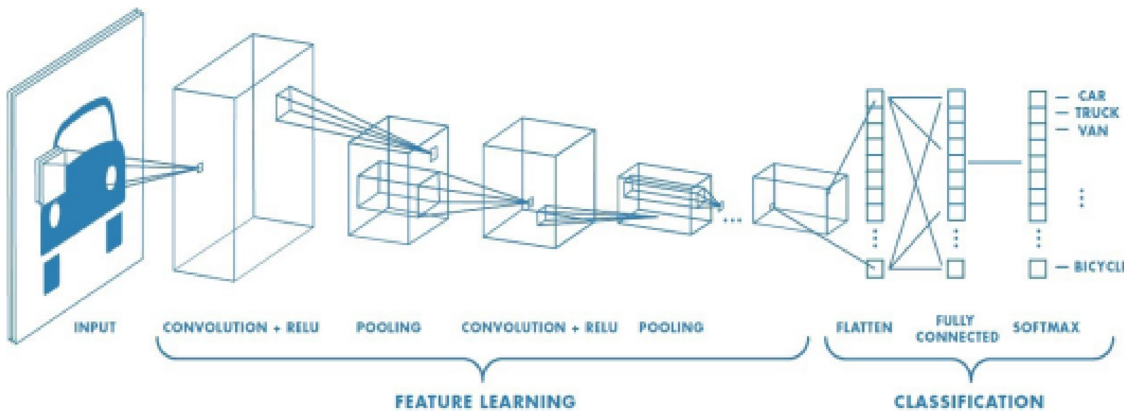

Figure 1.11. Convolutional neural networks(CNNs) .
[18]

- **Generative Adversarial Networks (GANs)**

GANs, or Generative Adversarial Networks are one of the most modern DL models.[23]

The use of the GAN for conditionally producing an output is a significant extension.[23]

The generative model may be trained to produce new instances from the input domain, where the input, a random vector from the latent space, is (conditionally) given.[23]

In the case of creating photos of handwritten numbers, the extra input may be a class value, such as male or female in the case of generating photographs of humans, or a digit in the case of generating photographs of handwritte digits.[23] As detailed in Figure 1.12.

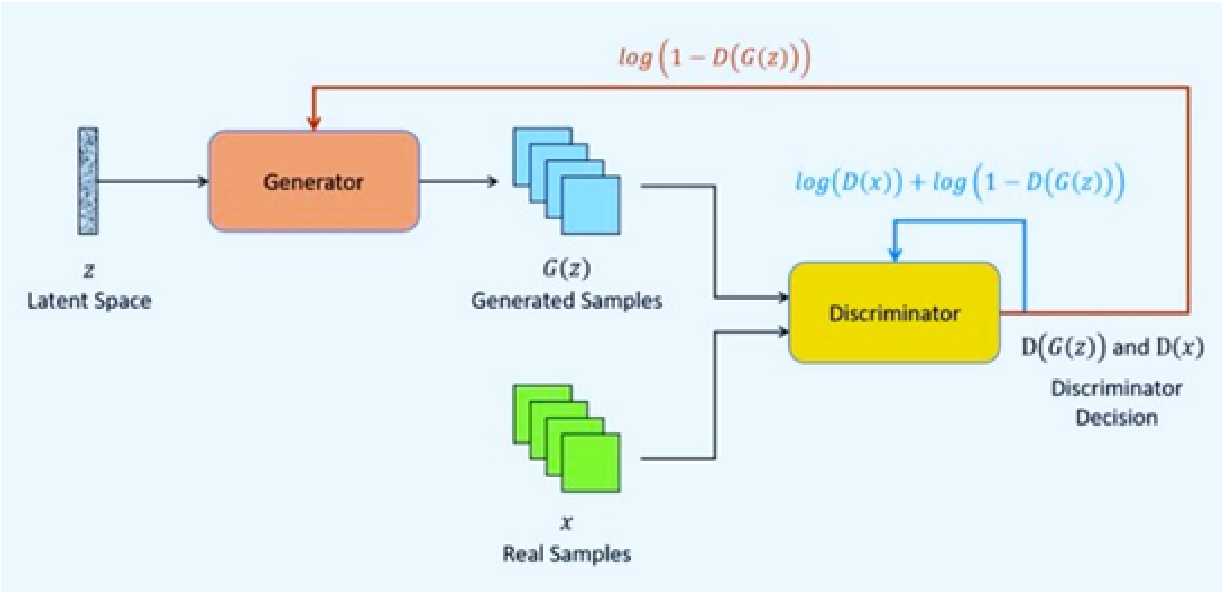

Figure 1.12. Generative Adversarial Networks (GANs).
[24]

- **Generator:** The generator in a GAN is like an art forger trying to create counterfeit currency. It takes random noise as input and tries to transform it into data samples that resemble the real thing. Just as a skilled forger might study real bills to learn how to mimic their appearance, the generator learns from real data samples to generate realistic fakes. [25] The process is delineated in Figure 1.13.

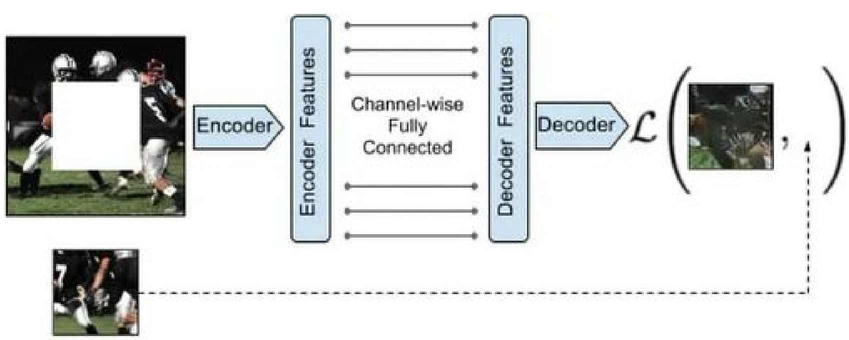

Figure 1.13. Generator.
[26]

- **Discriminator:** The discriminator in a GAN acts as a detective tasked with distinguishing between genuine and counterfeit currency. It's like a highly trained expert who knows all the subtle features of real bills and can spot a fake at a glance. Similarly, the discriminator learns to identify the unique characteristics of real data samples and differentiate them from the generator's creations.[25] As described in Figure 1.14.

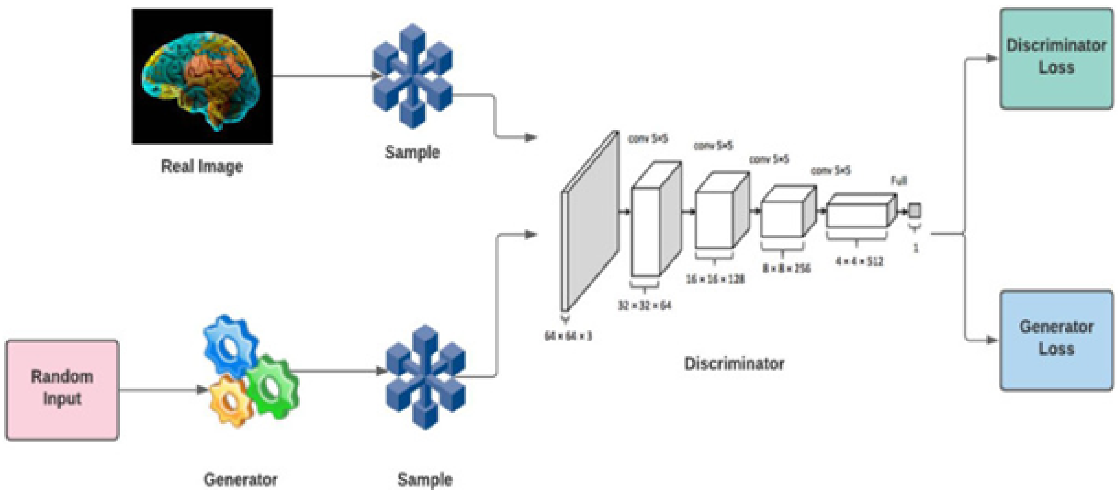

Figure 1.14. Discriminator.
[26]

- **Conditional GANs (cGANs)**

  Conditional GANs (cGANs) are an extension of the traditional GAN framework where both the generator and discriminator receive additional conditioning information (labels) to produce or evaluate images with specific characteristics. cGANs allow for the generation of images based on specific conditions or labels, making them suitable for tasks where the generation is conditioned on some input, such as generating images from text descriptions or translating images from one domain to another. [25]

- **Pix2pix GAN**

  pix2pix, short for "pixel to pixel," is a type of conditional GAN introduced for image-to-image translation tasks. Instead of generating images from random noise, pix2pix takes an input image from one domain and generates a corresponding output image in another domain. [27]

  pix2pix consists of a generator and a discriminator, similar to traditional GANs. However, the generator in pix2pix is a U-Net architecture, which is designed to handle image-to-image translation tasks effectively. [27] As depicted in Figure 1.15.

pix2pix has been successfully applied to various tasks, including image colorization, style transfer, and more.[27]

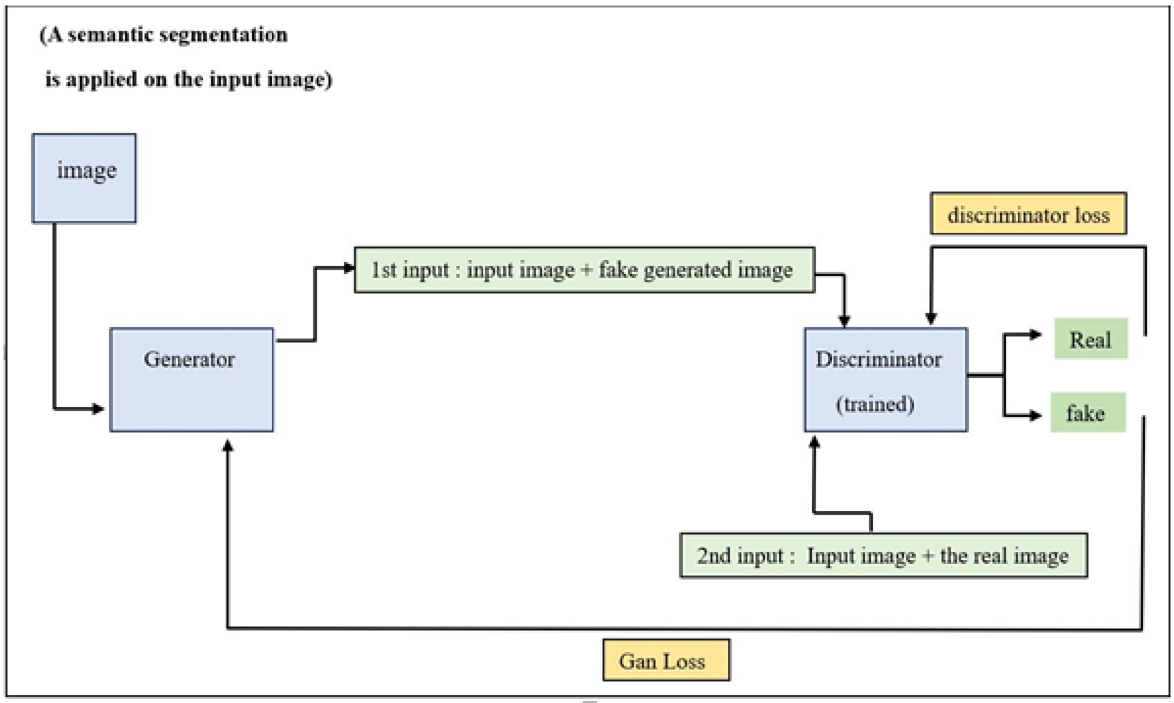

Figure 1.15. Pix2Pix GAN Architecture.
[28]

2.3 Vision Transformers(ViTs)

Vision Transformers (ViTs) are a novel architecture in the field of computer vision that have gained significant attention since their introduction. They represent a departure from the traditional Convolutional Neural Networks (CNNs) that have dominated the field for years [29]. ViTs apply the Transformer architecture, initially proposed for natural language processing tasks, to image recognition tasks. Here's a detailed overview:

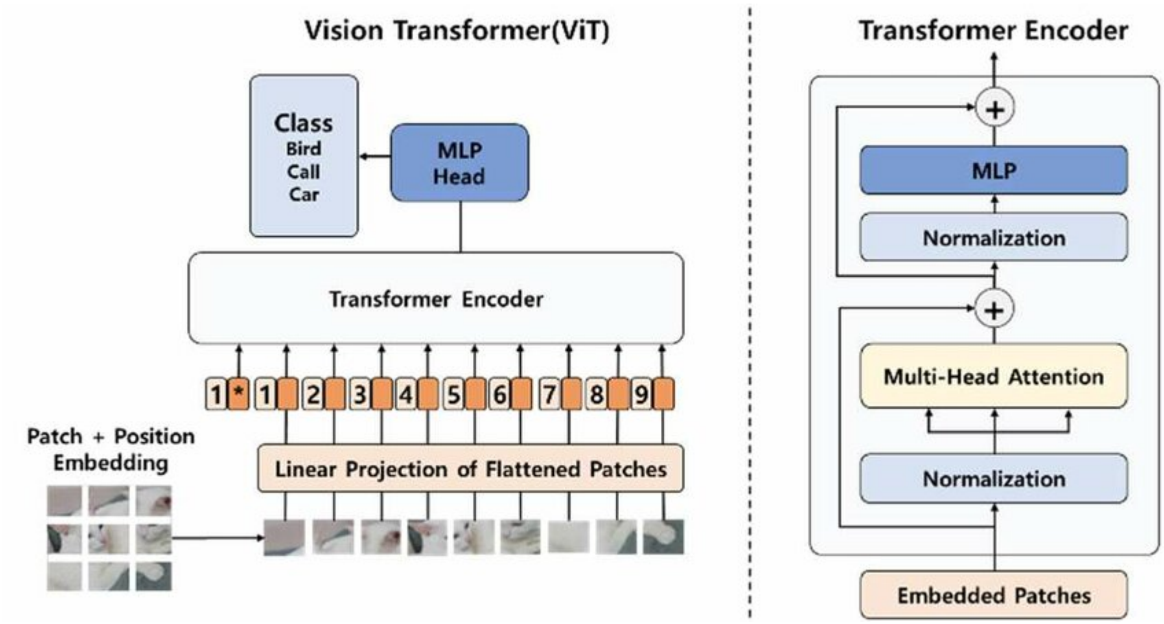

Figure 1.16. Vision transformer architecture

Convolutional Neural Networks (CNNs) have been the cornerstone of image recognition tasks, but they have certain limitations. For instance, CNNs require large amounts of data and extensive computational resources for training. Moreover, they struggle with capturing long-range dependencies in images. Vision Transformers aim to address these limitations by leveraging the self-attention mechanism of Transformers, which allows capturing global context efficiently [30].

2.3.1 Components of vision transformers:

The architecture of Vision Transformers closely resembles that of the original Transformer model. It consists of an encoder-decoder structure, but for vision tasks, typically only the encoder part is used. The key components of a Vision Transformer are:

- **Input Embedding:** Unlike CNNs, which directly process raw image pixels, ViTs first convert the image into a sequence of fixed-size patches[31]. Each patch is treated as a token and embedded into a high-dimensional vector space.
- **Positional Encoding:** Since Transformers do not inherently encode positional information like CNNs (where spatial location is preserved through convolutions), ViTs include positional encodings to inject spatial information into the input token sequence.
- **Transformer Encoder:** This consists of multiple layers of self-attention mechanisms and feed-forward neural networks. Self-attention allows each token to attend to all other tokens in the

sequence, capturing long-range dependencies effectively [31]. The feed-forward networks process the attended representations.

- **Classification Head:** The final layer of the Vision Transformer typically consists of a classification head, which takes the output of the encoder and predicts the class labels for the input image.

2.3.2 Types of vision transformers

There are several types of Vision Transformers (ViTs), each with its own variations and improvements. Here are some notable types:a

- **Original Vision Transformer (ViT):** [32], in the paper "An Image is Worth 16x16 Words: Transformers for Image Recognition" is the foundation for subsequent developments. It consists of a standard Transformer encoder architecture applied to image patches, with a zclassification head attached to the final token's representation.

- **DeiT (Data-efficient Image Transformer):** [33], DeiT aims to improve data efficiency by pretraining on large amounts of data with distillation techniques. DeiT utilizes knowledge distillation from a large teacher model, such as a CNN or a ViT pretrained on a large dataset, to distill information into a smaller ViT, enabling effective learning with less annotated data.

- **CoaT (Vision Transformer with Convolutions):** [34], combines convolutional layers with self-attention layers in a single architecture. It introduces convolutional tokens alongside the self-attention tokens to efficiently capture local features while still benefiting from the global context provided by self-attention.

- **Swin Transformer :**is another significant advancement in the realm of Vision Transformers. Introduced by [35], in the paper "Swin Transformer: Hierarchical Vision Transformer using Shifted Windows," Swin Transformer proposes a hierarchical architecture that leverages shifted windows to capture both local and global information efficiently.

- **Hybrid models:** Some recent research has explored hybrid models that combine the strengths of Vision Transformers with other architectures, such as CNNs or recurrent neural networks (RNNs), to create more versatile and effective models for specific tasks.

Conclusion

In this chapter, we have presented two main axes for our project: The first axis is skin cancer, where we defined skin cancer, its types, and discussed methods of diagnosing skin cancer. The second axis is artificial intelligence, where we defined artificial intelligence and machine learning, discussed its types, including deep learning such as CNN and GAN, and introduced Vision Transformers and their components and types.

In the following chapter, we will present related works to understand what should be included in our application and how to work on it.

Chapter 2

Related work

Introduction

In this chapter, we will begin by providing a synthesis of previous scientific contributions related to dermoscopic images in Section 1. Following this, in Section 2, we conduct a comparative study of existing mobile applications designed for diagnosing skin lesions.

1 Related Scientific work

In this section, we will analyze previous research related to the automatic diagnosis of skin cancer using AI techniques. We have curated papers from 2020 to 2024. The following table 2.1 illustrates the details of each selected paper.

- **Diverse Dataset Usage:** Researchers utilize various datasets such as ISIC2018 [36], ISIC2019, ISIC2020[37], and combinations thereof. but the majority have used ISIC2019 because of its diversity in types and samples.

- **Advancements in AI Techniques:** Different AI techniques are employed, ranging from machine learning methods like logistic regression and random forest [36]. Deep learning architectures in many versions like MobileNet, GoogleNet, ResNet,EfficientNet, VGG , DenseNet[38]. to vision transformers in various types such as original Vit architecture [39],swinVIT[40], and innovative ViTs like YoTransViT[40] and improved vision transformers [41] . This suggests ongoing exploration and adoption of newer AI models for improved performance in skin lesion classification tasks.

- **Preprocessing Techniques:** Preprocessing steps play a crucial role in enhancing the quality of input data. Techniques such as resizing[39] [42] [38], cropping, hair removal[37][41] [38], noise reduction, and color constancy are employed to standardize and clean the images before feeding them into classification models.

- **Segmentation :** Some works incorporate segmentation techniques like Fuzzy C-Means Clustering[43],YOLOv8 [40] Unet[36], and SAM[39], indicating a focus on precise delineation of lesion boundaries.

- **Data Augmentation:** data augmentation divided into two methods.The traditional techniques like random rotations, zooms, shifts, and flips [40][37][42] are used to increase the diversity of the training dataset and improve model generalization.and the advanced technique such as HEXA-GAN[44] ,“Naturalize” technique[39], SLA-StyleGAN[38]

1.1 Our Contribution in AI model

After analyzing previous work that contributed in skin cancer diagnosis from dermoscopic images, This synthesis clarifies our contribution, and we summarize it as follows:

- Improve data quality by pre process data by resizing, cropping, hair removal, noise reduction, and color constancy.

- Apply a semantic segmentation using fully Convolutional Networks in order to helps in precisely locating lesions within the dermoscopic image

- leverage the power of GANs in data generation to augment instances and balance the minority classes in ISIC2019. we will apply Pix2pix architecture.

- develop a ViT architecture for image classification

- Evaluate the effectiveness of our approach by comparing results with those obtained in the ISIC 2019 challenge.

- Realize a mobile application that will facilitate the use of our AI model and be accessible for everyone.

work	year	Dataset	AI technique	Preprocessing	Segmentation	Data augmentation
[43]	2020	ISIC2019	DE-ANN	median filter (remove the noise)	Fuzzy C-Means Clustering	NA
[38]	2021	ISIC2019	DenseNet201	removing hair resizing and tilling	NA	SLA-StyleGAN
[36]	2022	ISIC2018	InSiNet GoogleNet DenseNet-201 ResNet152V2 EfficientNetB0 , RBF-SVM logistic regression random forest	cropping with gaussianBlur	Unet	NA
[42]	2022	ISIC2019	mobileNet	resizing uniform resolution	NA	fills, zooms rotations flips
[37]	2023	ISIC2020 ISIC2019	CLCM net GoogleNet VGG19	hair is removed vintage boosting gray contrast DeTrop Noise by inpainting	YOLOv5 K means	rotations, zooms shifts
[45]	2023	ISIC2019	ResNeXt10132x	NA	NA	mixed sample data augmentation (MSDA)
[40]	2024	ISIC2019	YoTransViT swinVIT	Image resizing	YOLO V8	fills zooms, rotations flips
[39]	2024	ISIC2019	ConvNexTBase ConvNeXtLarge DenseNet201 EfficientNetV2 B0 nceptionResNet V2 VGG16VGG-19 ViT Xception	mage resizing	Segment Anything Model(SAM)	Naturalize technique augmentation
[41]	2024	ISIC2019	improved vision transformer	**Colour Constancy** Piecewise linear Bottom hat filtering **Image denoising** Adaptive median filtering and Gaussian filtering **Hair removal** Improved gradient intensity	Self-sparse watershed algorithm	NA
[44]	2024	ISIC2019	NA	NA	Unet	HEXA-GAN

Table 2.1. Previous Related Work on Automatic Skin Cancer Diagnosis

2 Existing similar mobile application

Now, let's begin examining the comparison table, which provides an overview of the various applications similar to the concept of our app. We conducted research on both the App Store and Google Play, using search terms such as "diagnosis," "skin cancer," "skin diseases," and "skin cancer detection," in both Arabic and English. We then proceeded to select applications that meet the following criteria: relevance to skin cancer and skin health in general, availability as free downloads, completeness in terms of programming, support for multiple languages with a focus on Arabic, and diversity in diagnosis capabilities.

We utilized a color-coded system in the table to indicate the performance of each application: red points highlight areas where the application may fail or need improvement, yellow points indicate areas with average performance, and green points signify strong performance. We will focus on the shortcomings in most of these applications to emphasize the importance of enhancements in our own application.

In each element of the table column illustrated in the following Figure 2.1, we observe that:

Mobile app name	Types of skin lesions treated	User Friendly Interface	Medical infos	Operating system	User Profiles & History	Multi language Support	Integration with dermatologists	Community forums, chat groups	Privacy & Security	Notifs and Reminders	Integration with Wearable Devices	The subscription price
scanoma	just **concern** or **benign**	🟢	🟡	IOS + Android	🟢	English	🟢	🔴	🟡	🔴	🔴	**just first diagnosis free** 3360,88DA
miiskin	just **monitoring skin changes**	🟢	🟡	IOS + Android	🟢	English	🟡	🔴	🟢	🟢	🔴	**just first diagnosis free** **1 MONTH:** 3360,88DA **1 YEAR:** 4031,71DA
AI Dermatologist	**Skin cancer** and **Papilloma virus** and **Benign formations** and **6 types of acne**	🟢	🟢	IOS (version is not available in Algeria) + Android	🟡	English	🔴	🔴	🟡	🟡	🔴	**just first diagnosis free** 400.00DA
MoleCare	just **monitoring skin changes**	🟢	🔴	just IOS	🟢	English	🟢	🔴	🟢	🟡	🔴	**FREE:** 0DA
MoleScope	just **concern** or **benign**	🟢	🟡	IOS + Android	🟢	English Spanish Italian French Portuguese German	🟢	🔴	🟡	🟢	🔴	**FREE:** 0DA
aysa	just **concern** or **benign** **(not a clear diagnosis)**	🟡	🟡	IOS + Android	🟢	English	🔴	🔴	🟢	🔴	🔴	**FREE:** 0DA
SkinVision	just **concern** or **benign**	🟢	🟢	IOS + Android	🟡	English	🟢	🔴	🟡	🟢	🔴	**just first diagnosis free** **3 MONTH**: 3300.00DA **1 YEAR:** 6500.00DA **single skin check:** 950.00DA
SkinVision	just **concern** or **benign**	🟢	🟢	IOS + Android	🟡	English	🟢	🔴	🟡	🟢	🔴	**just first diagnosis free** **3 MONTH**: 3300.00DA **1 YEAR:** 6500.00DA **single skin check:** 950.00DA
FIRST DERM	just **concern** or **benign**	🟢	🔴	IOS + Android	🟡	English	🟢	🔴	🟡	🔴	🔴	**8HOURS:** 9382,26DA **24HOURS:** 6699,70DA **48HOURS:** 4687,78DA
Skinive	**Viral Diseases** and **Benign Formations** and **skin Cancer** and **Acne** and **Overall Sensitivity**	🟢	🟢	IOS + Android	🟢	English Arabic	🟡	🔴	🟢	🟢	🔴	**just first diagnosis free** **MONTH**: 1525.00DA

Figure 2.1. Existing similar mobile application.

- **Types of skin lesions treated:** Most applications provide results for diagnosing cancer, whether malignant or benign, while the **MIISKIN** app and **Molecare** app merely monitors changes in the skin.

  Ai Dermatologist app diagnoses skin cancer, Papilloma virus, benign formations, and six types of acne, and **Skinive** app diagnoses skin cancer, Overall Sensitivity,Viral Diseases, benign formations, and acne, while the diagnosis of the **AYSA** application is unclear.

- **User Friendly Interface:**

  All applications have strong user interface performance, except for **AYSA**.

  It's important for the user interface to have high performance because it makes it easier for users to use and more comfortable for them.

- **Medical Iinfos :**

  Most applications lack medical information, while the **AI Dermatologist** app contains a wealth of medical information. However, the **FIRSTDERM** and **MoleCare** apps lack any medical information at all.

  The absence of medical information renders the user unable to benefit fully from the application and the diagnosis itself, as medical information guides and interprets their health condition more effectively.

- **Operating system:**

  All applications support both iOS and Android operating systems, except for the **Molecare** app support juste ios.

- **User Profiles and History**

  Most of the applications allow users to create an account and view previous diagnoses.

  It's beneficial for users to have a personal account where they can view their previous diagnoses or communicate with specialized doctors, and it provides enhanced protection for their privacy.

- **Multi language Support:**

  All applications support only the English language, except for Mole Scope, which supports English, Spanish, Italian, French, Portuguese, and German. Additionally, the **Skinive** app supports both English and Arabic, but Arabic language is only available in medical information.

It's unfortunate that the Arabic language is absent in skin disease diagnosis and skin cancer applications for the Arab world.

- **Integration with dermatologists:** Most applications allow communication with dermatologists for consultations, except for the **AYSA** and **AI Dermatologist** apps.

  Communicating with dermatologists enables users to inquire more about their condition and receive more accurate and precise guidance.

- **Community forums or chat groups:**

  All the applications do not include chat groups and forums for communication with others and sharing experiences, although this feature is considered important for individuals to share their experiences with a specific disease and for others to benefit from these experiences in terms of treatment and diagnosis.

- **Privacy and Security:**

  Most of the applications do not provide sufficient protection for user privacy and security. Despite the absence of this feature, it is important for user privacy and personal information to be protected.

- **Notifs and Reminders:**

  Most applications do not include reminders and notifications.

- **Integration with Wearable Devices:**

  All applications lack integration with wearable devices. If this feature were available, it would provide more accurate diagnosis and greater ease of use.

- **The subscription price:**

  Most of the applications offer initial diagnosis for free, then require a subscription for nominal fees ranging from 400.00DA to 9382.26DA.

And there are other applications, besides those listed in the table, that cannot be used because they are not free from the first use payment is required. Some of these apps are also incomplete in their development for diagnosis and have poor user interfaces.

Conclusion

In conclusion, this chapter has provided a comprehensive overview of two key aspects in the field of dermoscopic image analysis. Firstly, a synthesis of previous scientific contributions has been presented, offering valuable insights into the evolution of methodologies and approaches. Secondly, through a comparative study of existing mobile applications for skin lesion diagnosis, we have gained a deeper understanding of the current landscape and identified areas for further research and development.

In the next chapter, we will conduct an in-depth analysis and design of our system

Chapter 3

Analysis and Design

Introduction

In this chapter, we will study system analysis and design. These two fundamental stages are essential for developing our mobile applications. In the analysis phase, we will describe the functional and non-functional requirements along with the conceptual models. In the system design phase, we will outline the primary scenarios for the application (login, account creation, and diagnosis application), design the database, and detail the navigation scenarios of our application. We have chosen the standard language UML (Unified Modeling Language) to design our system.

1 System analysis

In the system analysis phase, the specifications are meticulously defined. It commences with a precise delineation of the system's objectives, followed by the identification of both functional and non-functional requirements anticipated from the system. These requirements encompass the system's expected capabilities, constraints, performance criteria, and other quality attributes. Furthermore, the interactions between the system and its users are intricately modeled using the Unified Modeling Language (UML) use case diagrams. These diagrams depict various scenarios of how users interact with the system to accomplish specific tasks or achieve certain goals, providing a comprehensive understanding of the system's functionality from the user's perspective.

Through this detailed modeling process, analysts ensure that the system's design aligns seamlessly with the needs and expectations of its intended users, laying a solid foundation for subsequent stages of system development.

1.1 Purpose of the application

The primary purpose of the application is to design and develop a mobile application aimed at simplifying the process of identifying different types of skin cancer. By leveraging modern technology, the application seeks to streamline and enhance the diagnosis process, enabling users to efficiently and accurately determine the type of skin cancer they may be suffering from. This comprehensive goal aligns with the broader objective of improving accessibility and efficiency in healthcare by providing individuals with a convenient tool for self-assessment and preliminary diagnosis.

Secondary goals of the application:

- **Facilitate Symptom Sharing:** Enable users to share their disease symptoms with others, fostering a collaborative environment for exchanging information and insights about various health conditions.
- **Enhance Utility and Flexibility:** By allowing users to share experiences and symptoms, enhance the application's utility and flexibility, creating a supportive community focused on collective health management.
- **Supportive Community Building:** Create a supportive community where users can learn from each other's experiences, promoting mutual support and collective contribution to health management.
- **Empower Users:** Provide users with valuable tools and resources for self-assessment and initial diagnosis, empowering them to take control of their health and well-being.
- **Improved Healthcare Outcomes:** Through the primary and secondary goals, contribute to improved healthcare outcomes and overall well-being for individuals from diverse demographics.

These secondary goals complement the primary goal of simplifying the skin cancer type determination process and contribute to the overarching goal of improving access to and efficiency of health care.

1.2 Functional requirement

Functional requirements outline the specific functionalities and features that the mobile application must possess to fulfill its objectives effectively. These requirements serve as guidelines for the development team, detailing what actions the application should perform and how it should behave in various scenarios. In addition to ensuring that the application meets its primary and secondary goals, the functional requirements also aim to enhance user experience, usability, and overall effectiveness.

The following points elaborate on key functional requirements:

- **Create an account:**Each visitor can create an account by entering their information(name, first name, age, password...).
- **Apply a diagnosis:** Both visitors and members can use Apply a Diagnosis However, for visitors, they are allowed to use Apply a Diagnosis only three times before being required to create an account.
- **log in:**The system allows the member to log in when entering the email and password.
- **Manage the profile:** Each member can manage his information (modify, add, delete...).
- **Review the previous diagnoses:** Any member can view previous diagnosis.
- **classify the lesion:**AI Model classifies the types of the skin lesion.
- **Show results:** Show result by classification of the types of lesion.
- **Review information related to the type of lesion :**After the diagnosis, the member can see information about the type of lesion.
- **Share experience with the other members:** Each member can share information about his illness with other members.
- **upload picture:** member downloads the image from the phone image file.

1.3 Non-functional requirement

The non-functional needs are essential and allow improvement of the software quality of our system. Among these needs are:

- **Usability:** The application should be intuitive and user-friendly, allowing users to navigate and utilize its features with ease. It should also be flexible to accommodate different user preferences and needs.

- **Security:** The application must prioritize the confidentiality and integrity of user data. It should implement robust security measures to protect against unauthorized access, data breaches, and other security threats.
- **Performance:** The system should be capable of handling a certain level of workload efficiently, ensuring acceptable response times and minimal downtime even under peak loads.
- **Reliability:** The system should operate consistently and reliably, minimizing the occurrence of failures or errors. It should be resilient to faults and able to recover gracefully in case of failures.

1.4 Use case diagram (system analysis model)

The use case diagram is a graphical representation that is used to show the interactions between the users of a system and the system itself.same For this we must:

1. Identify the actors of the system.
2. Identify the use cases of each actor.

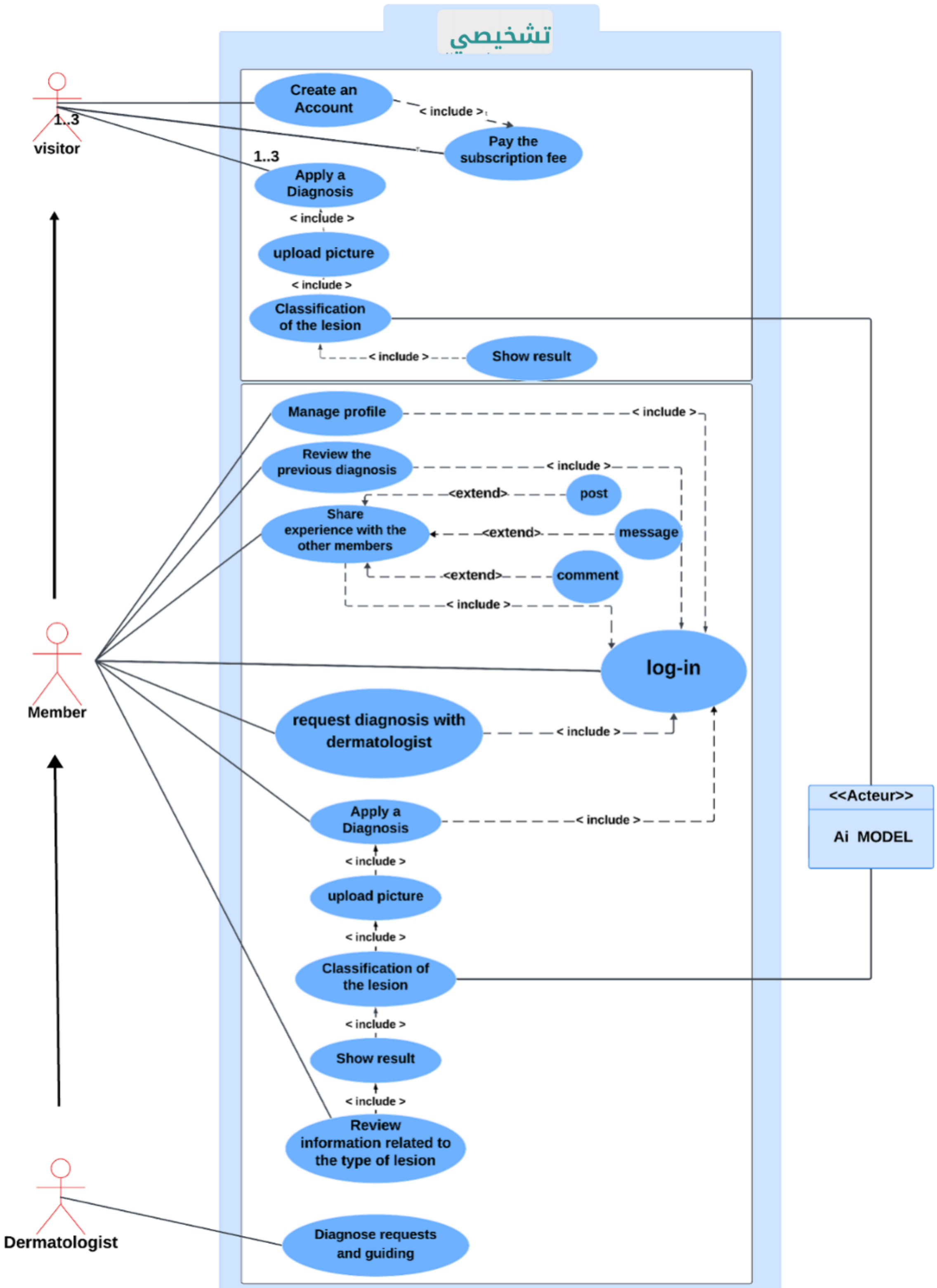

Figure 3.1. Use case diagram.

1.4.1 Identification of actors

- **Actors:** are external entities that represent roles played by users and who interact with the system The Figure 3.1 represents the actors and cases identified for our application.

For this model, we distinguish four actors who are:

- **AI Model:** it is the actor who classify the lesion.
- **Visitor:** The visitor is a user who can access the application, create an account, and also utilize apply diagnosis , only three times.
- **Member:** It is the visitor who registers in the application, and can also manage his profile.
- **Dermatologist:**A dermatologist answers people's questions, provides guidance, and has the ability to create an account for their practice or personal use.

1.4.2 Identification of use cases

A use case: is an organized sequence of activities. It describes the interactions that allow the actor to achieve his objective by using the system. Figure 3.1 shows the use cases identified for each actor in the system. These use cases are listed below:

The operations carried out by the visitor:

- **Register:** enter personal information (name, email, password. . .) to become a member.
- **Apply a diagnosis:**the visitor,they are allowed to use Apply a Diagnosis by taking a picture. but only three times before being required to create an account.

The operations carried out by the member:

- **Login:** Enter email address and password.
- **manage the profile:** the member can manage the profile that modifies him (the name and password.
- **Share experience:** A member can share their experience with other members by commenting or post or message.
- **Apply a diagnosis:** the member can make the diagnosis by taking a picture.

- **Review information related to the type of lesion :** the member can Review information related to the type of lesion after diagnosis.
- **request diagnosis with dermatologist:** Members can communicate and consult with a dermatologist about their diagnosis and condition.
- **Review the previous diagnosis:** Members can review previous diagnosis in history.

The operations carried out by the dermatologist:

- **Diagnose requests and guiding:** The dermatologist can answer members' inquiries, provide guidance, and offer advice.

The operations carried out by the AI model:

- **Classification of the lesion :** After taking the picture,AI Model classifies the lesion according to the picture taken.

2 System design

The design phase for describing so unambiguous structures and behaviors of the system .The result of this stage is a set of models representing the proposed solution .There are two aspects to model a system : the static aspect and the dynamic aspect

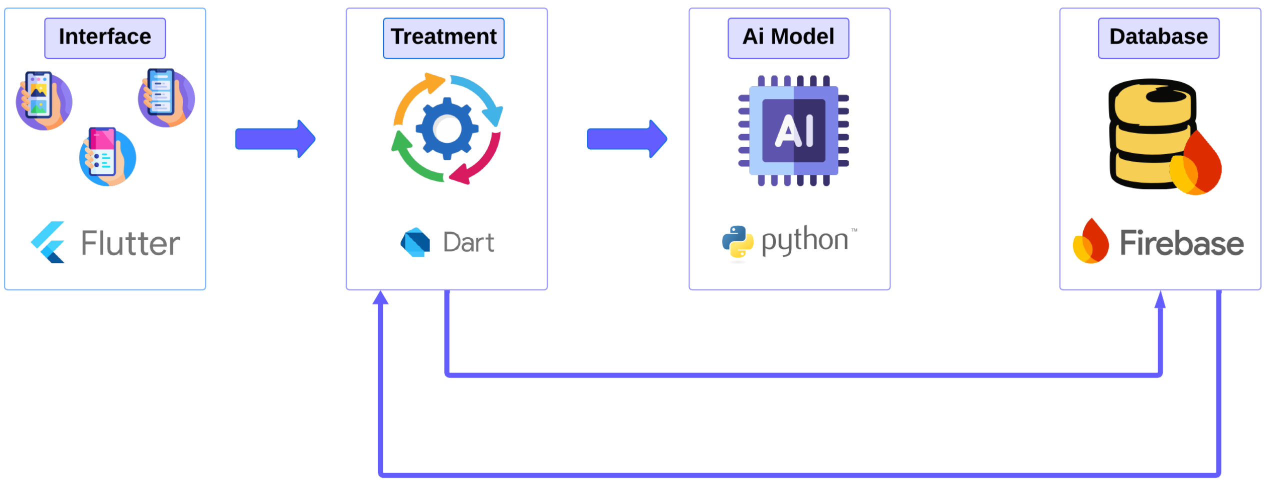

Figure 3.2. System Design Overview .

2.1 Global architecture of the system

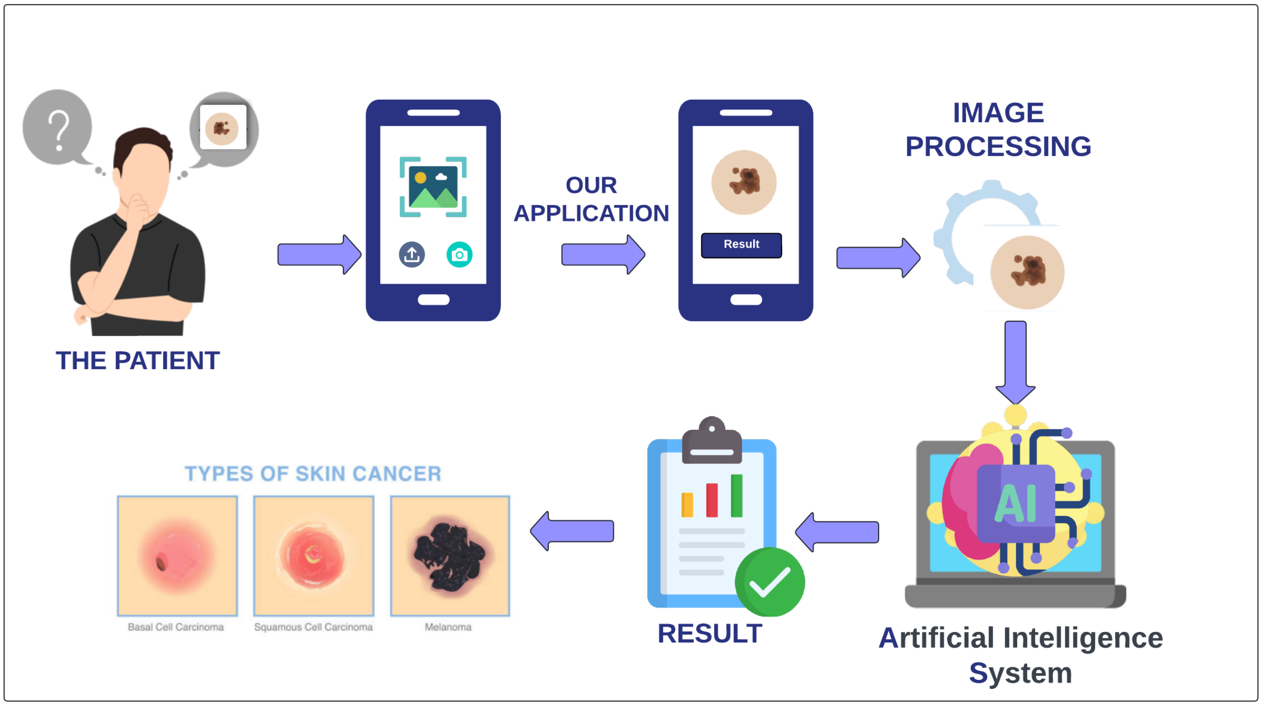

Figure 3.3. Image Processing Pipeline

This Figure 3.3 shows the Image processing pipeline in our app .

- Patients can use our application by taking a image of the suspected lesion using the camera or uploading it from their phone.
- Our application then processes the image using an artificial intelligence system .
- Our AI system provides the processing result ,which indicates the type of skin cancer

2.2 Definition of UML

UML stands for Unified Modeling Language. It's a standardized modeling language used in software engineering to visualize, specify, construct, and document the artifacts of a software-intensive system. It provides a set of graphic notation techniques to create visual models of software-intensive systems.[46]

UML encompasses a variety of diagram types, including class diagrams, sequence diagrams, use case diagrams, activity diagrams, and many more. Each diagram type serves a specific purpose in modeling different aspects of the system.[46]

2.3 Dynamic aspect

The dynamic aspect captures the operational behavior of structural elements. In our approach, we leverage UML sequence diagrams to illustrate the interactions among system components and objects during the execution of use cases, providing a temporal perspective.

Subsequently, we will detail the important sequence diagrams and interactions within our system.

2.3.1 Sequence diagram of the ”Register”scenario

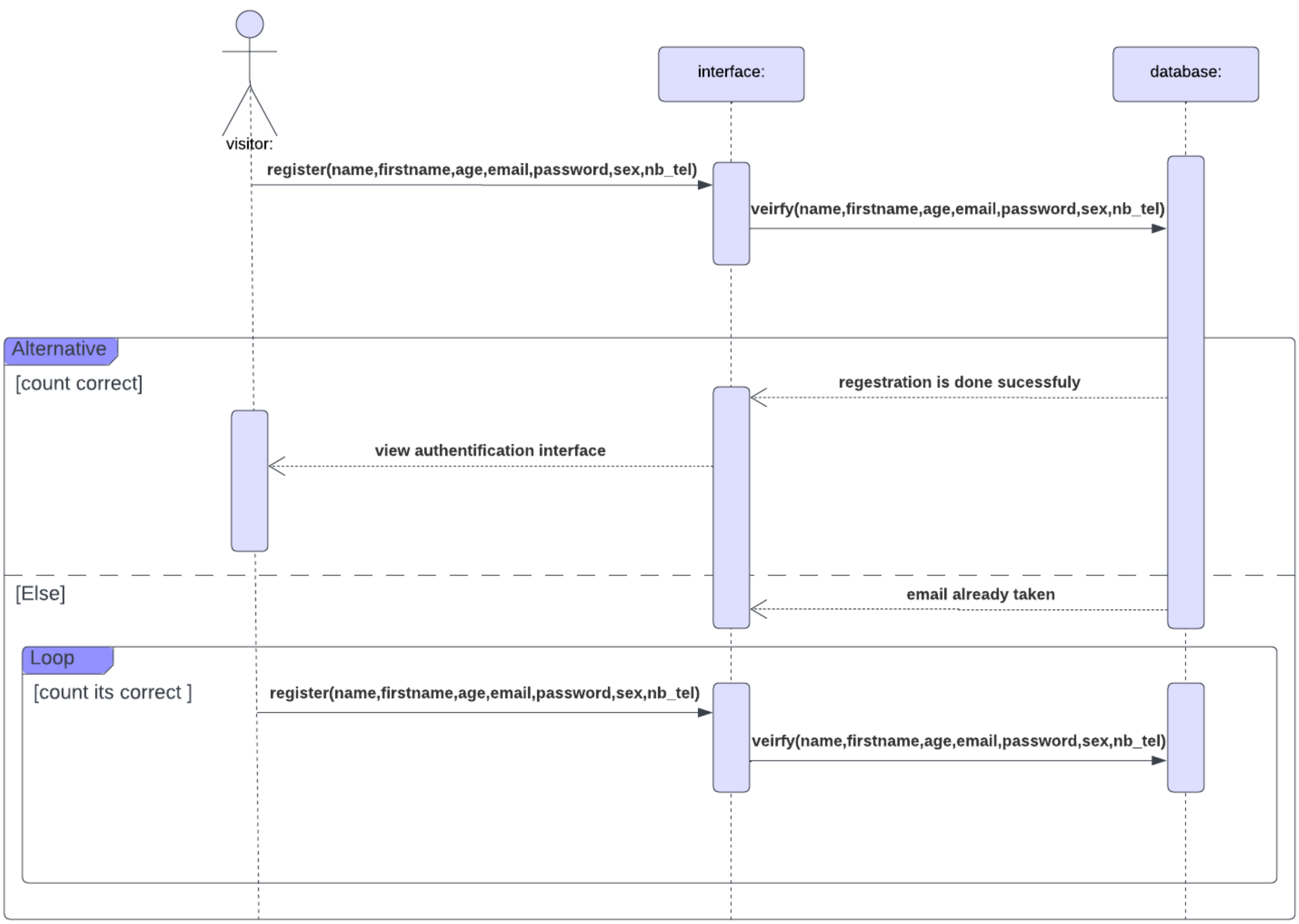

Figure 3.4. Sequence diagram of the ”Register”scenario.

This sequence diagram depicts a potential scenario for the enrollment process. Every visitor provides their personal details including surname, first name, email, password, telephone number, and address to register and acquire membership. The system validates the information provided by the visitor, subsequently either accepting the registration or issuing a failure message.

2.3.2 Sequence diagram of the ”Authentication” scenario

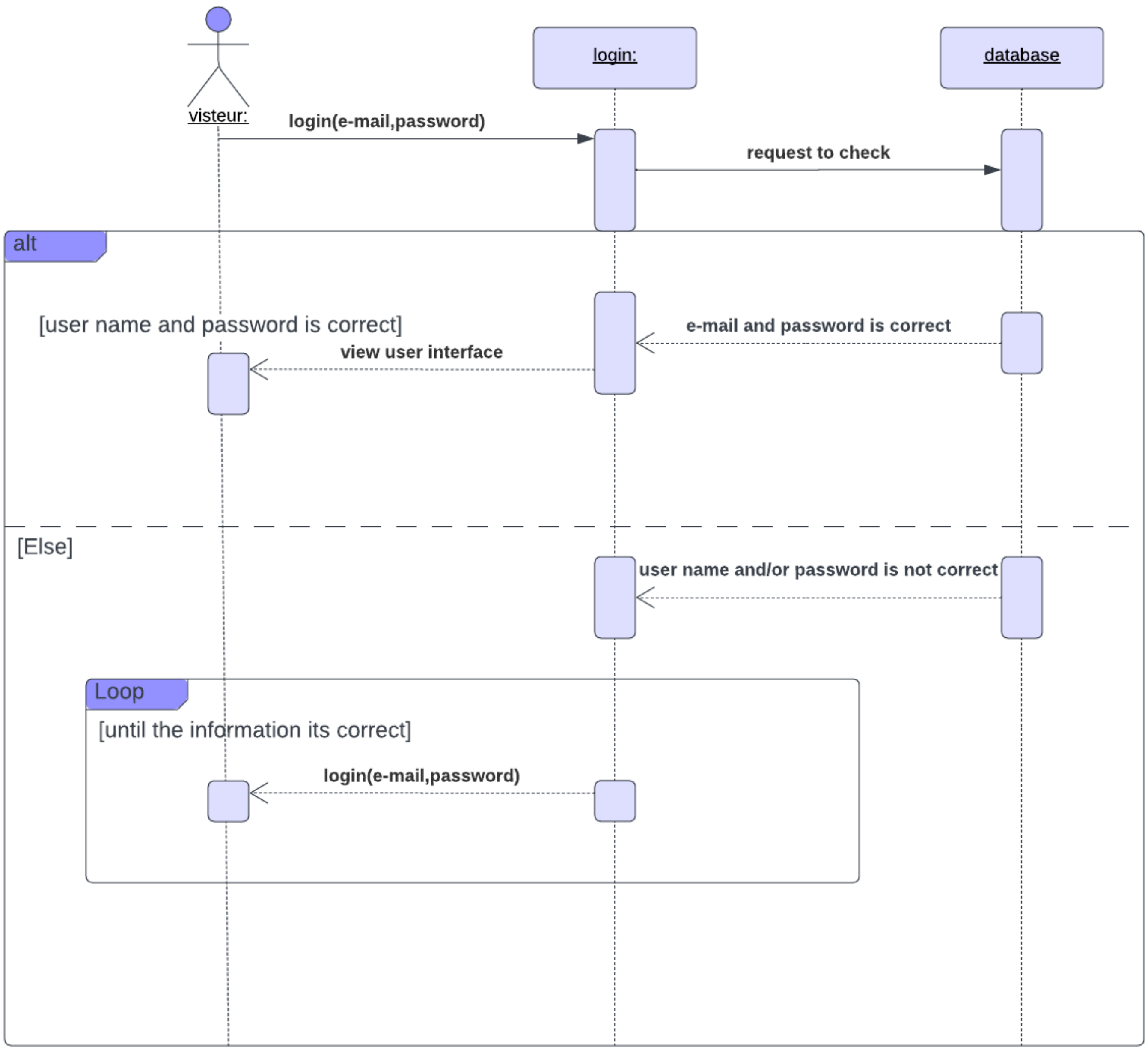

Figure 3.5. Sequence diagram of the ”Authentication” scenario.

The scenario outlined in Figure 3.5 pertains to authentication. Each member provides an email and password for authentication purposes. The system verifies the authentication process as follows:

- If the member does not exist or if the password is incorrect, the system displays an error message.
- If both the email and password are correct, the member gains access to their profile.

2.3.3 Sequence diagram of the "apply diagnostic" scenario

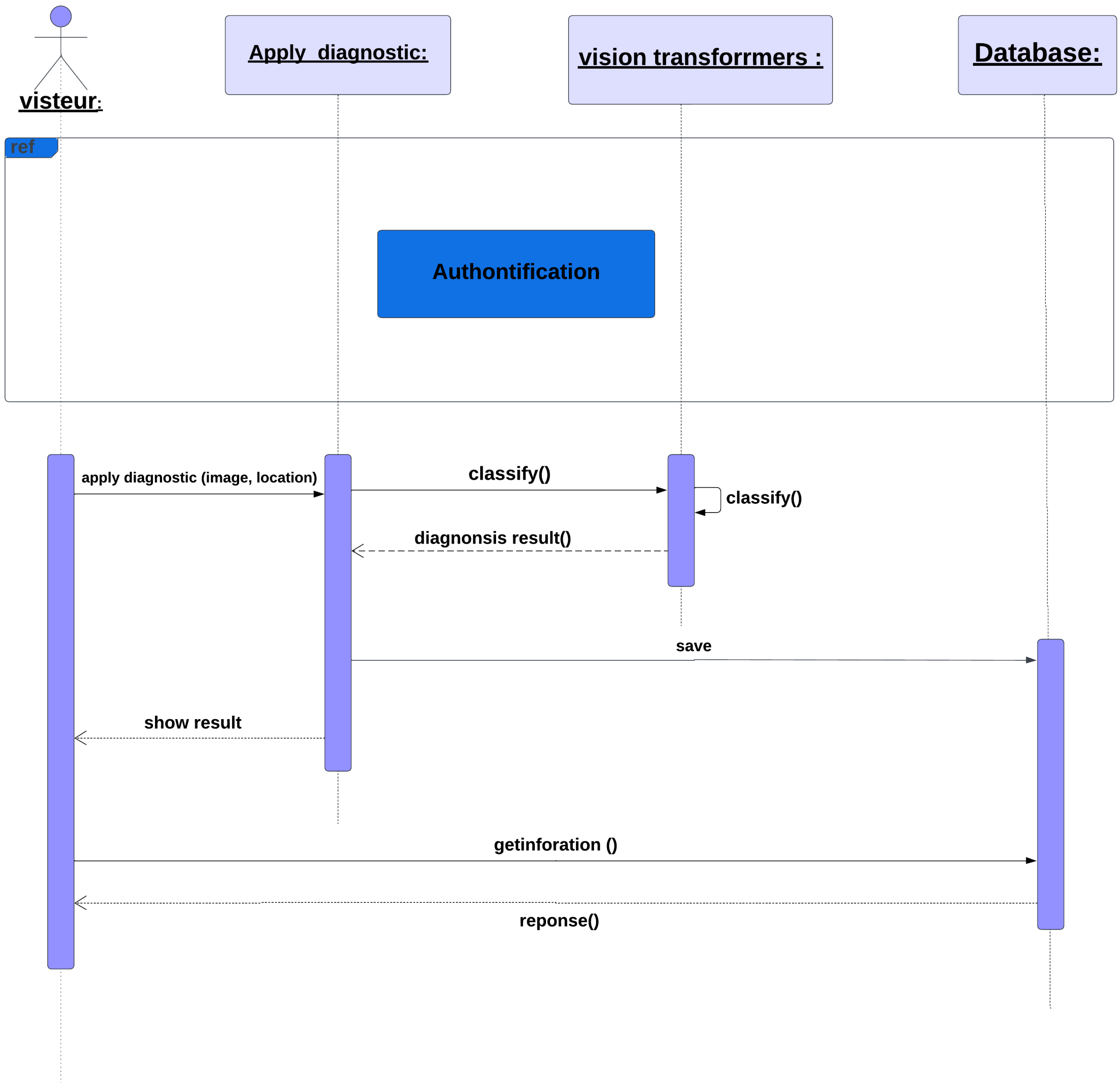

Figure 3.6. Sequence diagram of the "apply diagnostic".

The diagram depicted in Figure 3.6 illustrates the potential scenario for applying diagnostics. In this scenario, each member initiates the authentication process, following which they proceed to capture an image using the camera and select the location of the lesion. Subsequently, the system is tasked with classifying the lesion, after which it dispatches a message containing the classification results.

2.4 Database design

2.4.1 Entity-Association Model

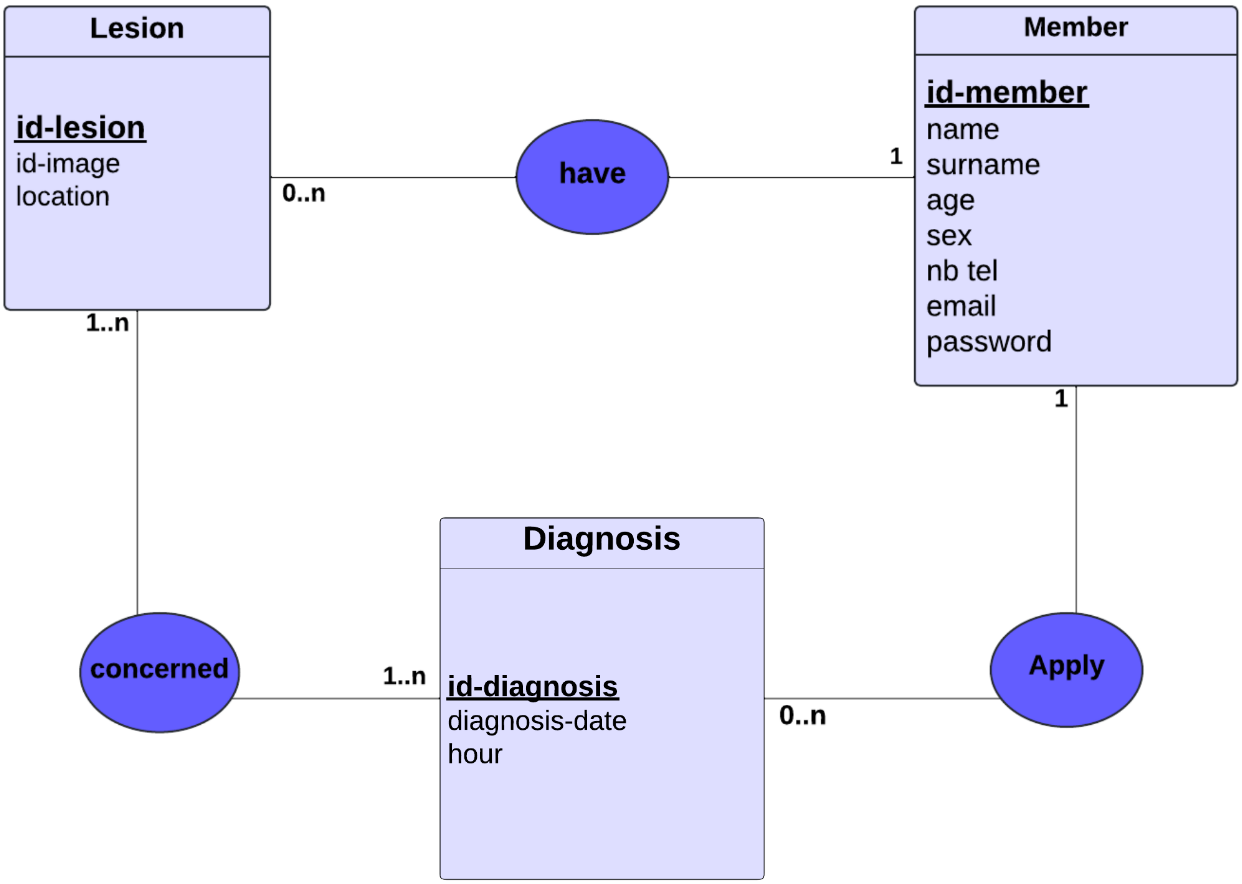

Figure 3.7. Entity-Association Model

Figure 3.7 provides an illustration of the association entity model, showcasing the structural layout of the tables employed within the database, along with their interrelationships. This diagram serves to depict the data aspect of the system, offering insights into how various entities within the database are organized and connected to one another.

2.4.2 Relational model

Tables used in our database:

```
Member (id_member, name, surname, age, sex, nb_tel,email,password,#id-lesion,
#id-diagnosis).

Lesion(id_lesion,id_image,location,#id_member,#id_diagnosis).

Diagnosis (id_diagnosis, diagnosis_date, hour, #id_member, #id_lesion).
```

2.5 The navigation model

The navigation model is crafted to enable mobile application architects to swiftly and effortlessly define the sequence of pages visited. The navigation scenarios of our application can be visualized graphically, as illustrated in Figure 3.8. This model represents the presentation layer of the system.

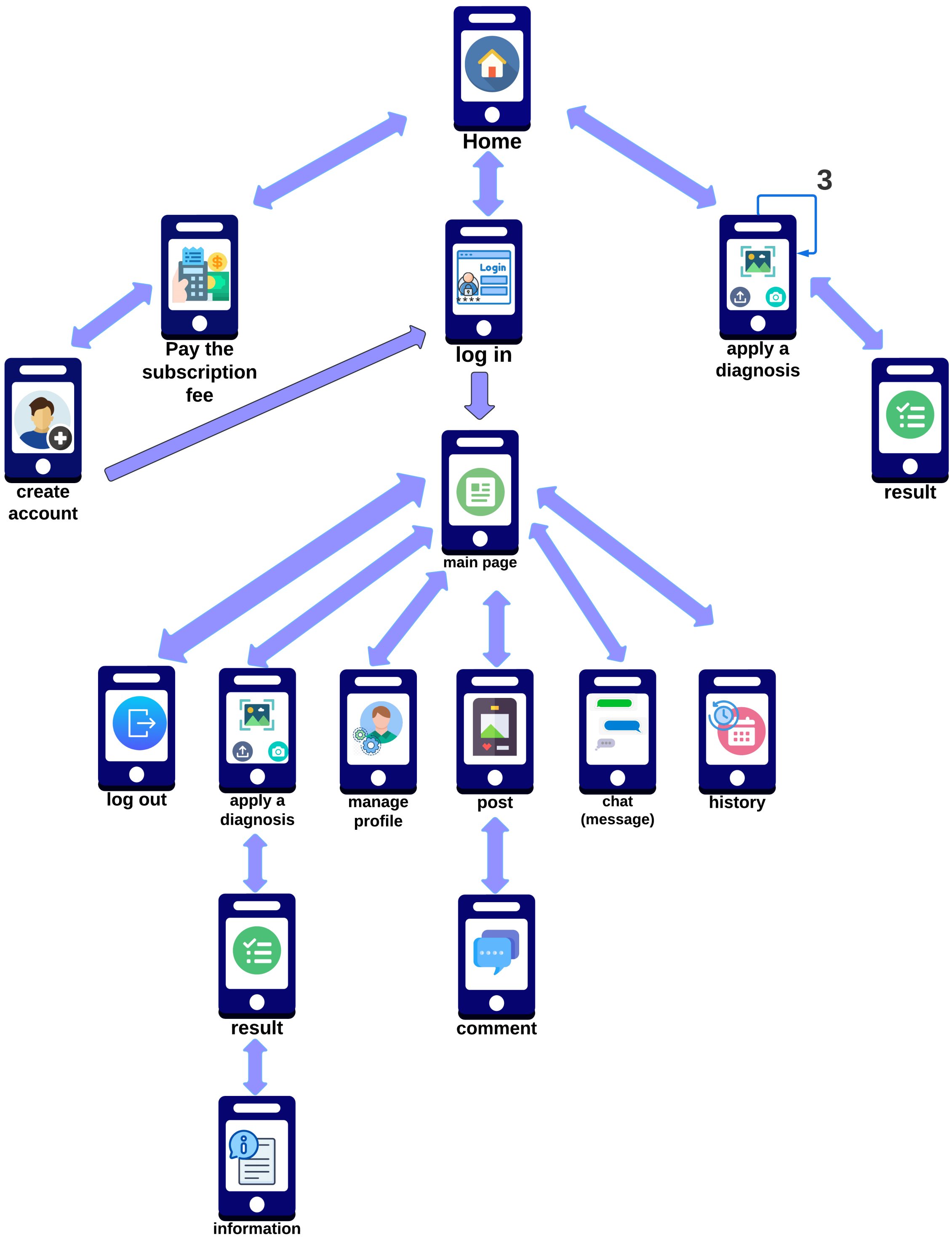

Figure 3.8. The navigation model.

Conclusion

In this section, we have outlined the analysis and design of our system through a series of diagrams including use case and sequence diagrams, as well as an association entity diagram. Additionally, we have introduced the fundamental data structures utilized in our application. The implementation phase will be detailed in the next chapter.

Chapter 4

Implementation

Introduction

This chapter provides a detailed explanation of the implementation of our project, which comprises three main parts as ilustrated in Figure 4.1 . Each section focuses on a critical component necessary for the successful development of our system for skin cancer diagnosis.

The first part addresses the development and testing of Pix2Pix GAN for data augmentation, aiming to solve the imbalance problem in the ISIC2019 dataset. We will outline the development tools and resources used, providing a comprehensive guide on how we approached the data augmentation to ensure a balanced dataset. The second part covers the implementation of the DeiT architecture for skin lesion classification, and a comprehensive overview of the tools, libraries, and datasets used to train our architecture. Additionally, we present detailed results and analysis of the performance improvements achieved through these advanced techniques. The final part focuses on the implementation of the mobile application itself. We will detail the development environment, tools, and resources that were instrumental in building the application, followed by screenshots of the different interfaces of our mobile application.

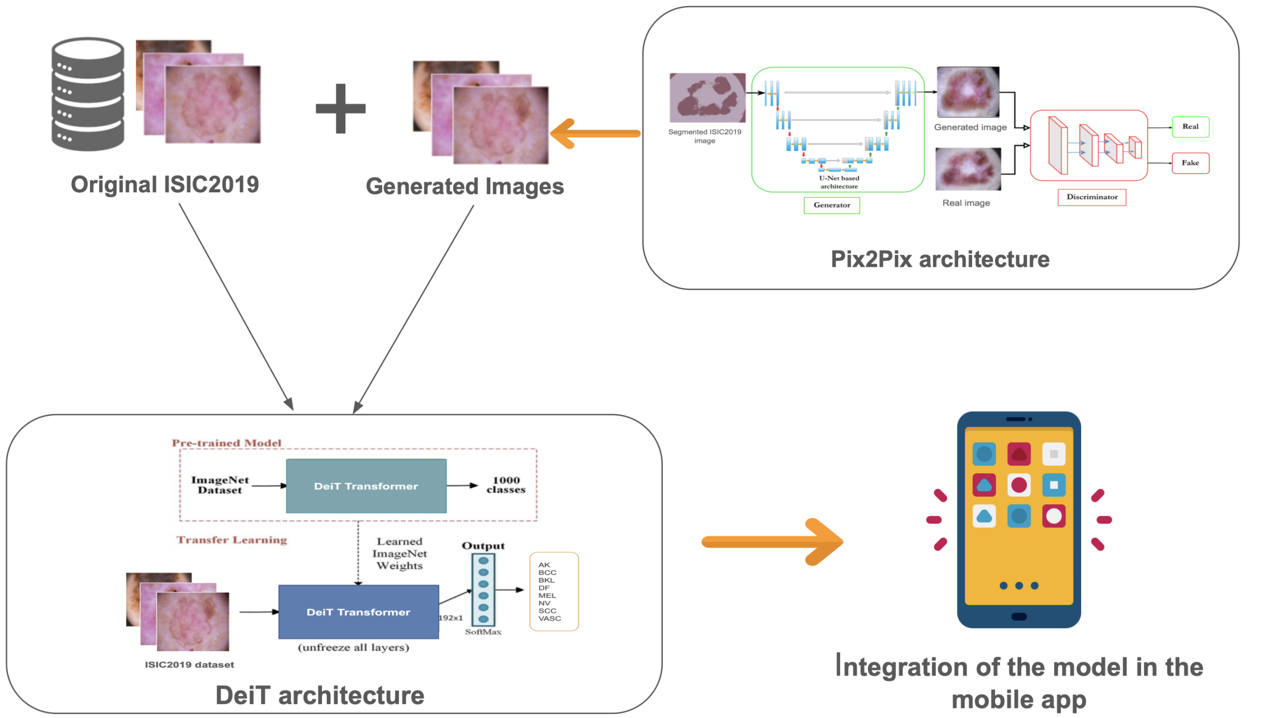

Figure 4.1. Global architecture of our system.

1 Pix2Pix GAN development

The primary objective of this project is to enhance the detection of skin cancer by addressing the data limitation and imbalance problems. By leveraging advanced techniques such as Generative Adversarial Networks (GANs), we aim to augment and balance existing datasets, thereby providing a richer and more diverse set of images for training machine learning models. This augmented dataset will improve the model's ability to identify various types of skin cancer more accurately and reliably, particularly rare malignant cases, ultimately contributing to better diagnostic tools and improved patient outcomes. The figure4.2 provides a visual representation of the pix2pix development workflow.

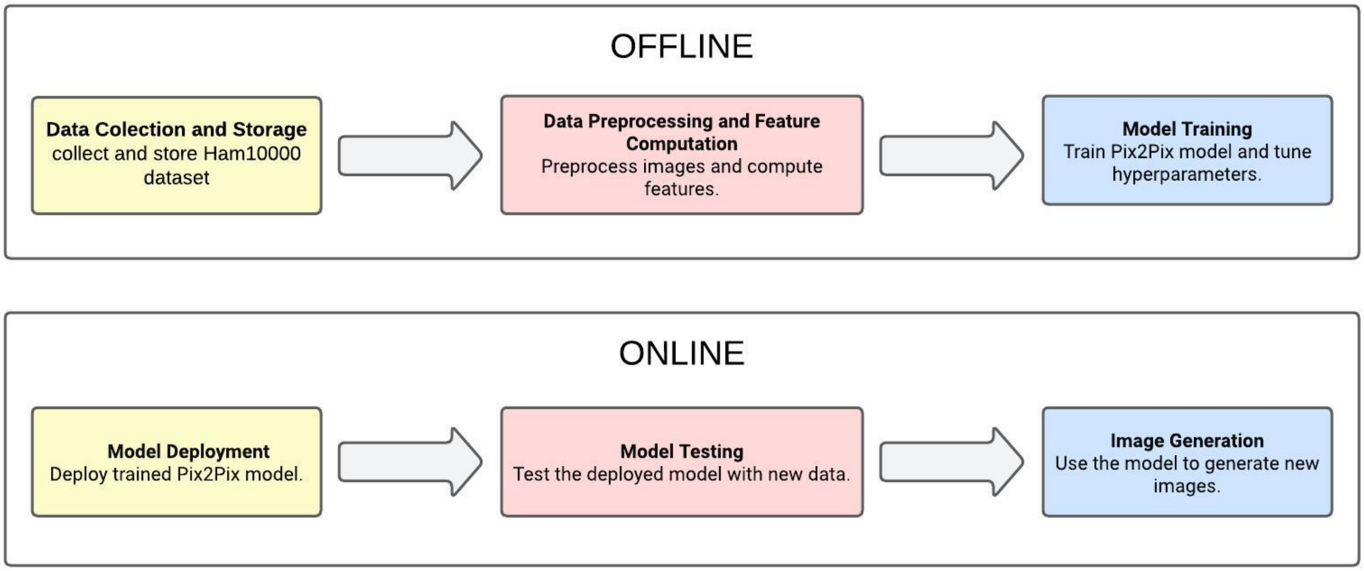

Figure 4.2. Process Outline for pix2pix Training and Testing .

1.1 Offline Step

In our project, we utilized the HAM10000 dataset to train and test the Pix2Pix model. The dataset was instrumental in providing the necessary data for training, allowing the Pix2Pix model to learn and perform image-to-image translation tasks effectively. Through this process, we aimed to assess the capabilities of Pix2Pix in generating accurate and realistic images based on the input data, thereby demonstrating its potential applications in various image processing and synthesis tasks.

1.1.1 Development Tools and Libraries

We employed several deep learning frameworks and libraries for our implementation,the figure4.3 highlights the important tools and their roles.

Icon	Its role
	· Keras with TensorFlow backend was used for certain preprocessing steps
ANACONDA	· Anaconda provided an integrated environment for managing these tools and dependencies.
jupyter	· Jupyter notebook for organizing data .
PyTorch	. PyTorch was employed for training Pix2pix Gan .
python	. phython as a programming language .

Figure 4.3. Functions of Development Tools and Libraries.

1.1.2 Data description

To begin our project, we collected a comprehensive set of dermoscopic images from the HAM10000 dataset, comprising 10,015 images of various skin lesion types. This extensive dataset includes different forms of skin conditions such as melanoma, basal cell carcinoma, squamous cell carcinoma, and five other kinds. Each image varied in resolution, lighting, and patient demographics, reflecting the diversity of real-world clinical scenarios.

1.1.3 Data Preprocessing

The preprocessing steps included resizing all images to a standardized resolution, normalizing pixel intensities, and applying basic data augmentation techniques such as rotation, flipping, and cropping to enhance the dataset's variability.

1.1.4 Semantic Segmentation

- **Objective**

  The primary purpose of semantic segmentation in this project was to highlight the real image details in a semantic way, specifically isolating and enhancing the features of lesion areas from the rest of the skin. This step is critical for generating high-quality, detailed images that can be used to train the GANs effectively.

- **Model Architecture**

  For the semantic segmentation task, we employed a neural network architecture tailored for this purpose. The model was designed to emphasize and highlight the significant features of skin lesions. The architecture was chosen to balance complexity and performance, ensuring accurate segmentation without excessive computational demands, furthermore it's well-suited for medical image segmentation due to its ability to capture fine-grained details and its capability to use as a pix2pix Gan input, as shown in figure4.4.

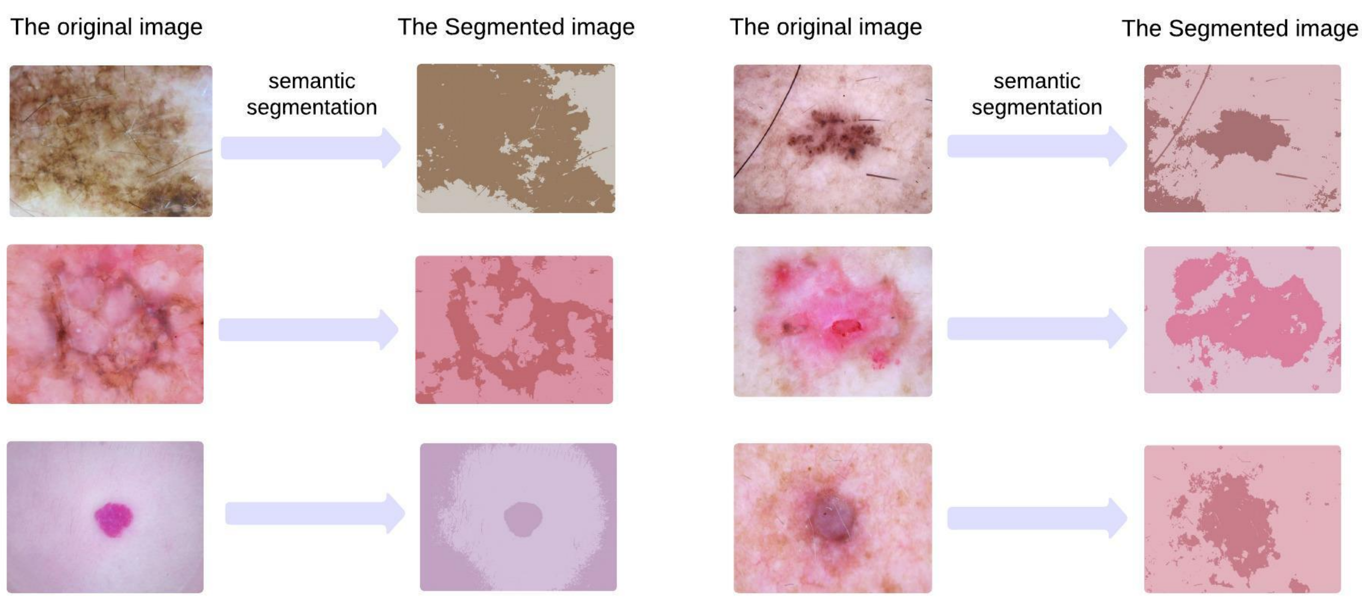

Figure 4.4. Semantic segmentation results on skin lesion images .

- **Pairing Real Images with Segmentation Masks**

  The input to the GAN consisted of pairs of real dermoscopic images and their corresponding segmentation masks. This step was crucial for providing the pix2pixGAN with accurate input data because this pairing ensures that the GAN learns the correct mapping from segmentation masks to realistic images as described in figure 4.5.

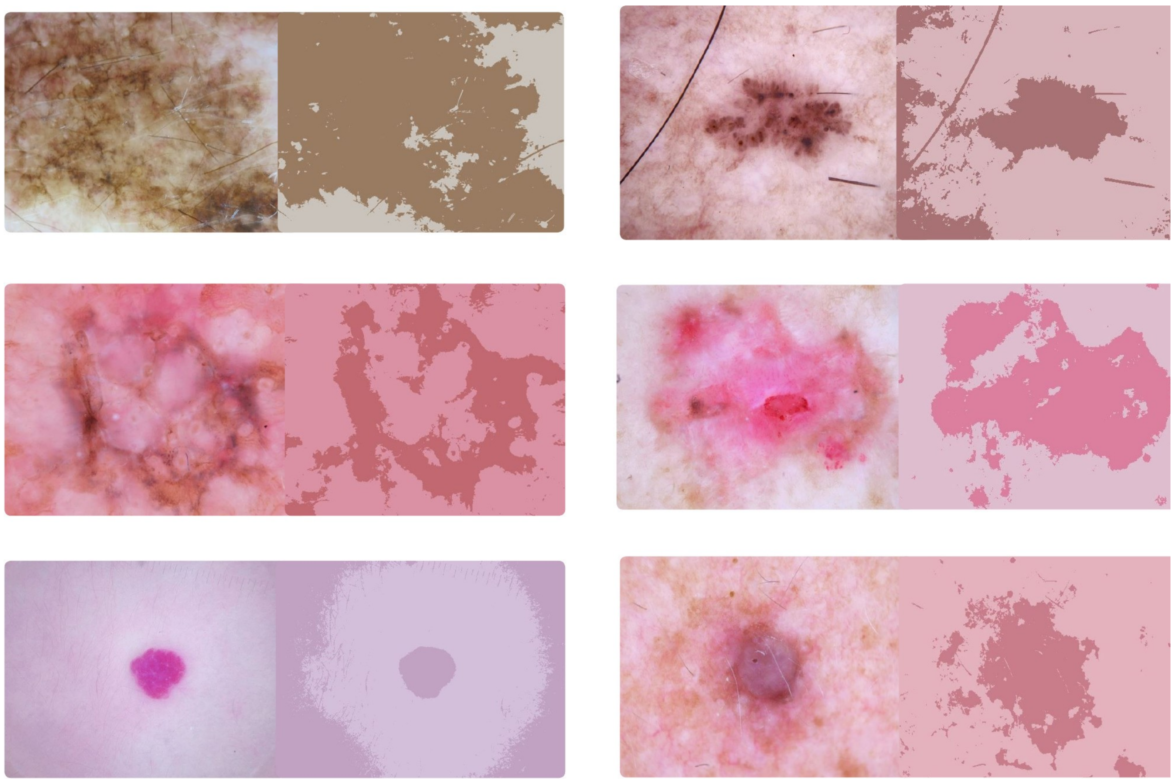

Figure 4.5. Pairing Real Images with Segmentation Masks.

1.1.5 Data analysis

- **Dataset Splitting**

  The dataset was split into training, validation, and test sets with a ratio of 80:10:10 , respectively. This splitting ensures that the model's performance is evaluated on unseen data, providing a robust assessment of its generalization capabilities.

- **Training Parameters**

  The paired images were then used to train a GAN, specifically a Pix2Pix model, which is designed for image-to-image translation tasks. The Pix2Pix model uses a conditional adversarial network to learn the mapping from input images to output images. We trained the pix2pix model using a learning rate of 0.0002, a batch size of 1, and for a total of 200 epochs.

- **Evaluation Metrics**

  The quality of the generated images was assessed through various metrics, including:

1. G_{GAN} **(Generator Adversarial Loss):**

   This metric represents the adversarial loss of the generator. It measures how well the generator is able to fool the discriminator into believing that its generated images are real.

   A lower G_{GAN} typically indicates better performance in generating realistic images.

2. G_{L1} **(Generator L1 Loss):**

   This is the L1 loss of the generator, which measures the pixel-wise difference between the generated image and the target image. It encourages the generated image to be similar to the target image in terms of pixel values.

   A lower G_{L1} indicates better reconstruction fidelity.

3. D_{real} **(Discriminator Real Loss):**

   This metric represents the loss incurred by the discriminator when classifying real images as real.

   A lower value indicates that the discriminator is better at correctly identifying real images.

4. D_{fake} **(Discriminator Fake Loss):**

   This is the loss incurred by the discriminator when classifying fake (generated) images as fake.

   A lower value suggests that the discriminator is better at distinguishing fake images from real ones.

Additionally, visual inspection was conducted to gauge the realism and diversity of the synthetic images.

1.1.6 Results:

```
learning rate 0.0000020 -> 0.0000000
(epoch: 200, iters: 20, time: 0.093, data: 0.002) G_GAN: 11.564 G_L1: 8.354 D_real: 0.009 D_fake: 0.000
(epoch: 200, iters: 120, time: 0.085, data: 0.002) G_GAN: 4.749 G_L1: 4.563 D_real: 0.040 D_fake: 0.041
(epoch: 200, iters: 220, time: 0.077, data: 0.002) G_GAN: 8.236 G_L1: 11.265 D_real: 0.005 D_fake: 0.017
(epoch: 200, iters: 320, time: 0.678, data: 0.004) G_GAN: 7.832 G_L1: 4.103 D_real: 0.016 D_fake: 0.002
(epoch: 200, iters: 420, time: 0.077, data: 0.003) G_GAN: 6.097 G_L1: 7.882 D_real: 0.003 D_fake: 0.015
saving the model at the end of epoch 200, iters 63360
End of epoch 200 / 200   Time Taken: 35 sec
```

Figure 4.6. Pix2pix model training results .

In the context of the mentioned results and according to the figure4.6, these values indicate the performance of the model at epoch 200. The G_{GAN} and G_{L1} losses are relatively low, suggesting that the generator is producing images that are both realistic and closely resemble the target images. Additionally, the discriminator's losses (D_{real} and D_{fake}) are also low, indicating that it can effectively distinguish between real and generated images. Overall, these results suggest that the model is performing well in generating high-quality synthetic dermoscopic images. Our objective is to generate new images with a percentage of error from the real image; and therefore, improving the performance of Pix2Pix is not our primary goal.

1.2 Online Step

1.2.1 Data description

To begin our project, we collected a comprehensive set of dermoscopic images from the 2019 ISIC Archive, comprising 25,331 images of various skin cancer types. This extensive dataset includes different forms of skin cancer such as melanoma, basal cell carcinoma, squamous cell carcinoma, and 5 other kinds. Each image varied in resolution, lighting, and patient demographics, reflecting the diversity of real-world clinical scenarios.

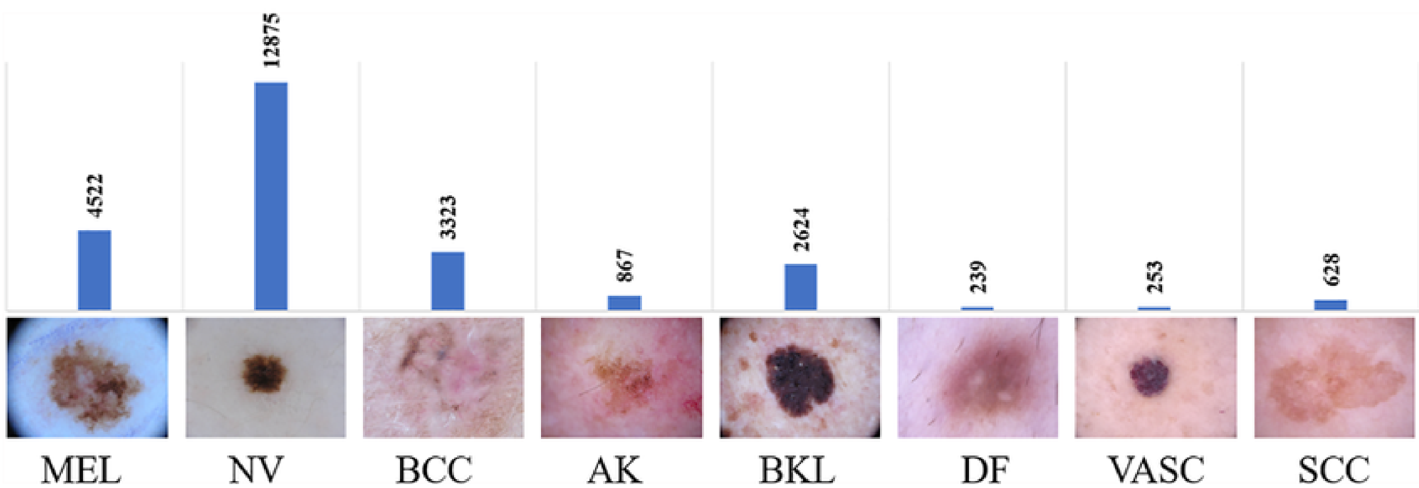

Figure 4.7. Isic 2019 dataset class distribution .

From the figure4.7 it is clear that the ISIC 2019 dataset exhibits a significant class imbalance, with some skin cancer types having far more examples than others. This disparity poses a challenge for machine learning models, particularly in accurately classifying underrepresented classes such as Basal Cell Carcinoma (BCC). Leveraging pix2pix, a generative adversarial network, offers a solution by generating synthetic images for the minority classes. It's worth noting that augmentation was not performed for the "Melanocytic Nevi (NV)" class due to its abundant representation in the dataset. By balancing the dataset in this targeted manner, the model's performance can be significantly improved, leading to more accurate and reliable skin cancer classification.

1.2.2 Generating New Images

Once the GAN was trained, it was used to generate new synthetic dermoscopic images. Only minority classes (we did not generate in NV type) as we mentioned before , present in the dataset (Testing phase). These generated images were designed to augment the original dataset, providing a more extensive and diverse set of training examples for further model development.

1.2.3 Results

The pix2pix GAN successfully generated high-quality synthetic dermoscopic images that closely resembled the real images in the dataset. The synthetic images effectively addressed the initial data limitations, providing a more balanced and comprehensive training set. results are shown in Figure4.8

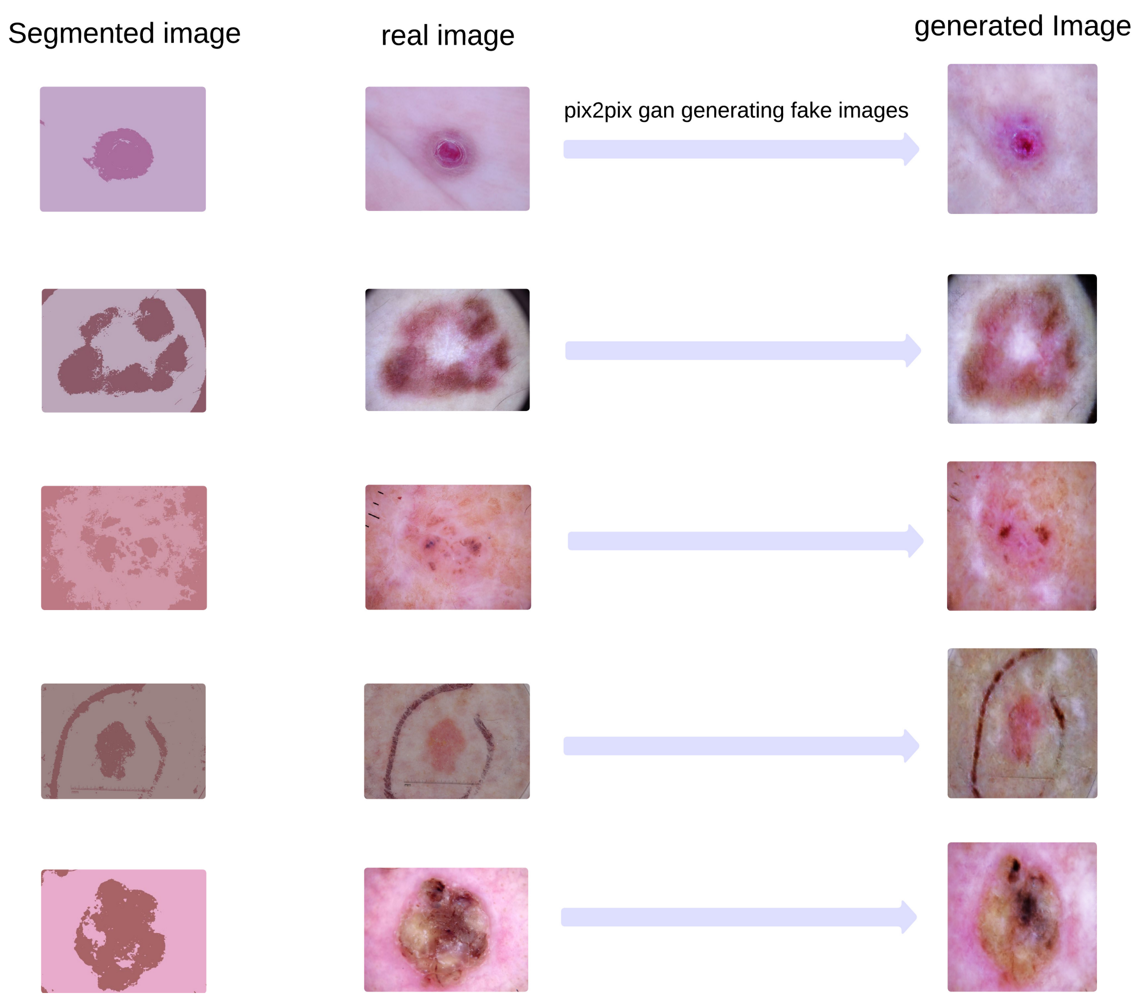

Figure 4.8. Results of fake image generation using the pix2pix Model.

2 Deit architecture development

In this section, we continue to explain the development of our model for classifying the eight skin lesions MEL: Melanoma, BKL: Benign Keratosis , NV: Melanocytic Nevus, DF: Dermatofibroma AK: Actinic Keratosis, BCC: Basal Cell Carcinoma, SCC: Squamous Cell Carcinoma, VASC: Vascular Lesion . We will delve into the following stages as illustrated in Figure4.9.

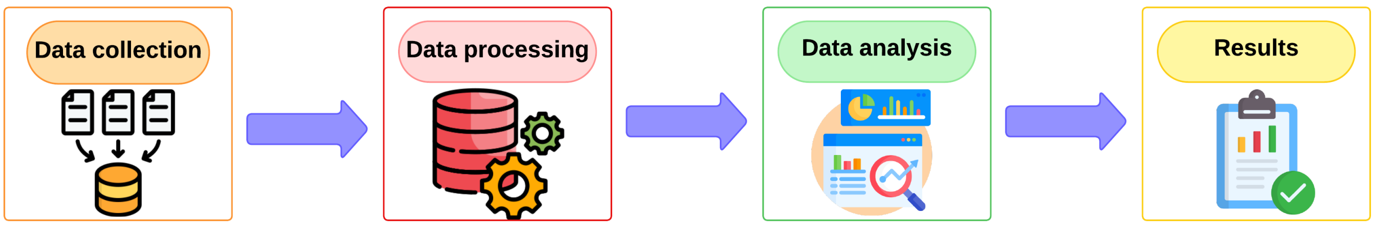

Figure 4.9. stages Deit architecture development.

2.1 Development tools

To implement the model, we utilized various tools as illustrated in the following Figure4.10.

Item	Details
Platform Used	Colab Pro
Programming Language	python™
Libraries Used	PyTorch
Cloud Resources	NVIDIA

Figure 4.10. Development tools .

2.2 Data collection

This section describes the public ISIC 2019 dataset used to train and test our transformer model. ISIC is an abbreviation of the International Skin Imaging Collaboration, sponsored by ISDIS (International Society for Digital Imaging of the Skin). Additionally, we employed data augmentation techniques with pix2pix (Conditional GAN) to enhance the dataset. Figure 4.14 shows some examples of dermoscopic images from the ISIC 2019 challenge and Figure4.12 shows images generated using pix2pix (Conditional GAN) used in this work.

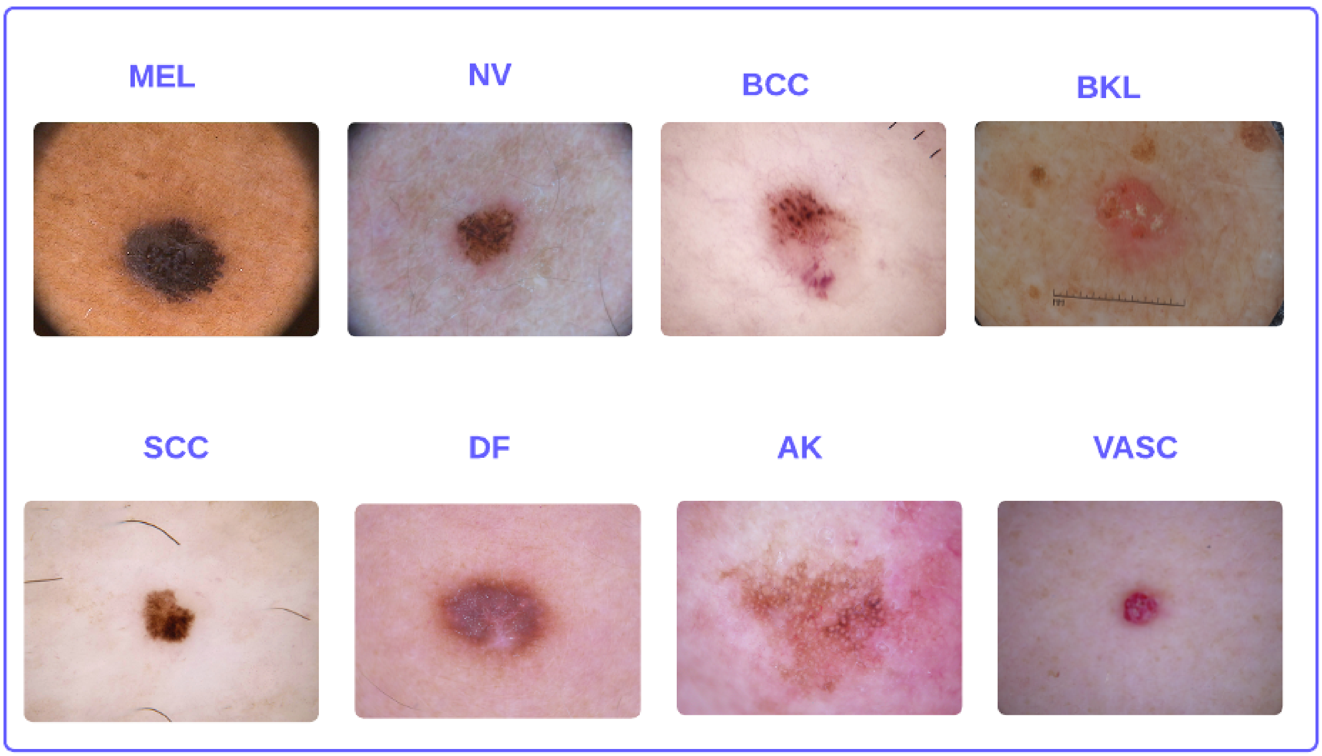

Figure 4.11. Dermoscopic images' example in ISIC 2019.

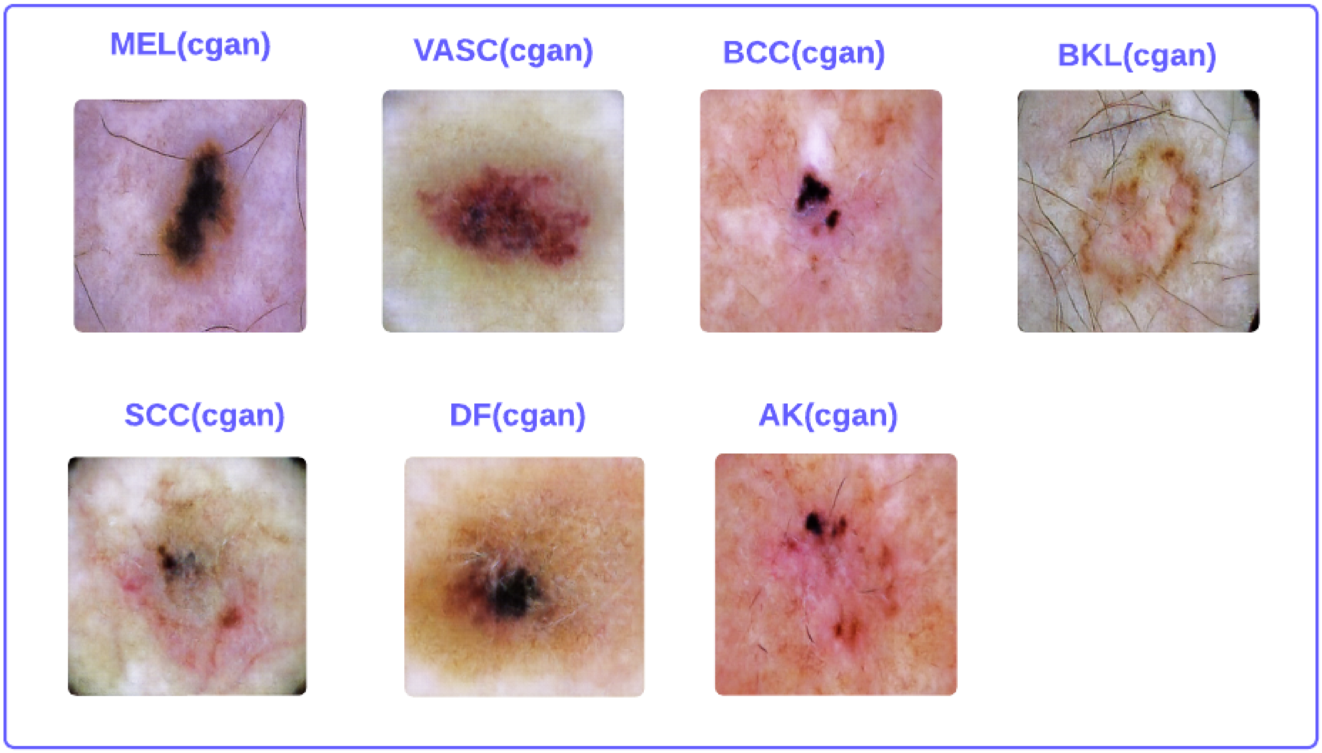

Figure 4.12. Images generated using pix2pix (Conditional GAN).

2.3 Data Preprocessing

For data preprocessing step, we defined several transformations to be applied to both the training and validation/test data. These transformations help in standardizing the input data and augmenting the training data for better model generalization.

2.3.1 Training Data Transformations

For the training data, we applied the following transformations:

- **Resize:** Resizes images to 224x224 pixels.
- **RandomHorizontalFlip:** Randomly flips images horizontally.
- **RandomVerticalFlip:** Randomly flips images vertically.
- **RandomRotation:** Randomly rotates images by up to 30 degrees.
- **ColorJitter:** Randomly adjusts brightness, contrast, saturation, and hue with parameters brightness=0.2, contrast=0.2, saturation=0.2, and hue=0.1.

- **ToTensor:** Converts the images to PyTorch tensors.
- **Normalize:** Normalizes pixel values using the mean [0.485, 0.456, 0.406] and standard deviation [0.229, 0.224, 0.225].

These transformations are implemented as follows:

```
# Define preprocessing transformations for training data
train_transform = Compose([
    Resize((224, 224)),  # Resize images to 224x224
    RandomHorizontalFlip(),  # Random horizontal flip
    RandomVerticalFlip(),    # Random vertical flip
    RandomRotation(30),      # Random rotation up to 30 degrees
    ColorJitter(brightness=0.2, contrast=0.2, saturation=0.2, hue=0.1),  # Color jitter
    ToTensor(),              # Convert image to tensor
    Normalize(mean=[0.485, 0.456, 0.406], std=[0.229, 0.224, 0.225])  # Normalize pixel values
])
```

Figure 4.13. Preprocessing transformation for training data (code).

2.3.2 Validation/Test Data Transformations

For the validation and test data, we applied a simpler set of transformations:

- **Resize:** Resizes images to 224x224 pixels.
- **ToTensor:** Converts the images to PyTorch tensors.
- **Normalize:** Normalizes pixel values using the same mean and standard deviation as the training data.

These transformations are implemented as follows:

```
# Define preprocessing transformations for validation/test data
val_transform = Compose([
    Resize((224, 224)),  # Resize images to 224x224
    ToTensor(),          # Convert image to tensor
    Normalize(mean=[0.485, 0.456, 0.406], std=[0.229, 0.224, 0.225])  # Normalize pixel values
])
```

Figure 4.14. Preprocessing transformations for validation /test data (code).

By applying these preprocessing steps,we ensure that the images fed into the model are standardized and augmented to improve the model's performance and generalization capabilities.

2.4 Data analysis

In this section, we are going to present our Vision Transformers architecture as illustrated in The figure4.15 and its use in transfer learning for image classification tasks.

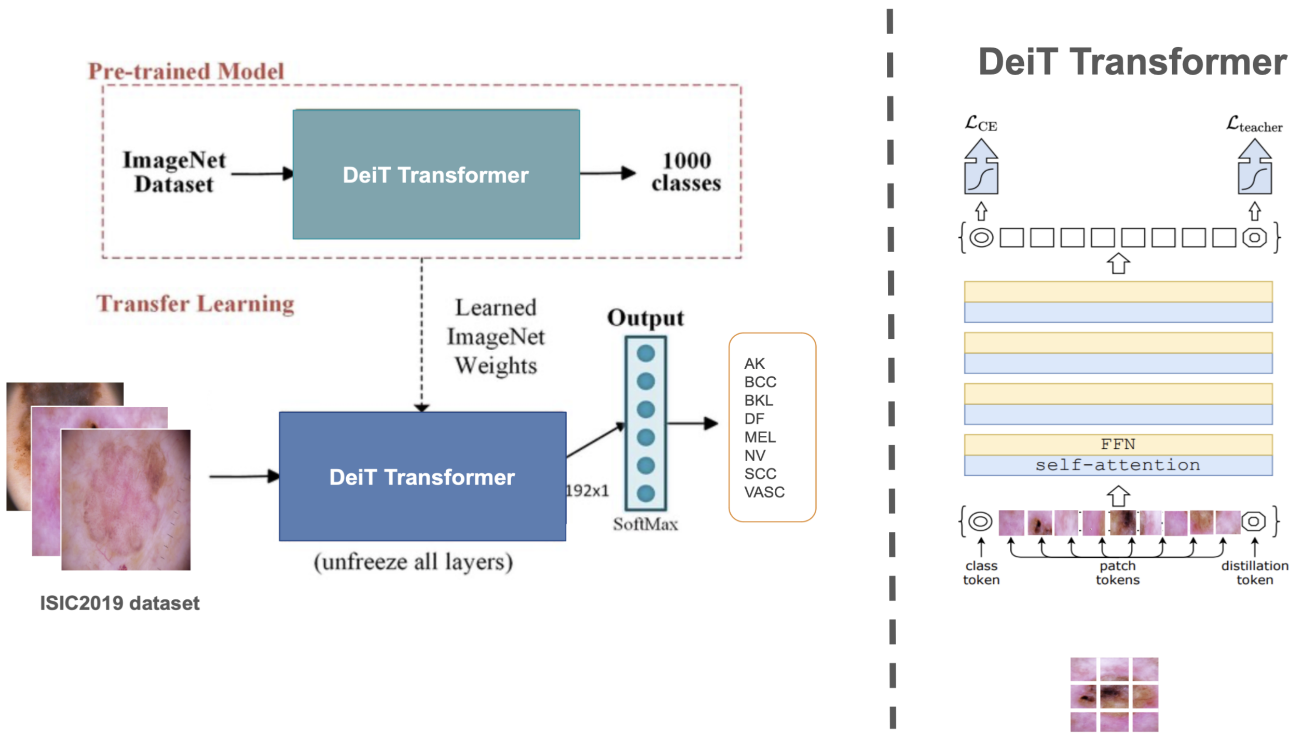

Figure 4.15. The structure of the DeiT Transformer.

Here's an explanation for each part of the image:

- **Left Side:**

  1. **Pre-trained Model**
     - ImageNet Dataset: The DeiT Transformer is initially trained using the ImageNet dataset.
     - DeiT Transformer: This model is trained to classify 1000 classes from the ImageNet dataset.
     - Learned Weights: The weights learned from this training are used for transfer learning.
  2. **Transfer Learning**
     - ISIC2019 Dataset: A dataset containing images of skin lesions used for classifying different types of skin diseases.

  - DeiT Transformer: The pre-trained model is fine-tuned using the ISIC2019 dataset, with the learned weights from ImageNet.
  - Output: The model produces outputs for specific classes such as AK, BCC, BKL, DF, MEL, NV, SCC, and VASC, representing different types of skin conditions.

- **Right Side:**

  1. DeiT Transformer Architecture
     - **Tokens:**
       * **Class token:** A special token used for the final classification.
       * **Patch tokens:** Tokens representing patches of the input image.
       * **Distillation token:** A special token used in the distillation process with a teacher model.
  2. **Self-Attention:** The self-attention mechanism processes the tokens to understand the interactions between different parts of the image.
  3. **FFN (Feed-Forward Network):** A feed-forward network processes the data after the self-attention layer.

  The model uses two loss functions:

  - **Cross-Entropy Loss** (L_{CE}): Used for the main classification task.
  - **Teacher Loss** ($L_{teacher}$): Used in conjunction with a teacher model for the distillation process to improve learning efficiency.

2.4.1 Training hyperparameters

for the training step, we have used the following hyperparameters:

- **Optimizer:** Adam with a learning rate of 3e-4.
- **Batch Size:** 30, specified in the DataLoader.
- **Epochs:** 100.

2.5 Testing Results

To assess performance, we conducted two experiments: one involving pix2pix image generation and one without, aiming to analyze its impact.

2.5.1 With out pix2pix image generation

The performance of our model was evaluated using the ISIC2019 dataset, The results, as shown in the figures below, provide a comprehensive overview of the model's precision, recall, and F1-score for each class, the overall ROC curve, and the confusion matrix.

- **Classification Report:**

  The Classification report in the following figure4.16 shows The model varying performance across different classes. For example:

  - 'NV' (with a support of 1349) has high precision (0.93) and a reasonably good recall (0.66), resulting in a high F1-score (0.77).

  - 'BCC' also has good precision (0.69) and high recall (0.85), leading to a high F1-score (0.76).

  - 'DF' has the lowest F1-score (0.47) due to low precision (0.46) and recall (0.48).

  - The macro average F1-score is 0.66, and the weighted average F1-score is 0.71, indicating overall decent performance with room for improvement.

	precision	recall	f1-score	support
AK	0.614458	0.573034	0.593023	89.000000
BCC	0.688312	0.852090	0.761494	311.000000
BKL	0.504902	0.746377	0.602339	276.000000
DF	0.464286	0.481481	0.472727	27.000000
MEL	0.518911	0.762222	0.617462	450.000000
NV	0.929916	0.659007	0.771367	1349.000000
SCC	0.779661	0.560976	0.652482	82.000000
VASC	0.769231	0.909091	0.833333	22.000000
accuracy	0.703377	0.703377	0.703377	0.703377
macro avg	0.658710	0.693035	0.663028	2606.000000
weighted avg	0.763416	0.703377	0.713308	2606.000000

Figure 4.16. Classification Report.

- **ROC Curve:**

  The ROC curve shown in the following figure4.17 shows the model's performance in all categories.

  - The AUC values are generally high, with 'VASC' achieving a perfect score (1.00), indicating excellent discrimination.

  - 'AK', 'BCC', 'DF', 'SCC', and 'VASC' all have AUC values of 0.95 or higher, suggesting good performance.

- ‘MEL‘ has the lowest AUC (0.89), but still indicates relatively good performance.

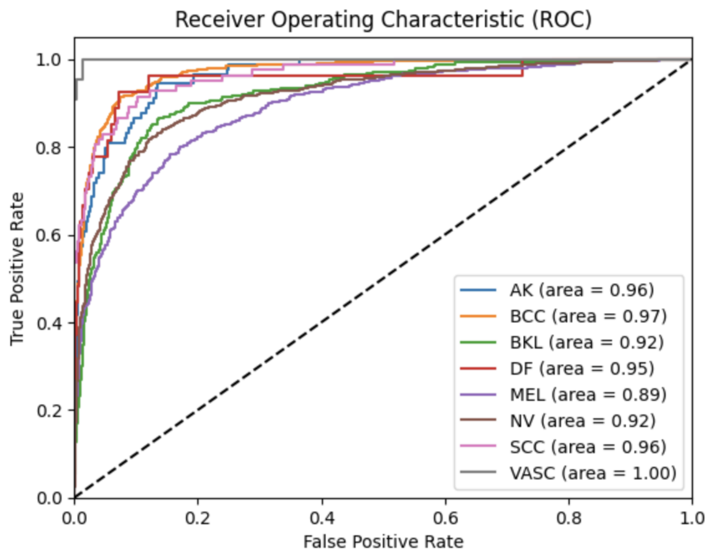

Figure 4.17. ROC Curve.

- **Confusion Matrix:**

  The confusion matrix shown in the following figure4.18 displays the number of correct and incorrect predictions for each category, highlighting the model’s ability to distinguish between different types of skin lesions.

  - The AUC values are generally high, with ‘VASC‘ achieving a perfect score (1.00), indicating excellent discrimination.

  - ‘AK‘, ‘BCC‘, ‘DF‘, ‘SCC‘, and ‘VASC‘ all have AUC values of 0.95 or higher, suggesting good performance.

  - ‘MEL‘ has the lowest AUC (0.89), but still indicates relatively good performance.

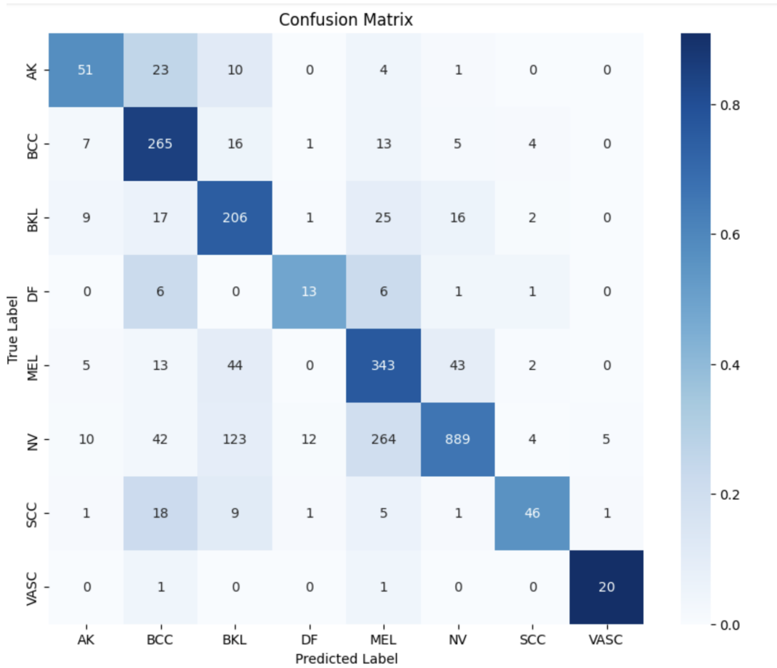

Figure 4.18. Confusion Matrix.

2.5.2 With pix2pix image generation

The performance of our model was evaluated using the ISIC2019 dataset, augmented with images generated using Pix2Pix (Conditional GAN). The results, as shown in the figures below, provide a comprehensive overview of the model's precision, recall, and F1-score for each class, the overall ROC curve, and the confusion matrix.

- **Classification Report:**

  The Classification report in the following figure4.19 shows high accuracy and strong performance metrics in all categories. Precision, recall, and F1 scores are consistently high, indicating reliability of the model. Minor challenges in melanoma staging (MEL) suggest potential areas for further improvement. Overall, the model is very effective in classifying skin lesions.

	precision	recall	f1-score	support
Ak	0.988636	0.977528	0.983051	89.000000
BCC	0.987179	0.990354	0.988764	311.000000
BKL	0.968310	0.996377	0.982143	276.000000
DF	1.000000	1.000000	1.000000	27.000000
MEL	0.917864	0.993333	0.954109	450.000000
NV	0.999234	0.966642	0.982668	1349.000000
SCC	0.987500	0.963415	0.975309	82.000000
VASC	0.956522	1.000000	0.977778	22.000000
accuracy	0.978127	0.978127	0.978127	0.978127
macro avg	0.975656	0.985956	0.980478	2606.000000
weighted avg	0.979386	0.978127	0.978328	2606.000000

Figure 4.19. Classification Report.

- **ROC Curve:**

  The ROC curve shown in the following figure4.20 shows the model's performance in all categories. Each class has an area under the curve (AUC) of 1.00, indicating excellent classification performance.

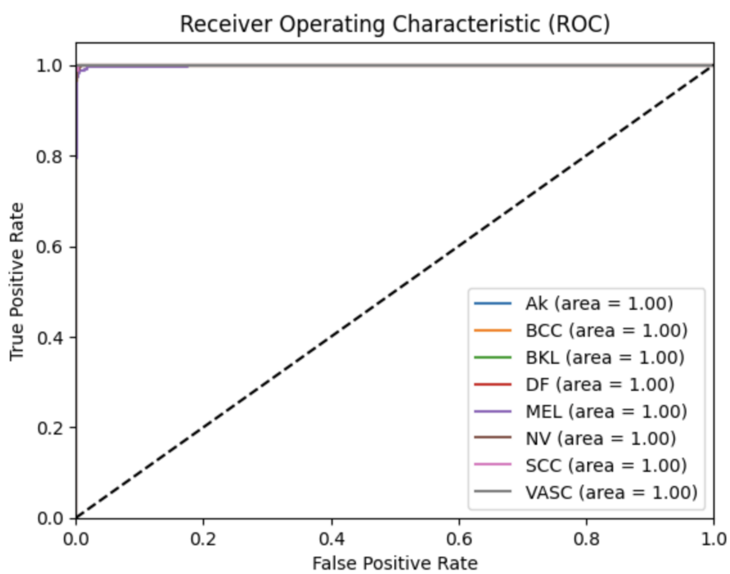

Figure 4.20. ROC Curve.

- **Confusion Matrix:**

  The confusion matrix shown in the following figure4.21 displays the number of correct and incorrect predictions for each category, highlighting the model's ability to distinguish between different types of skin lesions.

Correctly Classified Samples: The majority of samples are correctly classified for each class, as indicated by the diagonal values.

Misclassifications: Minimal misclassifications, primarily observed in classes with similar features.

we have saved our model in TensorFlow Lite (TFLite) format and it's ready to be used in our mobile application.

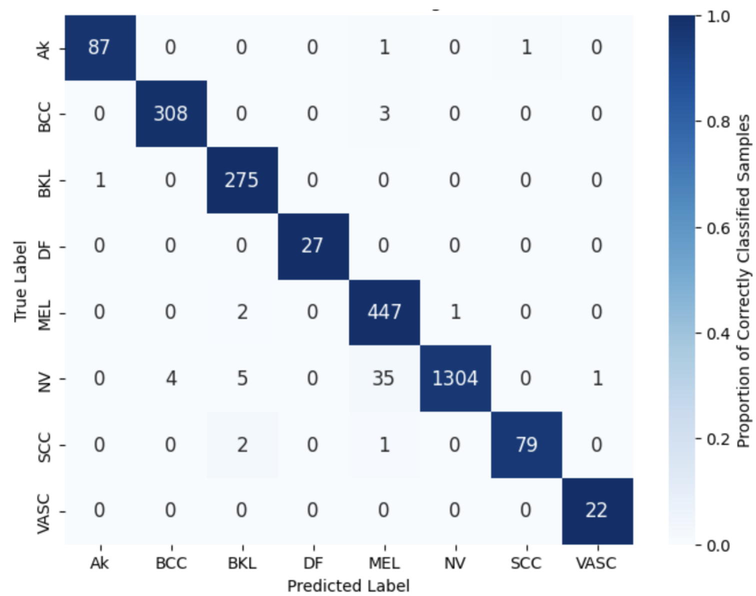

Figure 4.21. Confusion Matrix.

3 Mobile application development

Our aim is to develop a skin cancer detection app that leverages advanced image processing and machine learning algorithms to facilitate early detection of skin cancer. This app is designed for both healthcare professionals and the general public, providing a user-friendly, accessible, and reliable tool for initial skin cancer screening.

3.1 Logo

Concept: Letter D: Diagnosis

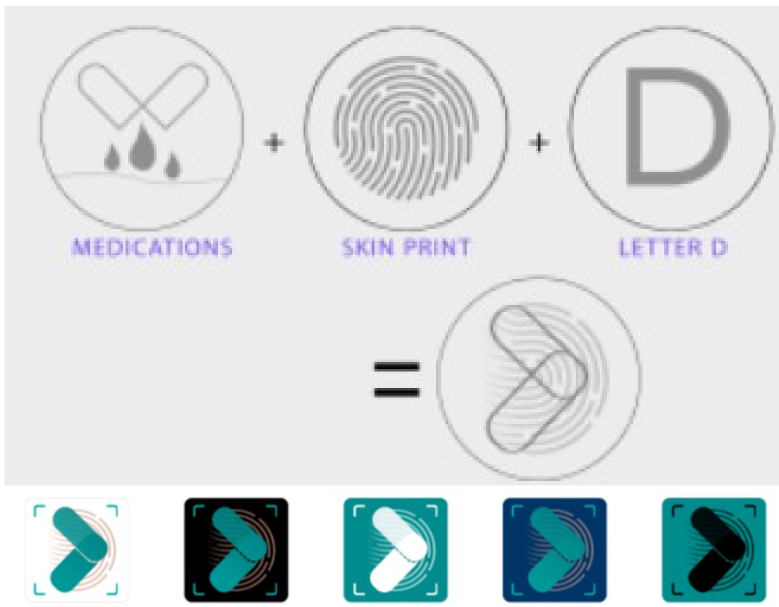

Figure 4.22. Logo.

Color:

Figure 4.23. Color.

Final logo:

Figure 4.24. Final logo.

3.2 Tools

Tool	logo	Idea of tool	Why we chose this tool
Android studio		A powerful IDE designed by Google for developing Android apps efficiently with robust tools for coding, design, testing, and deployment	Streamlines Android app development with powerful tools for coding, testing, and debugging, all within a unified environment.
Flutter	Flutter	An open-source UI toolkit by Google for building natively compiled applications for mobile, web, and desktop from a single codebase	Flutter's ability to create natively compiled apps for both iOS and Android from a single codebase, while maintaining high performance and native-like user experiences, makes it a powerful choice for cross-platform mobile development. Its support for platform-specific integrations and APIs ensures that developers can build robust applications that meet the requirements of both iOS and Android users effectively.
Dart	Dart	A programming language by Google optimized for building fast, scalable web, server, and mobile applications	Optimized for fast performance and scalability, ideal for modern web and mobile app development.
Fire base	Firebase	A platform by Google offering backend services and tools for building and scaling real-time applications.	Simplifies app development with real-time databases, authentication, analytics, awsnd hosting, all seamlessly integrated.
Tensorflow		An open-source platform by Google for machine learning and deep learning, enabling the development and deployment of ML models.	Offers a comprehensive ecosystem for building and deploying machine learning models, with strong community support and extensive documentation.

Figure 4.25. Tools.

3.3 Files structure

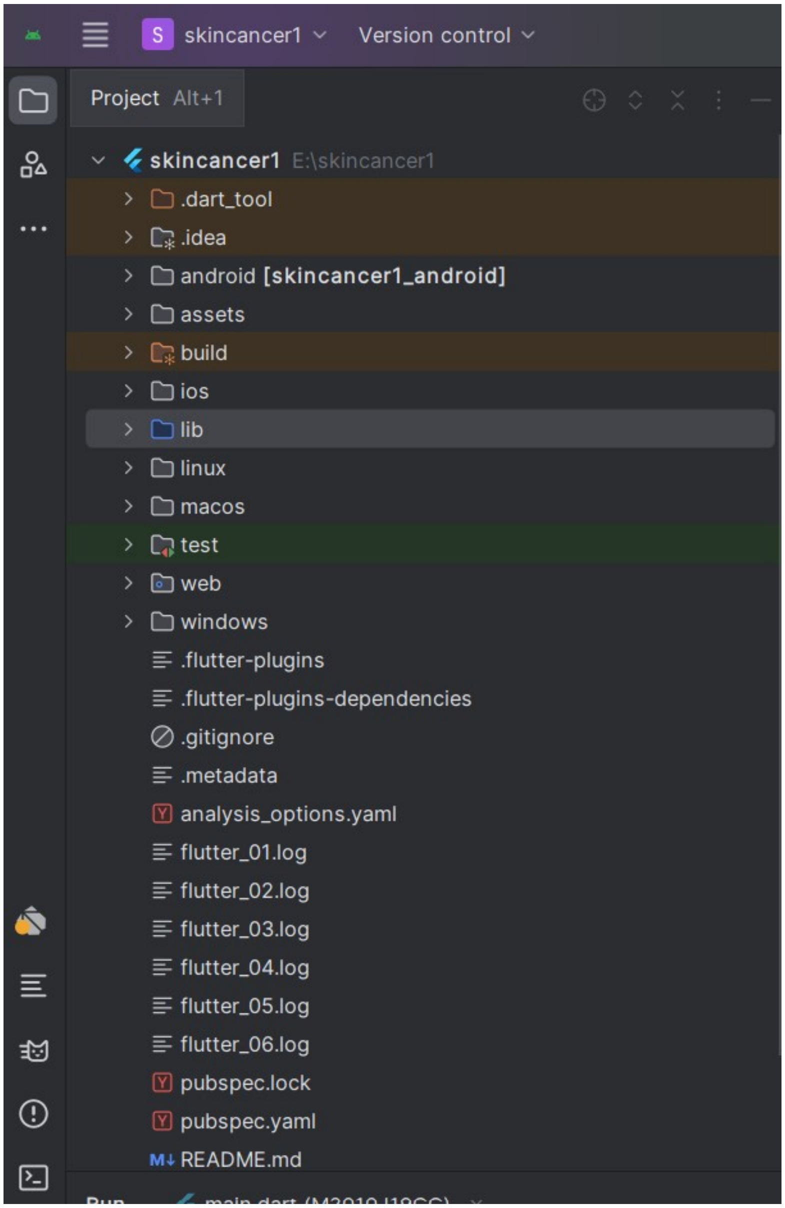

Figure 4.26. Files structure.

4 Overview of the application

We are going to present some GUIs of the application through screenshots.

4.1 Start screens

The following interfaces are shown to users who are not subscribed:

- Splash screen containing the logo
- An introduction screen about the application

Figure 4.27. Start screens.

4.2 Home page

In Figure 4.28, the homepage of the application is displayed. On this page, visitors have the options to create an account, log in, or try the diagnosis for free on their first visit. Subsequently, they are required to subscribe to access the diagnosis feature and share experiences, as well as view experiences from other users on the application.

Figure 4.28. Home page.

4.3 Payment GUI

In Figure III.11, the payment page is displayed. On this page, visitors can benefit from unlimited diagnoses, consult with a doctor, view their diagnostic history, and share experiences with other users. To access these features, they need to subscribe using the ELdahabia Card by paying a nominal fee on a weekly, monthly, or yearly basis. Note: that this page is still under development as the ELdahabia Card requires certain procedures before it can be used.

Figure 4.29. the payment page.

4.4 Sign up page

Figure4.30 shows The sign up page on our application. The visitor creates an account by entering his personal information and his password.

Figure 4.30. Sign up page.

4.5 Log in page

In Figure 4.31,login in page is displayed. The member logs into his account by entering his user email and password,and it must be correct. If it is not, he cannot login..

Figure 4.31. Log in page.

In Figure4.32, If the password is forgotten, an email is sent to reset the password.

Figure 4.32. The password is forgotten.

4.6 Apply Diagnosis page

In Figure 4.33, the diagnosis application page is displayed. The member can capture an image using the camera or select a photo from the gallery, then press the diagnose button. The AI model then diagnoses the image and displays the diagnosis results. Additionally, by clicking on "Read more about the disease," all information about the identified disease during the diagnosis is shown.

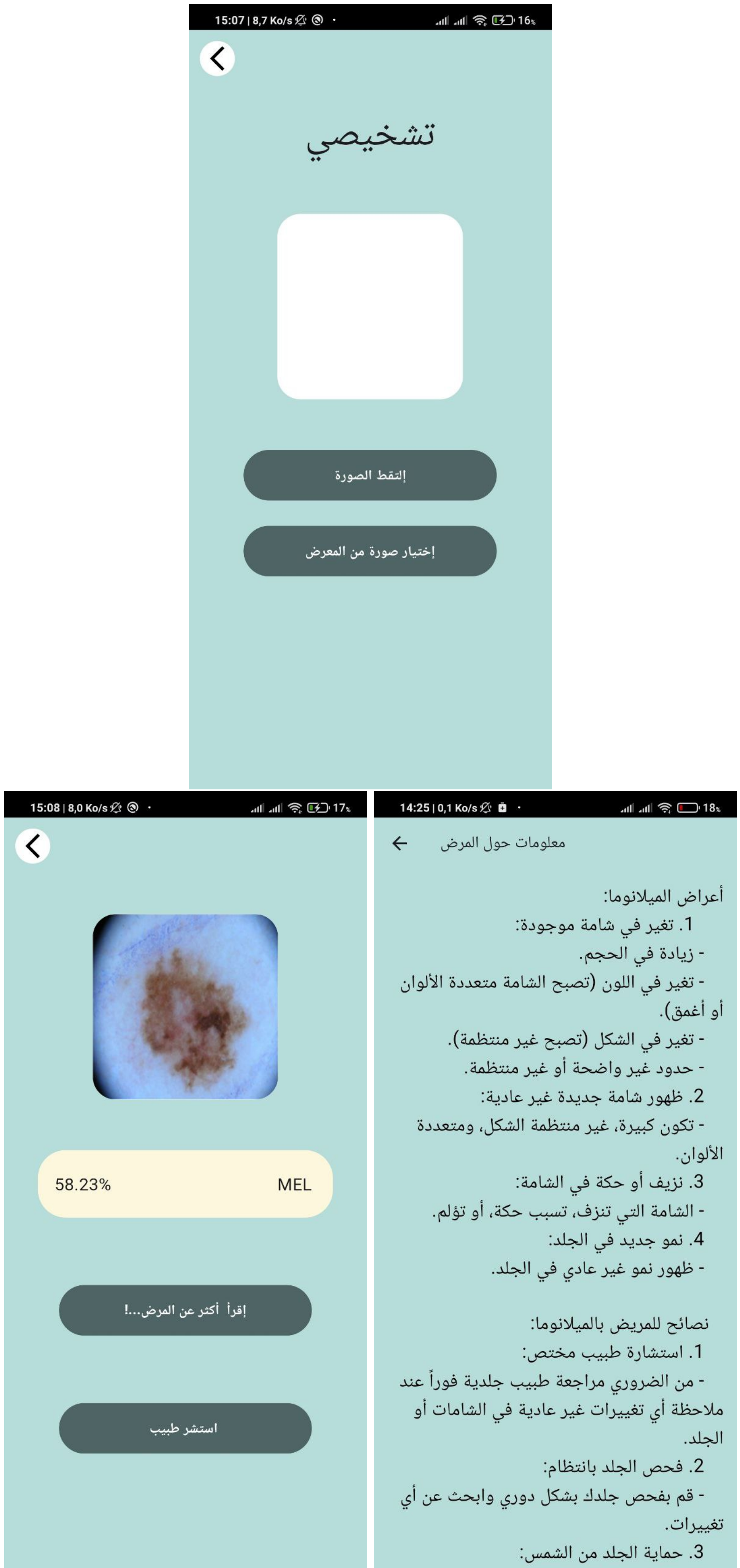

Figure 4.33. Apply Diagnosis page.

4.7 Sharing experiences page

In Figure 4.34, the sharing experiences page is displayed. On this page, members can share their own experiences and read about the experiences of others. This feature allows users to exchange insights, discuss their journeys, and gain support from the community by viewing and contributing personal stories and feedback related to their diagnoses and treatment.

Figure 4.34. Sharing experiences page.

4.8 Previous diagnosis results page

In Figure 4.35, the previous diagnosis results page is displayed. On this page, members can view all their past diagnosis results. This feature allows users to track their diagnostic history, review past assessments, and monitor changes over time. It provides a comprehensive record of their interactions.

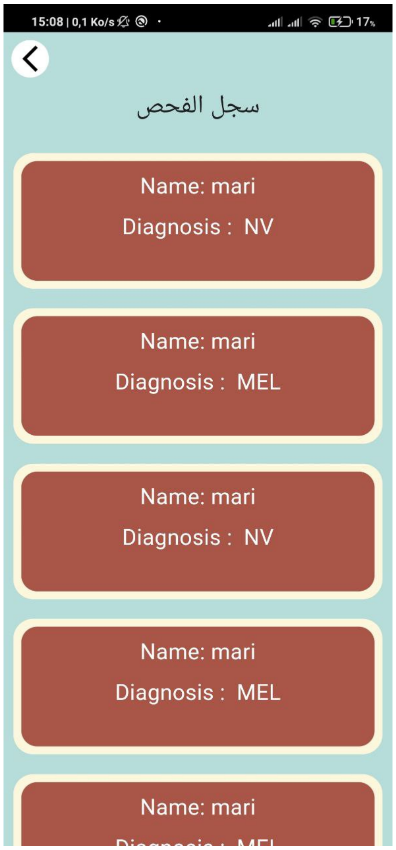

Figure 4.35. Previous diagnosis results page.

4.9 Dermatologist pages

In Figure 4.36, the dermatologist in this application confirms the AI-generated diagnosis. After reviewing the diagnosis, the dermatologist can provide their expert opinion and send a detailed message to the patient via the patient's email. This message can include further insights, recommended next steps, and any necessary medical advice.

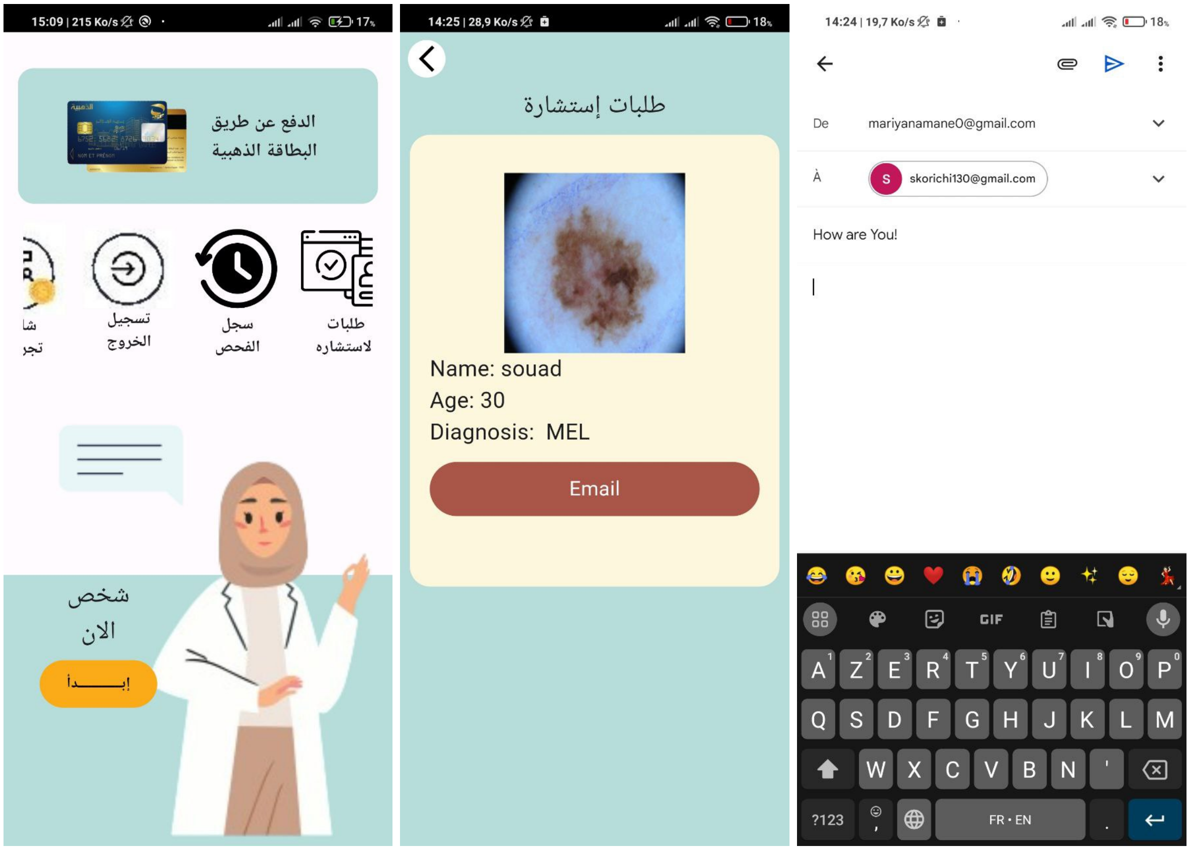

Figure 4.36. The dermatologist pages.

General Conclusion

In this thesis, we addressed the challenge of improving the early diagnosis of skin cancer using advanced artificial intelligence (AI) techniques. Recognizing the critical importance of early detection for effective treatment, we focused on overcoming significant obstacles such as data imbalance, high similarity among skin lesions, and the lack of rare skin lesions datasets.

Our approach involved leveraging Conditional Generative Adversarial Networks (cGANs) to generate synthetic images for minority classes within the ISIC2019 dataset, effectively mitigating class imbalance. We implemented a diagnostic model based on the Vision Transformer (DeiT), which has demonstrated exceptional performance in image classification tasks. This combination of synthetic data augmentation and advanced AI modeling significantly enhanced the accuracy and robustness of our diagnostic system.

Furthermore, we developed a mobile application that integrates our AI model, providing users with instant diagnostic feedback from images of their skin lesions. The app also facilitates communication with dermatologists for further diagnosis and advice, merging AI-driven insights with expert medical opinion. This mobile application aims to make early skin cancer detection more accessible, especially in regions with limited access to dermatological services.

Our results indicate substantial improvements in both the performance of our AI model and the practical usability of the mobile application. This research demonstrates the potential of combining state-of-the-art AI techniques to advance medical diagnostics. We believe that our work significantly contributes to the field of AI-assisted dermatology and has the potential to improve early detection and treatment outcomes for skin cancer patients.

Despite significant advancements, our research faces several limitations. The original dataset's imbalance might still affect the model's performance, particularly for rare skin lesion types, and the ISIC2019 dataset may not fully represent the global diversity of skin tones, lesion types, and imaging conditions, limiting the model's generalizability. While cGANs improve class representation, the synthetic images may not perfectly mimic real-world complexity, potentially affecting training quality. The DeiT model, though powerful, is complex and less interpretable than traditional models like CNNs, posing challenges for clinicians to understand the decision-making process. The mobile application's performance might vary across devices with different camera qualities and processing capabilities, impacting diagnostic accuracy.

By acknowledging these limitations, we aim to provide a balanced perspective on our research and highlight areas for future improvement and investigation we cite some of them as follows:

- Incorporate additional data modalities such as patient medical histories, genetic information, and histopathological images to provide a more comprehensive diagnostic tool.
- Develop mechanisms for the continuous learning and updating of the model based on new data and feedback from dermatologists and users.
- Optimize the app to provide faster and more accurate real-time diagnostic feedback.
- Conduct extensive user testing to refine the app's user interface and experience, ensuring it is intuitive and accessible to a broad user base.
- Foster ongoing collaboration with dermatologists to ensure the clinical relevance and accuracy of the AI model.
- Partner with technology companies to leverage the latest advancements in AI and mobile computing. Also, Enhance data privacy and security measures to protect user information.
- Extend the application of the AI model to diagnose other dermatological conditions such as psoriasis, eczema, and acne, making the app a comprehensive tool for skin health.

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الجمهورية الجزائرية الديمقراطية الشعبية

وزارة التعليم العالي و البلحث العلمي

جامعة محمد خيضر بسكرة

عنوان المشروع

Integrating GANs for Enhanced Data Augmentation
in AI-Driven Mobile Skin Cancer Detection

مشروع لنيل شهادة مؤسسة ناشئة في إطار القرار الوزاري 1275

صورة العلامة التجارية

الاسم التجاري

تشخيصي

الجامعية السنة

2023-2024

بطاقة معلومات:

حول فريق الإشراف وفريق العمل

1- فريق الإشراف:

فريق الإشراف	
المشرف الرئيسي (01): بلعلى عبير	التخصص: ذكاء إصطناعي
المشرف المساعد:عبد المؤمن زراري	التخصص:الصورة و الحياة الاصطناعية

2- فريق العمل:

فريق المشروع	التخصص	الكلية
الطالبة : طاهري آية الرحمان	الصورة والحياة الاصطناعية	كلية العلوم الدقيقة وعلوم الطبيعة والحياة
الطالبة: نعمان أماني ماريا	الصورة والحياة الاصطناعية	كلية العلوم الدقيقة وعلوم الطبيعة والحياة
الطالبة: بلعلى هناء	الصورة والحياة الاصطناعية	كلية العلوم الدقيقة وعلوم الطبيعة والحياة

فهرس المحتويات

المحور الأول: تقديم المشروع

في عصر الصحة الرقمية، يعد التشخيص الدقيق والفوري أمرًا حاسمًا للعلاج الفعال وإدارة الحالات الجلدية. "تشخيصي" هو تطبيق مبتكر للهواتف المحمولة مصمم لإحداث ثورة في الطريقة التي يدير بها الأفراد صحة بشرتهم. يعتمد تطبيقنا على معالجة الصور و خوارزميات التعلم الآلي المتقدمة لتشخيص الآفات الجلدية من الصور الملتقطة بكاميرا الهاتف الذكي. من خلال تقديم معلومات فورية حول حالة البشرة، يمكن لـ تطبيقنا تمكين الأفراد من اتخاذ خطوات استباقية نحو صحة الجلد.

1. فكرة المشروع (الحل المقترح)

فكرة مشروعنا تتمثل في تطوير تطبيق يحمل اسم "تشخيصي" ، وهو تطبيق مصمم لتشخيص الآفات الجلدية من خلال الصور الملتقطة بكاميرا الهاتف المحمول، وتقديم معلومات دقيقة حول نوع الآفة، ومن ثم تمكين المستخدم من التواصل مع أطباء الأمراض الجلدية للحصول على تشخيص دقيق ونصائح طبية.

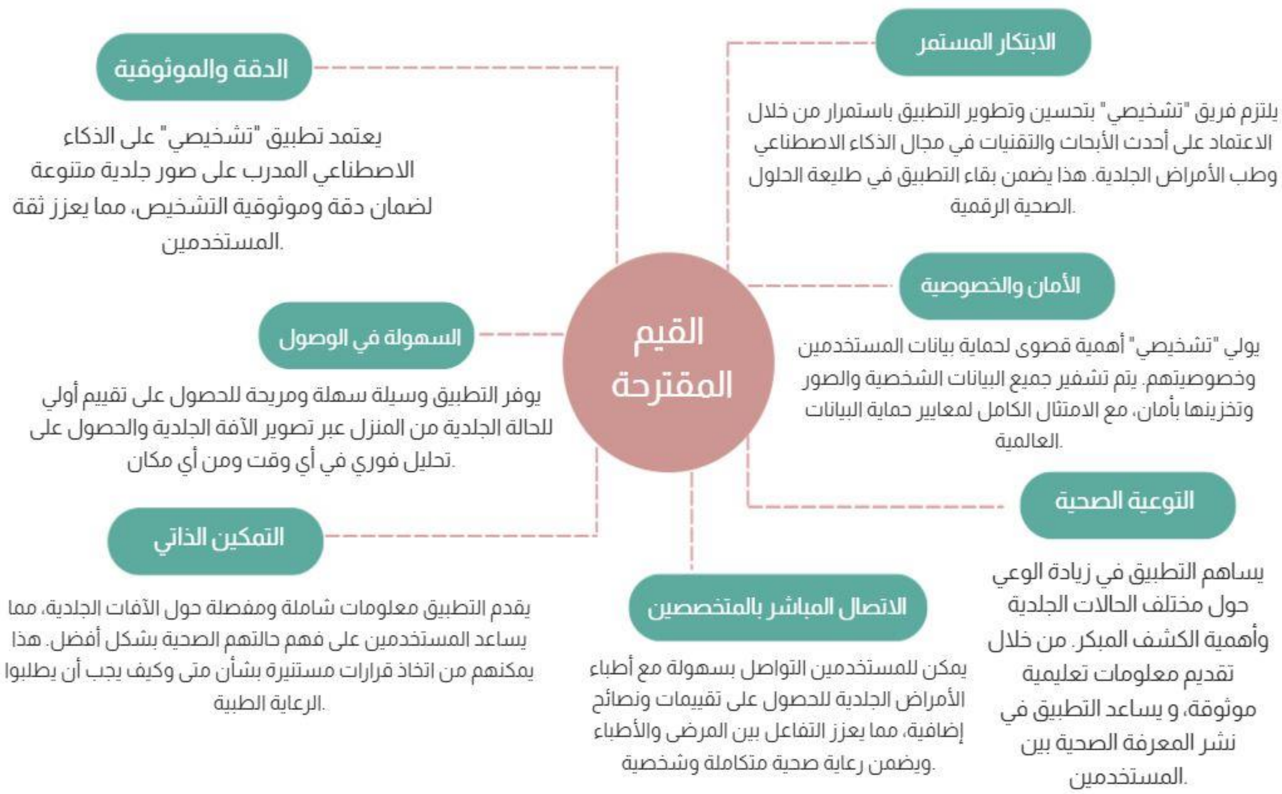
الحل المقترح:

1. تشخيص آلي باستخدام الذكاء الاصطناعي: سيستخدم تطبيق "تشخيصي" خوارزميات التعلم الآلي لتحليل الصور الملتقطة للآفات الجلدية. يتم تدريب الذكاء الاصطناعي على قاعدة بيانات ضخمة من الصور الجلدية للتعرف على الأنواع المختلفة للآفات مثل الشامات الحميدة، الورم الميلانيني الخبيث، والعديد من الحالات الجلدية الأخرى. يهدف هذا إلى توفير تشخيص فوري ودقيق للمستخدم.
2. تقديم معلومات تفصيلية: بعد تحديد نوع الآفة، يقدم التطبيق معلومات شاملة للمستخدم، تشمل وصف الحالة، الأسباب المحتملة، الأعراض النموذجية، والإجراءات الموصى بها. يساعد ذلك المستخدمين على فهم حالتهم الصحية وتقليل القلق من خلال توفير معلومات موثوقة ومفيدة.
3. استشارة مباشرة مع أطباء الأمراض الجلدية: يتيح التطبيق للمستخدمين التواصل المباشر مع أطباء الأمراض الجلدية المعتمدين. يمكن للمستخدمين إرسال صور الآفة الجلدية والتشخيص الأولي الذي يولده الذكاء الاصطناعي إلى الأطباء للحصول على تقييم إضافي ونصائح طبية شخصية. يضمن هذا الجمع بين التقنية المتقدمة والخبرة الطبية لتحقيق أفضل رعاية صحية ممكنة.

4. واجهة مستخدم سهلة وبديهية: تم تصميم التطبيق بواجهة سهلة الاستخدام وبديهية، مما يسهل على المستخدمين من جميع الأعمار استخدامه بسهولة. يتم توجيه المستخدمين خلال خطوات بسيطة لالتقاط صور واضحة لآفاتهم الجلدية، والحصول على معلومات مفيدة، والتواصل مع الأطباء.
5. حماية البيانات وخصوصية المستخدم: يضمن تطبيق "تشخيصي" أعلى مستويات الحماية لبيانات المستخدم وخصوصيته. يتم تشفير جميع الصور والمعلومات الشخصية وتخزينها بأمان، مع الامتثال لأعلى معايير حماية البيانات والخصوصية.

من خلال تقديم هذا الحل المتكامل، يهدف مشروع "تشخيصي" إلى تحسين الكشف المبكر عن الحالات الجلدية الخطيرة، وتوفير الرعاية الصحية بسهولة وراحة للمستخدمين، وزيادة الوعي الصحي حول الأمراض الجلدية.

2. القيم المقترحة



3. فريق العمل

يتكون فريق المشروع من الآتي:

4. أهداف المشروع

تشخيص مبكر ودقيق: يهدف تطبيق "تشخيصي" إلى توفير تشخيص مبكر ودقيق للآفات الجلدية باستخدام تقنيات الذكاء الاصطناعي المتقدمة، مما يمكن المستخدمين من اتخاذ خطوات سريعة وفعالة للعلاج والوقاية.

تحسين الوصول إلى الرعاية الصحية: يسعى المشروع إلى تسهيل وصول المستخدمين إلى خدمات الرعاية الصحية المتخصصة، من خلال توفير وسيلة مريحة وسهلة للتواصل مع أطباء الأمراض الجلدية المعتمدين دون الحاجة إلى زيارات متكررة للعيادات.

تمكين المستخدمين من إدارة صحتهم: يهدف التطبيق إلى تزويد المستخدمين بالمعلومات والأدوات اللازمة لإدارة صحتهم الجلدية بأنفسهم، من خلال تقديم معلومات شاملة حول الحالات الجلدية والنصائح الوقائية.

زيادة الوعي الصحي: يسعى "تشخيصي" إلى رفع مستوى الوعي حول الأمراض الجلدية وأهمية الكشف المبكر، من خلال توفير محتوى تعليمي موثوق ومتاح بسهولة للمستخدمين.

تعزيز الخصوصية وحماية البيانات: يهدف المشروع إلى ضمان حماية بيانات المستخدمين وخصوصيتهم، من خلال تطبيق أعلى معايير الأمان لتخزين البيانات ومعالجتها.

دعم الأبحاث والتطوير المستمر: يلتزم المشروع بدعم الأبحاث والتطوير المستمر في مجال الذكاء الاصطناعي وطب الأمراض الجلدية، بهدف تحسين دقة وجودة التشخيصات المقدمة وتقديم حلول مبتكرة تواكب التطورات التكنولوجية.

تقديم رعاية صحية مخصصة: يهدف "تشخيصي" إلى تقديم رعاية صحية مخصصة تتناسب مع احتياجات كل مستخدم، من خلال التقييمات الشخصية والتواصل المباشر مع الأطباء.

تقليل العبء على الأنظمة الصحية: من خلال توفير حل رقمي يمكن المستخدمين من الحصول على تشخيصات أولية ونصائح طبية، يساهم المشروع في تقليل العبء على العيادات والمستشفيات ويساعد في تخصيص الموارد الطبية لحالات أكثر حاجة للرعاية المباشرة.

5. جدول زمني لتحقيق المشروع :

		1	2	3	4	5	6	7
1	تجهيز التطبيق بالكامل و الوثائق المطلوبة	X	X	X	X			
2	إدماج الأطباء في التطبيق				X	X		
3	البحث و كراء مقر العمل					X	X	
4	تقديم أول خدمة							X

المحور الثاني: الجوانب الابتكارية

- استخدام الذكاء الاصطناعي :يعتمد "تشخيصي" على خوارزميات متقدمة لتحليل صور الآفات الجلدية بدقة.
- التعلم المستمر :يحدث التطبيق نموذجه الذكي بانتظام بناءً على البيانات الجديدة وردود الفعل.

- معلومات شاملة :يقدم التطبيق معلومات حول الأعراض والأسباب والعلاج والنصائح الوقائية للحالات الجلدية.
- واجهة سهلة الاستخدام :يتميز التطبيق بواجهة بسيطة تسهل التقاط الصور والحصول على التشخيص بسرعة.
- التواصل مع الأطباء :يتيح التطبيق التواصل مع أطباء الجلدية للحصول على تقييمات ونصائح إضافية.
- حماية البيانات :يضمن التطبيق حماية بيانات المستخدمين بتشفيرها وتخزينها بأمان.
- التكامل مع الأجهزة الذكية :يتكامل التطبيق مع أجهزة الصحة الذكية لتحسين دقة التشخيص.
- الوعي الصحي :يوفر التطبيق محتوى تعليمي موثوق حول الأمراض الجلدية وأهمية الكشف المبكر.
- تحسين الكفاءة الصحية :يساعد التطبيق في تقليل الزيارات غير الضرورية للعيادات، مما يحسن كفاءة الأنظمة الصحية.

المحور الثالث: التحليل الاستراتيجي للسوق

تحليل السوق المستهدف:

- الفئة العمرية: يستهدف تطبيق " تشخيصي" الأفراد من مختلف الفئات العمرية في الجزائر، خصوصًا الأشخاص الذين تتراوح أعمارهم بين 18 و60 عامًا، الذين يهتمون بصحة بشرتهم ويبحثون عن حلول مبتكرة وسهلة الاستخدام للكشف المبكر عن الآفات الجلدية.
- الجغرافيا: يركز التطبيق على المستخدمين الجزائرين مع إمكانية الاستخدام العالمي .

حجم السوق والنمو المتوقع:

- السوق المحلي لصحة الجلد: يعد سوق الرعاية الصحية في الجزائر في نمو مستمر، مع زيادة الوعي بأهمية الصحة الجلدية. هناك طلب متزايد على خدمات التشخيص المبكر نتيجة ارتفاع معدل الأمراض الجلدية.

- التطبيقات الصحية الرقمية: مع تزايد استخدام الهواتف الذكية وانتشار الإنترنت في الجزائر، يوجد فرصة كبيرة لنمو سوق التطبيقات الصحية الرقمية، حيث يتوقع أن يزداد الاعتماد على هذه التطبيقات لتحسين الوصول إلى الرعاية الصحية.

تحليل المنافسين:

- التطبيقات المنافسة المحلية: حاليًا، نلحظ انعداما في التطبيقات المحلية المتخصصة في تشخيص الآفات الجلدية باستخدام الذكاء الاصطناعي. هذا يتيح فرصة كبيرة لـ "تشخيصي" ليكون رائدًا في هذا المجال.
- نقاط القوة: تشمل القدرة على تقديم خدمة باللغة العربية، والتواصل مع الأطباء المحليين، وفهم احتياجات السوق الجزائرية ،البنية التحتية الرقمية في بعض المناطق الريفية، وقلة الوعي بالتكنولوجيا المتقدمة في الطب .

تحليل القوى الخمس لبورتر:

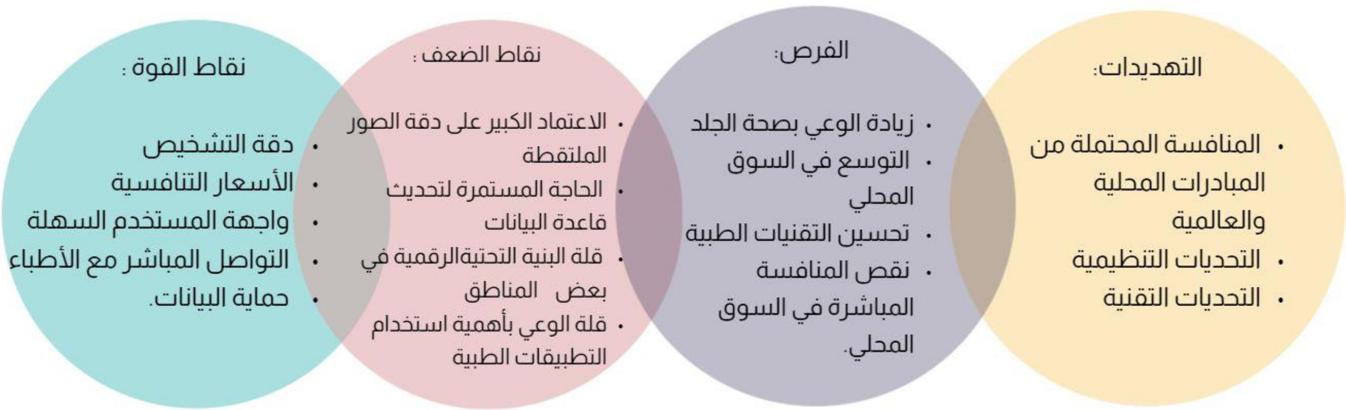
- تهديد الدخول الجديد: منخفض إلى متوسط، نظرًا للحواجز التقنية والحاجة إلى شهادات وتراخيص طبية.
- قوة الموردين: منخفضة، حيث أن البيانات الصحية والتقنيات متاحة على نطاق واسع.
- قوة المشترين: مرتفعة، نظرًا لتعدد الخيارات والحساسية تجاه دقة التشخيص وخصوصية البيانات.
- تهديد المنتجات البديلة: منخفض، نظرًا لقلة الحلول الرقمية البديلة المتاحة حاليًا في السوق الجزائري.
- حدة المنافسة: منخفضة، لقلة المبادرات المحلية أي فرصة كبيرة للتميز.

استراتيجية التسويق:

- التوعية والتثقيف: نشر مقالات وفيديوهات تعليمية باللغة العربية والفرنسية حول أهمية الكشف المبكر عن الآفات الجلدية و أهمية الذكاء الاصطناعي في الرعاية الصحية.

- الشراكات: عقد شراكات مع العيادات المحلية وأطباء الجلدية في الجزائر لتعزيز مصداقية التطبيق وزيادة قاعدة المستخدمين.
- التسويق الرقمي: استخدام استراتيجيات التسويق الرقمي عبر الإنترنت، وسائل التواصل الاجتماعي، وتحسين محركات البحث لزيادة الوعي بالتطبيق وجذب المستخدمين.
- التجربة المجانية: تقديم فترة تجربة مجانية للمستخدمين الجدد لتمكينهم من تجربة التطبيق وبناء ثقتهم في دقته وجودته.

تحليل **SWOT**:



المحور الرابع :خطة الإنتاج والتنظيم

1. تطوير التطبيق:
   - يتم تكوين فريق تطوير مختص يتولى تطوير وبرمجة التطبيق بأحدث التقنيات والأدوات البرمجية.
   - يجري العمل بشكل مستمر على تحسين وتطوير التطبيق بناءً على ردود الفعل من المستخدمين وآراء الخبراء في مجال الطب الجلدية.
2. قاعدة بيانات شاملة:

- يتم بناء قاعدة بيانات ضخمة تضم مجموعة كبيرة من الصور للآفات الجلدية المختلفة، مما يساعد على تحسين دقة التشخيص باستخدام الذكاء الاصطناعي.
- تُجرى عمليات تحديث مستمرة لقاعدة البيانات لتضمن توفير معلومات دقيقة ومحدثة للمستخدمين.

3. توفير الدعم الفني:
   - يُنشأ فريق دعم فني متخصص لتقديم المساعدة والدعم الفني للمستخدمين في حال واجهوا مشاكل في استخدام التطبيق أو تواجهم لأي استفسارات.
4. الشراكات مع الأطباء الجلدية:
   - يتم التعاون مع مجموعة من أطباء الجلدية المحليين لتقديم الدعم والمشورة حول دقة التشخيص وتوجيهات العلاج.
   - يتم توفير وسيلة للتواصل المباشر مع الأطباء الجلدية للمستخدمين الذين يحتاجون إلى استشارة طبية مباشرة.
5. تسويق وترويج التطبيق:
   - تُنفذ حملات تسويقية متعددة القنوات تستهدف الجمهور الجزائري المستهدف، بما في ذلك الإعلانات عبر الإنترنت ووسائل التواصل الاجتماعي والتسويق المباشر.
   - يتم الترويج لميزات التطبيق الفريدة مثل دقة التشخيص والتواصل المباشر مع أطباء الجلدية.
6. ضمان الجودة:
   - يتم تطبيق إجراءات صارمة لضمان جودة التطبيق ودقة التشخيص، بما في ذلك اختبارات الجودة والتحقق المستمر من أداء التطبيق.
7. تطوير خطة الدفع:
   - يُعد فريق التطوير خطة دفع شاملة تتضمن العديد من الخيارات بما في ذلك البطاقات الائتمانية والبطاقات المحلية بما في ذلك البطاقة الذهبية الجزائرية.
8. توسيع الخدمات:
   - يتم التفكير في توسيع خدمات التطبيق لتشمل ميزات إضافية مثل ....
9. تطبيق اللوائح والقوانين:

○ يلتزم التطبيق بجميع اللوائح والقوانين المتعلقة بحماية البيانات الصحية وتقديم الخدمات الطبية عبر الإنترنت.

10. قنوات التواصل:

- يتم توفير قنوات تواصل متعددة مع المستخدمين، بما في ذلك البريد الإلكتروني والدردشة المباشرة، لتلبية احتياجاتهم وتقديم الدعم اللازم.

المحور الخامس: الخطة المالية PLAN FINANCIER

تكلفة الاستثمار (معدات وتجهيزات) موزعة كالتالي :

N°	تعيين	كمية	سعر الوحدة	مبلغ
01	حواسيب مزودة بوحدة معالجة البيانات GPU	03	150.000.00	450.000.00
02	كاميرات مراقبة عادية	04	30.000.00	120.000.00
	تجهيزات مكتبية(طابعات+ناسخات+مكاتب+كراسي+خزائن.....)	LOT	250.000.00	250.000.00
			مجموع H.T	820.000.00

هيكل الاستثمار:

التكلفة الإجمالية للاستثمار تبلغ: 2.266.000.00 دج موزعة كما يلي:

آلات و معدات الانتاج	:	820.000.00 DA
تكاليف الاستغلال	:	1.446.000.00 DA
TOTAL		2.266.000.00 DA

مطلوب تمويل المشروع بنسبة : 100 %

الوظائف موزعة حسب الفئة الاجتماعية-المهنية:

الوظائف موزعة حسب الفئة الاجتماعية-المهنية	1ère année N+1
اطارات أصحاب المشروع	03
المجموع	03

تكاليف الاستغلال :

مبلغ	سعر الوحدة	المدة	تعيينات	
720.000.00	60.000.00	12 شهر	كراء المقر	01
180.000.00	15.000.00		انترنات وكهرباء	02
60.000.00	5.000.00		اتصالات سلكية	03
48.000.00	4.000.00		دعاية واعلانات	04
18.000.00	1.500.00		اشتراك App store+Play store	
420.000.00	70.000.00	06 أشهر	اجرة عامل واحد	
1.446.000.00	المجموع			

كتلة الأجور الشهرية والسنوية :

كتلة الأجور السنوية	كتلة الأجور الشهرية	عدد	أجور شهرية	تعيين
2.520.000.00	210.000.00	03	70.000.00	إطارات
2.520.000.00	210.000.00	المجموع		

المؤسسة بحاجة لتمويل تكلفة أجور عامل واحد فقط (لمدة 06 أشهر) 420.000.00 دج. والباقي يتم تمويله عن طريق التمويل الذاتي للمؤسسة

المحور السادس : النموذج الأولي التجريبي

النموذج الأولي التجريبي لتطبيق"تشخيصي" يتضمن مجموعة من الوظائف الأساسية التي تمثل الفكرة الرئيسية للتطبيق. إليك نظرة عامة على النموذج الأولي التجريبي:

1. واجهة المستخدم:
   - تصميم واجهة مستخدم بسيطة وسهلة الاستخدام.
   - خيارات تسجيل الدخول وإنشاء حساب جديد للمستخدمين.
   - إمكانية التصفح بسلاسة بين القوائم والصفحات.
2. التقاط الصور:
   - خاصية التقاط صور للآفات الجلدية باستخدام كاميرا الهاتف.
   - إمكانية تحميل الصور الموجودة في معرض الصور على الهاتف.
3. التحليل الذاتي:
   - استخدام تقنيات الذكاء الاصطناعي لتحليل الصور وتشخيص الآفات الجلدية.
   - عرض النتائج بشكل فوري مع توضيحات بسيطة للمستخدم.
4. معلومات الآفات الجلدية:
   - توفير معلومات شاملة حول الآفات الجلدية المشخصة.
   - شرح الأسباب والأعراض وطرق العلاج المقترحة.
5. التواصل مع الأطباء:
   - امكانية طلب استشارة طبية مباشرة عبر التطبيق.
   - جدولة مواعيد للمشاورة مع أطباء الجلدية المتاحين.
6. الإعدادات والملف الشخصي:
   - إعدادات لتخصيص تجربة المستخدم وتفضيلات التطبيق.
   - ملف شخصي يحتوي على معلومات المستخدم وسجل التشخيصات السابقة.
7. تجربة محاكاة الدفع:
   - محاكاة عملية الدفع للاشتراكات الشهرية أو الاستشارات الطبية.

هذا النموذج الأولي يتيح للمستخدمين تجربة الفكرة الأساسية للتطبيق وتقييم الوظائف الرئيسية، مما يساعد في تحديد الميزات التي يجب تحسينها أو إضافتها في الإصدارات القادمة.

- الجداول والأشكال

رقم الأعمال:

الجدول (01): **اشتراكات المستخدمين المحليين :**

	العدد	اشتراك شهري	اشتراك سنوي
الافراد	2.000	500.00	1.000.000.00
المؤسسات	200	10.000	2.000.000.00
المجموع			3.000.000.00

الجدول (**02**): **اشتراكات الأجانب (شهريا):**

	العدد	اشتراك شهري	اشتراك سنوي
الافراد	1.000	1.000	1.000.000.
المؤسسات	100	5.000.	500.000.00
المجموع			1.500.000.00

الجدول (**03**): **بيع التطبيق مع التطوير و الصيانة :**

	العدد	سعر التطبيق	مبيعات سنوية
الافراد	50	200.000	10.000.000.00
المؤسسات	10	250.000	2.500.000.00
المجموع			12.500.000.00

الجدو ل(**04**): **الاعلانات على التطبيق :**

	العدد	سعر الاعلان	اشهار شهريا	اشهار سنوي
الافراد	50	2.000.00	100.000.00	1.200.000.00
المؤسسات	50	2.000.00	100.000.00	1.200.000.00
المجموع				2.400.000.00

الجدو ل(**05**): **رقم الأعمال الإجمالي:**

أصناف العملاء	رقم الأعمال السنوي
اشتراكات المستخدمين المحليين	3.000.000.00
اشتراكات المستخدمين الأجانب	1.500.000.00
بيع التطبيق مع التطوير والصيانة	12.500.000.00
الاعلانات والاشهار	2.400.000.00
المجموع	19.400.000.00

يتوقع تحقيق رقم أعمال في السنة الأولى (ن+1) من النشاط : 19.400.000.00 دج وهو يمثل التوقعات التشاؤمية حيث يعتمد على نمو أبطأ في المبيعات.

وبالنسبة للسنوات الأربعة التالية يتوقع (توقعات تشاؤمية أيضا) : (يرتفع رقم الأعمال بنسبة تقارب 10 بالمئة سنويا).

رقم الأعمال	السنة
21.500.000.00	N+2
23.600.000.00	N+3
26.000.000.00	N+4
28.600.000.00	N+5

قائمة الملاحق :

الملحق رقم 01: الميزانية التقديرية للمؤسسة الناشئة

BILANS PREVISIONNELS DE STARTUP :Integrating GANs for Enhanced Data Augmentation in AI-Driven Mobile Skin Cancer Detection

(ACTIVE + PASSIVE)

(N+1) (N+2) (N+3) (N+4) (N+5)

ACTIF	***Brut***	***Amortis. Prov***	***N+1***	***N+2***	***N+3***	***N+4***	***N+5***
ACTIFS NON COURANTS :							
Immobilisations incorporelles							
Immobilisations corporelles	***820.000.00***	***164.000.00***	***656.000.00***	***492.000.00***	***328.000.00***	***164.000.00***	***0.00***
Terrains							
Constructions							
Autres immobilisations corporelles(1)							
Autres immobilisations corporelles(2)							
Immobilisations financières							

Prêts et autres actifs financiers non courants							
TOTAL ACTIF NON COURANT	***820.000.00***	***164.000.00***	***656.000.00***	***492.000.00***	***328.000.00***	***164.000.00***	***0.00***
ACTIF COURANT:							
Stocks et encours							
Créances et emplois assimilés							
Clients							
Autres débiteurs							
Impôts et assimilés							
Autres créances et emplois assimilés							
Disponibilités et assimilés							
Disponibilités	*0.00*	*0.00*	*17.300.000.00*	*35.150.000.00*	*54.710.000.00*	*76.550.000.00*	*100.650.000.00*
TOTAL ACTIF COURANT	***0.00***		***17.300.000.00***	***35.150.000.00***	***54.710.000.00***	***76.550.000.00***	***100.650.000.00***
TOTAL GENERAL ACTIF	**820.000.00**	**164.000.00**	**17.956.000.00**	**35.642.000.00**	**55.038.000.00**	**76.714.000.00**	**100.650.000.00**

PASSIF	*N+1*	*N+2*	*N+3*	*N+4*	*N+5*
CAPITAUX PROPRES :					
Capital émis :					
Fonds d'exploitation					
Primes et réserves					
Résultat net	*15.690.000.00*	*17.686.000.00*	*19.396.000.00*	*21.676.000.00*	*23.936.000.00*
Autres capitaux propres- Report à nouveau		*15.690.000.00*	*33.376.000.00*	*52.772.000.00*	*74.448.000.00*
TOTAL I	*15.690.000.00*	*33.376.000.00*	*52.772.000.00*	*74.448.000.00*	*98.384.000.00*
PASSIFS NON COURANTS :					
Emprunts et dettes financières	*2.266.000.00*	*2.266.000.00*	*2.266.000.00*	*2.266.000.00*	*2.266.000.00*
Impôts (différés et provisionnés)					
Autres dettes non courantes					
Provisions et produits constatés d'avance					
TOTAL PASSIFS NON COURANTS II	*2.266.000.00*	*2.266.000.00*	*2.266.000.00*	*2.266.000.00*	*2.266.000.00*
PASSIFS COURANTS :					
Fournisseurs et comptes rattachés					

Impôts					
Autres dettes					
Trésorerie passif					
TOTAL PASSIF COURANT III	***0.00***	***0.00***	***0.00***	***0.00***	***0.00***
TOTAL GENERAL PASSIF	***17.956.000.00***	***35.642.000.00***	***55.038.000.00***	***76.714.000.0***	***100.650.000.00***

الملحق رقم 02: جدول حسابات النتائج المتوقعة

TABLEAUX DE COMPTES RESULTATS PREVISIONNELS DE STARTUP : Integrating GANs for Enhanced Data Augmentation in AI-Driven Mobile Skin Cancer Detection

Evolution des indicateurs de gestion et des résultats intermédiaires (T.C.R Prévisionnels)

(N+1) (N+2) (N+3) (N+4) (N+5) *(Unité: En DA)*

Désignation	**Années**				
	N+1	**N+2**	**N+3**	**N+4**	**N+5**
Chiffre d'affaires	**19.400.000.00**	**21.500.000.00**	**23.600.000.00**	**26.000.000.00**	**28.600.000.00**
Production stockée					
Achats mat/fournit. consommées					
Services(+locations)	**1.026.000.00**	**1.130.000.00**	**1.240.000.00**	**1.360.000.00**	**1.500.000.00**
Valeur ajoutée	**18.374.000.00**	**20.370.000.00**	**22.360.000.00**	**24.640.000.00**	**27.100.000.00**
Charges de personnel	**2.520.000.00**	**2.520.000.00**	**2.800.000.00**	**2.800.000.00**	**3.000.000.00**
E.B.E	**15.854.000.00**	**17.850.000.00**	**19.560.000.00**	**21.840.000.00**	**24.100.000.00**
Autres produits					

Integrating GANs for Enhanced Data Augmentation in AI-Driven Mobile Skin Cancer Detection

Autres Charges					
Dotations aux amortis.& provisions	***164.000.00***	***164.000.00***	***164.000.00***	***164.000.00***	***164.000.00***
Résultat opérationnel	***15.690.000.00***	***17.686.000.00***	***19.396.000.00***	***21.676.000.00***	***23.936.000.00***
Produits financiers	***0.00***	***0.00***	***0.00***	***0.00***	***0.00***
Charges financières	***0.00***	***0.00***	***0.00***	***0.00***	***0.00***
Résultat financier	***0.00***	***0.00***	***0.00***	***0.00***	***0.00***
Résultat ordinaire avant impôts	***15.690.000.00***	***17.686.000.00***	***19.396.000.00***	***21.676.000.00***	***23.936.000.00***
Impôts sur résultat ordinaire	***0.00***	***0.00***	***0.00***	***0.00***	***0.00***
Résultat net des activités ordinaires	***15.690.000.00***	***17.686.000.00***	***19.396.000.00***	***21.676.000.00***	***23.936.000.00***
Produits extraordinaires	***0.00***	***0.00***	***0.00***	***0.00***	***0.00***
Charges extraordinaires	***0.00***	***0.00***	***0.00***	***0.00***	***0.00***
Résultat extraordinaire	***0.00***				
Résultat net de l'exercice	***15.690.000.00***	***17.686.000.00***	***19.396.000.00***	***21.676.000.00***	***23.936.000.00***

الملحق رقم 03: حسابات الخزينة

TABLEAUX DE FLUX DE TRESORERIE

STARTUP : Integrating GANs for Enhanced Data Augmentation in AI-Driven Mobile Skin Cancer Detection

Années	*N+1*	*N+2*	*N+3*	*N+4*	*N+5*
ENCAISSEMENTS					
SOLDE DEBUT DE PERIODE	*0.00*	*17.300.000.00*	*35.150.000.00*	*54.710.000.00*	*76.550.000.00*
CAPITAL SOCIAL					
COMPTES COURANTS ASSOCIES					
CREDITS	*2.266.000.00*	*0.00*	*0.00*	*0.00*	*0.00*
AUTRES ENCAISSEMENTS (APPORTS)					
REMBOURSEMENT TVA à RECUPERER					
RECETTES EXPLOITATION (C.A)	*19.400.000.00*	*21.500.000.00*	*23.600.000.00*	*26.000.000.00*	*28.600.000.00*

CREANCES CLIENTS					
TOTAL ENCAISSEMENTS	***21.666.000.00***	***21.500.000.00***	***23.600.000.00***	***26.000.000.00***	***28.600.000.00***
DECAISSEMENTS					
Achats mat/fournit/consomm+services	***1.026.000.00***	***1.130.000.00***	***1.240.000.00***	***1.360.000.00***	***1.500.000.00***
FOURNISSEURS					
FRAIS DE PERSONNEL	***2.520.000.00***	***2.520.000.00***	***2.800.000.00***	***2.800.000.00***	***3.000.000.00***
IMPOTS ET TAXES					
FRAIS FINANCIERS					
INVESTISSEMENTS	***820.000.00***	***0.00***	***0.00***	***0.00***	***0.00***
REMBOURSEMENT EMPRUNTS (CMT)					
REMBOURSEMENT COMPTES COURANTS ASSOCIES					
TOTAL DECAISSEMENTS	***4.366.000.00***	***3.650.000.00***	***4.040.000.00***	***4.160.000.00***	***4.500.000.00***
SOLDE DE TRESORERIE/AN (CFN)	***17.300.000.00***	***17.850.000.00***	***19.560.000.00***	***21.840.000.00***	***24.100.000.00***
TRESORERIE CUMULEE	***17.300.000.00***	***35.150.000.00***	***54.710.000.00***	***76.550.000.00***	***100.650.000.00***

الملحق رقم 04: نموذج العمل التجاري

شرائح العملاء	العلاقات مع الزبائن	القيمة المقدمة	الأنشطة الرئيسية	الشركاء
• مستخدمي الهواتف الذكية • الأطباء • المؤسسات الإستشفائية • مراكز التجميل و العناية بالبشرة	• التشخيص الذاتي • علاقة عميل لعميل (تبادل الخبرات بين المرضى)	• التشخيص بنموذج ذكاء اصطناعي في وقت قياسي • توفير جهد التشخيص في المؤسسات الإستشفائية في حالة الأورام الحميدة • توفير خدمة طبية حقيقية بأسعار منخفضة • الدقة في التشخيص • سهولة الاستخدام • بساطة التصميم • تقديم معلومات طبية حول الحالة المرضية المشخصة	• خدمة طبية (تشخيص الأمراض الجلدية) • إدماج خبرات الأطباء في التطبيق	• المؤسسات الإستشفائية الخاصة و العامة • الأطباء ذوي العيادات الخاصة • مراكز التجميل و العناية بالبشرة
	القنوات		**الموارد الرئيسية**	
	• مواقع التواصل الإجتماعي • تطبيق الهاتف الذكي • الأطباء		• المطورين • الخوادم لتخزين قواعد البيانات • خوارزميات التشخيص • الحواسيب المجهزة بوحدات معالجة البيانات (GPU)	

مصادر الإيرادات	التكاليف
• الإعلانات على التطبيق • الاشتراكات المدفوعة لمختلف العروض • بيع التطبيق مع التطوير و الصيانة	• التسويق • مركز البيانات • التكاليف القانونية و الإدارية • صيانة العتاد و تطوير البرمجيات