Al Imam Mohammad ibn Saud Islamic University

College of Sharia and Islamic Studies in Al-Ahsa

Computer and Information Science Department

Melanoma Classification Model Using Deep Learning

By:

Mohammed Al-Klulaib	**440007409**
Khaled Al-Qahtani	**440009030**
Saad Al-Dossari	**439007523**
Fahad Al-Taher	**439006194**

Supervised by:

Dr. Mohammed Abu Al-Rub

Project Submitted in Fulfillment for the CS492 Course requirements

24/2/2023

Declaration

We Mohammed Al-Kulaib , Khaled Al-Qahtani , Saad Al-Dossari , and Fahad Al-Taher being members of final year project group number **(108)** declare that this report contains only work completed by members of our group except for information obtained in a legitimate way from literature, company or university sources. All information from these other sources has been duly referenced and acknowledged in accordance with the University Policy on Plagiarism.

Furthermore, we declare that in completing the project, the individual group members had the following responsibilities and contributed in the following proportions to the final outcomes of the project:

Student ID	**Responsibilities[1]**	**Contribution[2] %**	**Signature**
440007409	All	25%	✓
440009030	All	25%	✓
439007523	All	25%	✓
439006194	All	25%	✓

[1] Write down your responsibilities in the project
[2] Must add to 100%

Dedication

We dedicate this work to our parents, who taught us how to live with dignity and honor, for their unwavering love and support during our work on this thesis. We also dictate this work to our brothers, sisters, and professors who have alwaysencouraged and supported us and who did not hesitate to extend a helping hand to us.

Acknowledgment

First and foremost, we would like to express our gratitude to Great Allah for blessing us and providing us with the strength to carry out and finish this work. Aswe take our last steps in university life, we must stop and go back to the years we spent on the university campus, and to our honorable professors who gave us a lot, who carried the most sacred message in life, and who paved the way for us with science and knowledge. Therefore, we offer the highest verses of thanks, gratitude, appreciation, and love to all our distinguished professors - and in particular - to our honorable professor, Dr. Mohammed Abu Al-Rub, for her kindness insupervising this project. We have been honored to learn from her hands and had it not been for her broad-mindedness, her abundant knowledge, her sound, and useful guidance, and her generous humility, this study would not have been accomplished.

Abstract

Skin cancer is a quite common type of cancer. Its incidence is more often in Caucasian people, and melanoma is the most lethal one. To increase patient prognosis, developing tools to assist in early diagnosis is quite important. In this work, we developed an easy and accessible deep-learning model to classify melanoma cancer. The classification model classifies the images as Melanoma or not motivated by the performance of Convolutional Neural Networks (CNN) in computer vision trained on images collected from lesion clinical information. Since the occurrence of melanoma is much smaller than other skin lesions, most of the datasets for this problem are imbalanced. To deal with this issue, we present an approach based on an evolutionary algorithm to balance datasets.

Keywords**:** Image classification, Computer vision, Convolutional Neural Networks (CNN), Malignant Melanoma.

Abstract (in Arabic)

سرطان الجلد هو نوع شائع من السرطان. تحدث الإصابة به في كثير من الأحيان في القوقاز ، وسرطان الجلد هو الأكثر فتكًا. من أجل زيادة تشخيص المريض ، يعد تطوير أدوات للمساعدة في التشخيص المبكر أمرًا مهمًا للغاية. في هذا العمل ، قمنا بتطوير نموذج تعليم عميق سهل الوصول إليه لتصنيف سرطان الجلد. يصنف نموذج التصنيف الصور على أنها ورم ميلاني أو غير مدفوعة بأداء الشبكات العصبية التلافيفية في رؤية الكمبيوتر المدربة على الصور التي تم جمعها من المعلومات السريرية الخاصة بالآفة. نظرًا لأن حدوث الورم الميلانيني أصغر بكثير من الآفات الجلدية الأخرى ، فإن معظم مجموعات البيانات الخاصة بهذه المشكلة غير متوازنة. للتعامل مع هذه المشكلة ، نقدم نهجًا يعتمد على خوارزمية تطورية لموازنة مجموعات البيانات.

List of Abbreviations

UV	Ultraviolet
CAD	Computer-Aided Diagnosis
CNN	Convolutional Neural Networks
ML	Machine Learning
ISIC	International Skin Imaging Collaboration

Table of Contents

List of Figures

List of Tables

Chapter 1 : Introduction

1.1 Project Overview

Skin cancer develops when abnormal skin cells grow out of control, causing the skin to quickly proliferate and develop cancerous tumors. The number of new aggressive Melanoma cases significantly increased by 54% between 2008 and 2019 [1].

The cells (melanocytes) that make melanin, the pigment responsible for your skin's color, grow into Melanoma, the most dangerous type of skin cancer. The actual reason why all Melanomas occur is unknown, although being exposed to ultraviolet (UV) radiation from sunshine, tanning beds, or tanning lamps increases your risk of getting the disease. You can lower your chance of developing Melanoma by limiting your exposure to UV light [2].

People under 40, particularly women, appear to be at increased risk for Melanoma. It is possible to prevent the spread of skin cancer by being aware of the warning signals of the condition. Early detection is key to the successful treatment of Melanoma [2].

According to [3] in 2020, there will be almost seven thousand Melanoma death and about a million new cases in the United States. Researchers have discovered that skin cancer increases the chance of other cancers, thus early detection of skin cancer is critical since it can dramatically reduce death from this dangerous malignancy [4]. The following are the two primary issues in this regard:

- Most skin lesions become malignant because of a failure to pay attention to skin lesions on the body's surface or a lack of access to skilled dermatologists.
- Because of the significant closeness of their characteristics, clinicians frequently misdiagnose skin lesions.

1.2 Problem Statement

Melanoma is one of the most deadly types of skin cancer because it spreads fast throughout the body. With the increasing prevalence and lethality of Melanoma, it is critical to develop CAD support systems to assist physicians in diagnosing skin cancer. Many studies have been conducted throughout the past two decades on the rapid and reliable identification of Melanoma using dermoscopic images, with diagnostic accuracy ranging from 70% to 95% [5] so, we must launch and advance methods to help medical professionals identify skin cancer in its early stages in light of this significant uptick.

When it comes to diagnosis and evaluation in medical imaging, computer-aided decision support systems are crucial. For diagnostic and prognostic purposes, predictive models are applied in some medical disciplines. These models are created using experience, which consists of information gathered from real-world situations. Data that has been preprocessed and stated in a set of rules, as is frequently the case with knowledge-based expert systems, can be used as training data for statistical and Machine Learning (ML) models

1.3 Project Impact

Melanoma Classification desktop Using Machine Learning helps develop diagnostic systems that have great potential for screening and early detection of malignant melanoma and assisting medical professionals in diagnosing melanoma in its early stages as early detection is critical to raising patient expectations, reducing mortality, and saving people's lives.

1.4 Project Scope

The proposed project is an desktop application with AI model used to detect 4 of the most common type of melanoma, namely:

- Superficial Spreading Melanoma (SSM),
- Nodular Melanoma (NM),
- Lentigo Maligna Melanoma (LMM),
- Acral Lentiginous Melanoma (ALM),

It will not detect other diseases specifically and doesn't give a specific percentage of the extent of the diseases. The project uses both breasts of the same person for examination, the model will be trained on more than 8.000 high-resolution images of diseases and it will be tested on 900 high-resolution images

1.5 Aims and Objectives

In this project, we aim to build a desktop application with an AI model using machine learning with a classification model

for classifying the images as Melanoma or not by CNN.

Objectives:

- To reduce the ill effects and different artifacts such as hair that may be present in thermoscopic images.
- To determine the location of a lesion using the image segmentation technique.
- To estimate illness likelihood.
- To choose the most accurate model

1.6 Existing Solutions and Their Limitations

In this section, we will discuss similar models of our model As:

1.6.1 Skin Lesion Analysis Towards Melanoma Detection Using Deep Learning Network

This research proposed two deep learning methods to address three main tasks emerging in the area of skin lesion image processing, i.e., lesion segmentation (task 1), lesion dermoscopic feature extraction (task 2), and lesion classification (task 3). A deep learning framework consisting of two fully convolutional residual networks (FCRN) is proposed to simultaneously produce the segmentation result and the coarse classification result. A lesion index calculation unit (LICU) is developed to refine the coarse classification results by calculating the distance heat map. A straightforward CNN is proposed for the dermoscopic feature extraction task. The proposed deep learning frameworks were evaluated on the ISIC 2017 dataset. Experimental results show the promising accuracies of our frameworks, i.e., 0.753 for task 1, 0.848 for task 2, and 0.912 for task 3 were achieved[6].

❖ **Advantage:**

- High accurcy.
- High result to detect melanoma

❖ **Disadvantage:**

- High cost.
- Low performance to use
- Not speed of response to detecting melanoma

1.6.2 Deep Learning-Based System for Automatic Melanoma Detection

This paper proposed a deep learning-based method that overcomes these limitations for automatic melanoma lesion detection and segmentation. An enhanced encoder-decoder network with encoder and decoder sub-networks connected through a series of skip pathways which brings the semantic level of the encoder feature maps closer to that of the decoder feature maps is proposed for efficient learning and feature extraction. The system employs a multi-stage and multi-scale approach and utilizes a softmax classifier for pixel-wise classification of melanoma lesions. We devise a new method called Lesionclassifier that performs the classification of skin lesions into melanoma and non-melanoma based on results derived from pixel-wise classification. Our experiments on two well-established public benchmark skin lesion datasets, International Symposium on Biomedical Imaging(ISBI)2017 and Hospital Pedro Hispano (PH2), demonstrate that our method is more effective than some state-of-the-art methods. We achieved an accuracy and dice coefficient of 95% and 92% on the ISIC 2017 dataset and an accuracy and dice coefficient of 95% and 93% on the PH2 datasets[7].

❖ **Advantage:**

- High accurcy.
- High result to detect melanoma
- High performance to use

❖ **Disadvantage:**

- High cost.
- Not speed of response to detecting melanoma

1.6.3 Melanoma diagnosis using deep learning techniques on dermatoscopic images

This paper proposed among state-of-the-art methods used for automated or computer-assisted medical diagnosis, attention should be drawn to Deep Learning based on Convolutional Neural Networks, wherewith segmentation, classification, and detection systems for several diseases have been implemented. The method proposed in this paper involves an initial stage that automatically crops the region of interest within a dermatoscopic image using the Mask and Region-based Convolutional Neural Network technique, and a second stage based on a ResNet152 structure, which classifies lesions as either “benign” or “malignant”.On the test data set, the proposed model achieves an increase in accuracy and balanced accuracy of 3.66% and 9.96%, respectively, concerning the best accuracy and the best sensitivity/specificity ratio reported to date for melanoma detection in this challenge. [8].

- **Advantage:**
- High performance to use.
- low cost.
- **Disadvantage:**
- low accuracy
- low result to detect melanoma
- not speed of response to detecting melanoma

1.6.4 Automated Melanoma Recognition in Dermoscopy Images via Very Deep Residual Networks

This paper proposed a new technique for melanoma detection that makes use of very deep CNNs and some techniques to enable efficient training and learning with less training data. Using ISBI 2016, the Skin Lesion Analysis Towards Melanoma Detection Challenge dataset [15]. The ISIC Archive1, a subset of representative photos, served as the foundation for this dataset. 900 images served as training data, while 350 images served as testing data.

- **Advantage:**
- High performance to use.
- low cost.
- **Disadvantage:**
- low accuracy
- low result to detect melanoma
- not speed of response to detecting melanoma

1.6.5 Accessible Melanoma Detection Using Smartphones and Mobile Image Analysis

This paper proposed a detection system that is optimized to run entirely on the resource-constrained smartphone. They make use of a dataset given by Singapore's National Skin Center (NSC). There are 184 color photographs in all, including 117 images of benign nevus and 67 images of Melanoma taken by cameras of various resolutions, sizes, and situations. Because of differences in acquisition settings (such as illumination and focus) and the existence of additional anatomical characteristics (e.g., eye, eyebrow, nail, etc.)

❖ **Advantage:**

- speed of response to detecting melanoma

❖ **Disadvantage:**

- low accuracy
- High cost
- low result to detect melanoma
- not speed of response to detecting melanoma

Chapter 2 : Literature Review

2.1 Introduction

In the previous chapter, we talked about the problem of skin cancer detection delay and project impact, and project scope, we reviewed our project's aims, objectives, existing solutions, and their limitations and timeline. In this chapter, we will talk about a literature review to compare, analyze, explore, and understand the attempts and directions for finding research gaps in illustrating the future scope of this project

2.2 Backgroud

This section explains some of the concepts used in our system such as melanoma, Melanoma types, and talks about some of the technical backgrounds.

2.2.1 Melanoma Concept

Melanoma is a type of skin cancer that develops when melanocytes (the cells that give the skin its tan) start to grow out of control. Cancer starts when cells in the body begin to grow out of control. Cells in nearly any part of the body can become cancerous and can then spread to other areas of the body[9].

2.2.2 Types of Melanoma

Melanoma types are based on the way a sample of cells from a tumor looks under a microscope. These cells are collected during a biopsy or surgery. Determining the type is important because it can help your doctor understand where the melanoma is likely to grow and how quickly [9].

There are four main types of skin melanoma:

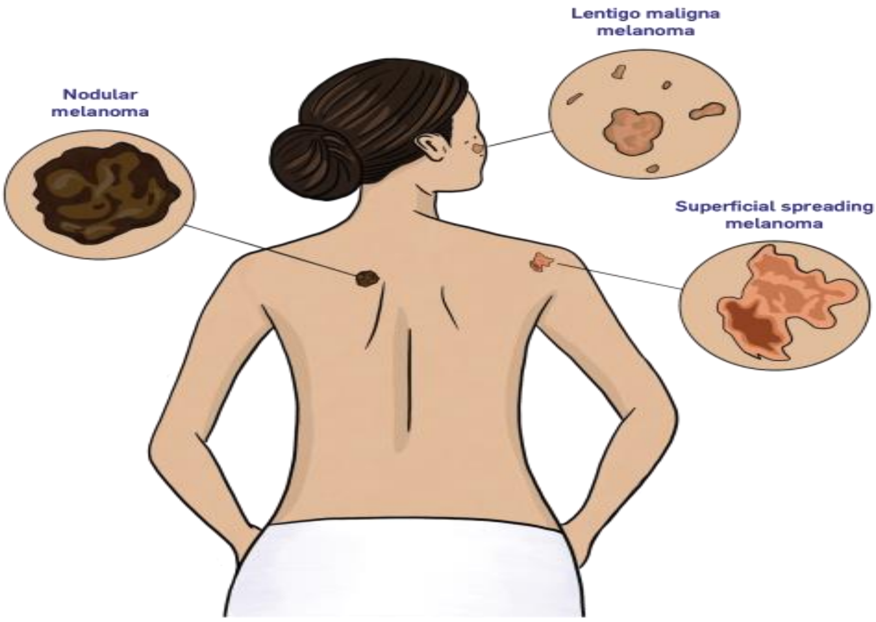

Figure 2:1 types of melanoma

- **Superficial Spreading Melanoma**

Superficial spreading melanoma is a type of skin cancer. It begins when the melanocytes in the skin grow out of control and form tumors. Melanocytes are the cells responsible for making melanin, the pigment that determines the color of the skin. Superficial spreading melanoma is the most common type of melanoma, accounting for around 70 percent of all cases. It starts growing along the top layer of the skin. Over time it penetrates deeper into the skin [9]. This cancer can occur in adults of all ages. When people under 40 develop melanoma, it tends to be superficial spreading melanoma.

- ### Nodular Melanoma

Nodular melanoma is a type of skin cancer It begins when the melanocytes in the skin grow out of control and form tumors. Melanocytes are the cells responsible for making melanin, the pigment that determines the color of the skin. Nodular melanoma is the second most common type of melanoma, accounting for around 15 percent of all cases. It grows faster than other forms of the disease, which is why it’s considered aggressive. Nodular melanoma can occur in people of all ages and all races. It is much more common in people with a light complexion and people over 65 [9].

- ### Lentigo Maligna Melanoma

Lentigo Maligna (LM) and lentigo Maligna melanoma (LMM) are types of skin cancer. They begin when the melanocytes in the skin grow out of control and form tumors. Melanocytes are the cells responsible for making melanin, the pigment that determines the color of the skin. LM refers to the early stage of the disease when the cancer is confined to the top layer of the skin. LMM refers to the disease after it has grown deeper into the skin and is considered invasive. Together, LM and LMM account for about 4 to 15 percent of the melanomas diagnosed worldwide[9].

- ### Acral Lentiginous Melanoma

Acral lentiginous melanoma is a rare type of skin cancer. It begins when the melanocytes in the skin grow out of control and form tumors. Melanocytes are the cells responsible for making melanin, the pigment that determines the color of the skin. The main sign of acral lentiginous melanoma is a black or brown discoloration that appears on the sole or palm. It may resemble a bruise or stain, but over time it grows in size [9].

2.2.3 Technical Background

- **Machine learning:** is a branch of artificial intelligence (AI) and computer science that focuses on the use of data and algorithms to imitate the way that humans learn, gradually improving its accuracy [10].

- **Image Processing (IP):** this is always a great area for further study. Image Processing is a procedure used to improve the quality of raw images from cameras/sensors on satellites, space probes, and aircraft, as well as images captured in everyday life. In recent years, Image Processing has advanced significantly and now includes a wide range of scientific and technological disciplines. Image Processing is primarily concerned with image acquisition, optimization, segmentation, feature extraction, and classification, among other things. [11]

- **Python** is an open-source object-oriented programming language similar to Perl, Scheme, Ruby, and Java. Raspberry PI may be used for a variety of purposes, most notably data science, but it can also be used for IoT development [12].

- **Jupiter Notebook**: this is the latest web-based interactive development environment for notebooks, code, and data. Its flexible interface allows users to configure and arrange workflows in data science, scientific computing, computational journalism, and machine learning. A modular design invites extensions to expand and enrich functionality [13].

- **The Visual Studio IDE** is a creative launching pad that you can use to edit, debug, and build code, and then publish an app.

2.3 Related work

In this section, we compare systems that are similar to our project and describe the tools,

2.3.1 Automated Melanoma Recognition in Dermoscopy Images via Very Deep Residual Networks

processes, and results of each system along with their unique qualities, strengths, and limitations.

Research Title	**Automated Melanoma Recognition in Dermoscopy Images via Very Deep Residual Networks**
Proposed solution	A new technique for melanoma detection that makes use of very deep CNNs and some techniques to enable efficient training and learning with less training data.
Dataset	Using ISBI 2016, the Skin Lesion Analysis Towards Melanoma Detection Challenge dataset [15]. The ISIC Archive1, a subset of representative photos, served as the foundation for this dataset. 900 images served as training data, while 350 images served as testing data.

Table 2.1 System1 information [14].

- **Methods (algorithms)**

They suggested an innovative and comprehensive two-stage strategy based on extremely deep CNNs with little training data for automated melanoma identification, which is a summary of the work's primary contributions in Fig. 6. Experiments show that highly deep CNNs are capable of accumulating richer and more discriminative features and obtaining superior performance when compared to much shallower versions. For precise skin lesion segmentation, they suggest an extremely deep completely convolutional residual network (FCRN) [14].

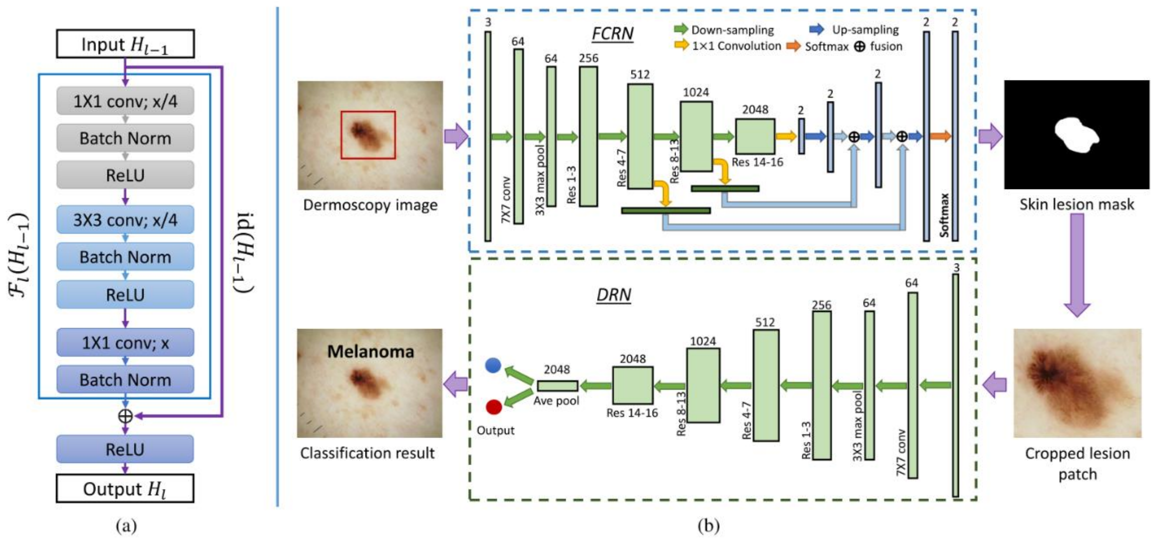

Figure 2:2 The workflow of the framework for system 1[14].

➢ Conclusion/ Discussion

The major point of this research is that they developed an automated system with extremely deep CNNs that can create features with strong discriminating capabilities for both segmentation and classification tasks and a unique FCRN for precise skin lesion segmentation. This experiment is quite difficult since it uses a very deep network that takes a long time to learn and a powerful GPU. The dataset itself also presents a hurdle.

Another important observation is that the classification with segmentation is much better than without segmentation by 11.4% due to the variation of lesion size in the dataset being very large.

❖ **Advantage:**

- High performance to use.
- low cost.

❖ **Disadvantage:**

- low accuracy
- low result to detect melanoma
- not speed of response to detecting melanoma

2.3.2 Accessible Melanoma Detection Using Smartphones and Mobile Image Analysis

Table 2.2.2 System 2 information [16].

Research Title	**Accessible Melanoma Detection Using Smartphones and Mobile Image Analysis**
Proposed solution	A detection system that is optimized to run entirely on the resource-constrained smartphone.
Dataset	They make use of a dataset given by Singapore's National Skin Center (NSC). There are 184 color photographs in all, including 117 images of benign nevus and 67 images of Melanoma taken by cameras of various resolutions, sizes, and situations. Because of differences in acquisition settings (such as illumination and focus) and the existence of additional anatomical characteristics (e.g., eye, eyebrow, nail, etc.)

- **Methods (algorithms)**

They propose using a combination of skin detection and rapid hierarchical segmentation to find the skin lesion, which may be computationally cheaper than using complicated segmentation approaches. They first downsample the skin image, and then the system uses the downsampled version to combine two rudimentary segmentation algorithms to give a rough depiction of the lesion. Then, with the coarse segmentation result as input, we apply fine segmentation to create the outline of the lesion. They choose four feature categories from the final segmented region that precisely define the lesion's color, shape, border, and texture. To categorize the skin lesion, a classifier is constructed for each feature category, and the final findings are obtained by merging their output [16].

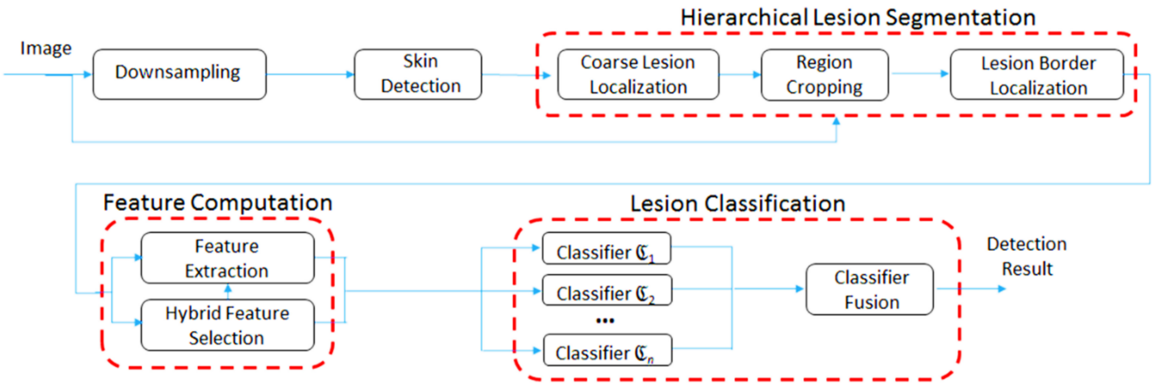

Figure 2:3 The workflow of system 2 [16].

➢ Conclusion/ Discussion

In this application, they used a hierarchical segmentation strategy made up of two quick segmentation approaches to apply a skin lesion localization technique. As they seek to attain high sensitivity while keeping a decent specificity, they imposed a greater penalty for each Meneloma sample misclassification than for each benign sample misclassification (i.e., the penalty is 1.5 and 1 for Meneloma and benign, respectively)

❖ **Advantage:**

- speed of response to detecting melanoma

❖ **Disadvantage:**

- low accuracy
- High cost
- the low result to detect melanoma
- not speed of response to detecting melanoma

Table 2.2.3 System3 information [17].

2.3.3 Melanoma diagnosis using deep learning techniques on dermatoscopic images	
Research Title	**Melanoma diagnosis using deep learning techniques on dermatoscopic images**
Proposed solution	wherewith segmentation, classification, and detection systems for several diseases have been implemented. The method proposed in this paper involves an initial stage that automatically crops the region of interest within a dermatoscopic image using the Mask and Region-based Convolutional Neural Network technique, and a second stage based on a ResNet152 structure, which classifies lesions as either "benign" or "malignant".
Dataset	They utilise a dataset provided by the National Skin Center of Singapore (NSC). There are a total of 184 colour images, comprising 117 pictures of benign nevi and 67 pictures of melanoma that were all captured with different resolutions, sizes, and circumstances. Due to variations in acquisition conditions (such as lighting and focus), as well as the presence of additional anatomical features (e.g., eye, eyebrow, nail, etc.)

- **Methods (algorithms)**

We propose an automated classification method for a cutaneous lesion in digital dermatoscopic images, to detect the presence of melanoma. This method comprises two fundamental stages, which are: Stage 1: Cropping a bounding box around only the skin lesion in the input image, using Mask R_CNN; and Stage 2: Classification of the cropped bounding box using ResNet152, as described in Fig. 2.4 with a functional block diagram of the system[17].

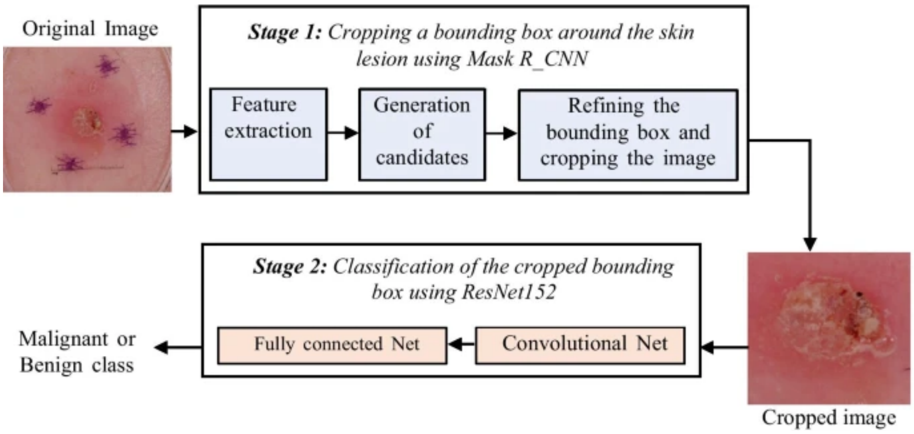

Figure 2.4 Functional block diagram of the proposed system [17]

➢ Conclusion/ Discussion

Finally, the eVida M6 model is a reliable predictor with an excellent balance between overall accuracy (0.904), sensitivity (0.820) and specificity (0.925). Within the set of tested models and also comparing with the best results reported in melanoma detection for the ISIC 2017 challenge, eVida M6 is an improvement in the state-of-the-art for automatic diagnosis of melanoma from dermatoscopic images[17].

❖ **Advantage:**

- High performance to use.
- low cost.

❖ **Disadvantage:**

- low accuracy
- low result to detect melanoma
- not speed of response to detecting melanoma

This research proposed two deep learning methods to address three main tasks emerging in

2.3.4 Skin Lesion Analysis Towards Melanoma Detection Using Deep Learning Network

the area of skin lesion image processing, i.e., lesion segmentation (task 1), lesion dermoscopic feature extraction (task 2), and lesion classification (task 3). A deep learning framework consisting of two fully convolutional residual networks (FCRN) is proposed to simultaneously produce the segmentation result and the coarse classification result. A lesion index calculation unit (LICU) is developed to refine the coarse classification results by calculating the distance heat map. A straightforward CNN is proposed for the dermoscopic feature extraction task. The proposed deep learning frameworks were evaluated on the ISIC 2017 dataset. Experimental results show the promising accuracies of our frameworks, i.e., 0.753 for task 1, 0.848 for task 2, and 0.912 for task 3 were achieved[6].

❖ Methods

1) Lesion Segmentation and Classification (Tasks 1 & 3)

1.1 Pre-Processing

The original training set contains 2000 skin lesion images of different resolutions. The resolutions of some lesion images are above 1000 × 700, which requires a high cost of computation[6].

1.2 Data Augmentation

The dataset contains three categories of skin lesions, i.e., Melanoma, Seborrheic keratosis, and Nevus. As the number of images of different categories varies widely, we accordingly rotated the images belonging to different classes to establish a class-balanced dataset[6].

1.3 Lesion Indexing Network (LIN)

Network Architecture

The fully convolutional residual network, i.e., FCRN-88, proposed in our previous work, which outperforms the FCRN-50 and FCRN-101, was extended to simultaneously address the tasks of lesion segmentation[6].

2) Dermoscopic Feature Extraction (Task 2)

Dermoscopic feature extraction is a new task announced in ISIC 2017, which aims to extract clinical features from dermoscopic images. Little previous work has addressed this task. In this section, we introduce a CNN-based approach, i.e., the Lesion Feature Network (LFN), developed to address the challenge[6].

2.1 Superpixel Extraction

The ISIC dermoscopic images contain four kinds of dermoscopic features, i.e., Pigment Network (PN), Negative Network (NN), Streaks (S), and Milia-like Cysts (MC). To locate the positions of dermoscopic features[6].

2.2 Data Augmentation

The extracted patch dataset is extremely imbalanced. Most patches only contain background information. Hence, data augmentation processing is needed to balance the number of images of different categories[6].

2.3 Lesion Feature Network (LFN)

The augmented training set was used to train our Lesion Feature Network (LFN), whose architecture is presented in Figure 2.5.

Figure 2.5 Flowchart of Lesion Feature Network (LFN)

This paper proposed a deep learning-based method that overcomes these limitations for automatic melanoma lesion detection and segmentation. An enhanced encoder-decoder

2.3.5 Deep Learning-Based System for Automatic Melanoma Detection

network with encoder and decoder sub-networks connected through a series of skip pathways which brings the semantic level of the encoder feature maps closer to that of the decoder feature maps is proposed for efficient learning and feature extraction. The system employs a multi-stage and multi-scale approach and utilizes a softmax classifier for pixel-wise classification of melanoma lesions. We devise a new method called Lesionclassifier that performs the classification of skin lesions into melanoma and non-melanoma based on results derived from pixel-wise classification. Our experiments on two well-established public benchmark skin lesion datasets, International Symposium on Biomedical Imaging(ISBI)2017 and Hospital Pedro Hispano (PH2), demonstrate that our method is more effective than some state-of-the-art methods. We achieved an accuracy and dice coefficient of 95% and 92% on the ISIC 2017 dataset and an accuracy and dice coefficient of 95% and 93% on the PH2 datasets[7].

❖ Methods

1) Deep Convolutional Encoder-Decoder Architecture

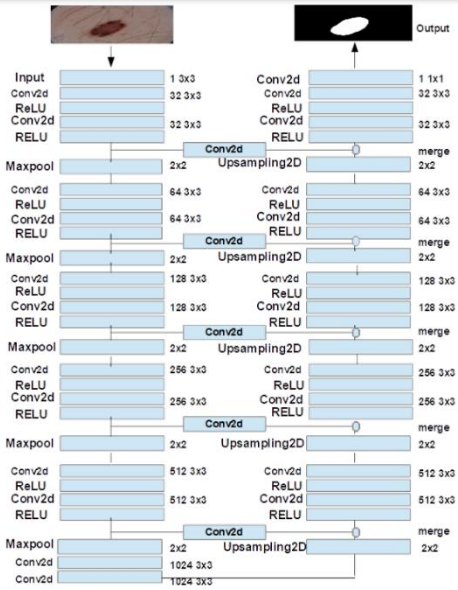

Figure 2.6 Achitectural Diagram for Deep Convolutional Encoder-Decoder Network

We propose a Deep Convolutional Architecture that is interconnected through a series of skip pathways as shown in Figure 2.6. This brings the semantic level of the encoder feature maps closer to that of the decoder feature maps and is proposed to enhance the feature learning ability of the network and feature extraction[7].

2) **Multistage and Multi-scale Approach**

The Encoder-Decoder network is enhanced into a moderate size with a multi-stage and

2.3.6 A comparison table showing the difference between our applications and other applications

multi-scale approach to enhance the learning of the complex features and handle various sizes of skin lesions images[7].

3) **Lesion-classifier**

We devise a new predictive method called Lesion-classifier which is computationally efficient to classify skin lesions into melanoma and non-melanoma in a pixel-wise manner

to distinguish melanoma lesions from non-melanoma images using the output of the softmax modules. Our method is particularly effective for analyzing challenging skin lesions, which usually have fuzzy boundaries and heterogeneous textures, for melanoma detection[7].

- **Advantage:**
- High accurcy.
- High result to detect melanoma
- High performance to use
- **Disadvantage:**
- High cost.
- Not speed of response to detecting melanoma

A comparison between the models reviewed in the previous section and our model is given in Table (1). It shows the characteristics of the models where our model has an advantage over other similar models.

	Melanoma Classification Model Using Machine Learning	**Automated Melanoma Recognition in Dermoscopy Images via Very Deep Residual Networks**	**Accessible Melanoma Detection Using Smartphones and Mobile Image Analysis**	**Melanoma diagnosis using deep learning techniques on dermatoscopic images**	**Skin Lesion Analysis Towards Melanoma Detection Using Deep Learning Network**	**Deep Learning-Based System for Automatic Melanoma Detection**
High accuracy	✓	✗	✗	✗	✓	✓
Low cost	✓	✓	✗	✓	✗	✗
It's a High result to detect melanoma	✓	✗	✗	✗	✓	✓
It's High performance	✓	✓	✗	✓	✗	✓
Speed of response to detecting melanoma	✓	✗	✓	✗	✗	✗

Table 2.2.4 Review the similar and different features of our app.

2.4 Summary

Due to the poor contrast of skin lesions, the large intraclass variance of melanomas, the high degree of a visual resemblance between melanoma and non-melanoma lesions, and the presence of many artifacts in the picture, automated melanoma detection in dermo copy images is a very difficult task. To address these difficulties, based on what has been provided before from systems similar to ours, there are a few aspects that need to be enhanced to achieve a perfect system. To acquire the best accuracy, use a variety of classification algorithms and adjust the hyperparameters of each kind. Second, the solution should be applied to an appropriate dataset, not only to thermoscopic images.

Chapter 3 : Method

3.1 Requirement Gathering Techniques

The descriptive questionnaire technique was used as the primary instrument for data collection in this study. We gather information from participants and collect their recommendations and comments to achieve reliable findings and make crucial decisions based on the responses supplied by users. The major goal of this is to learn about the needs of the users. A "google form" was used to develop an online questionnaire in Arabic, and 50 people responded. The questionnaire questions and replays are as follows:

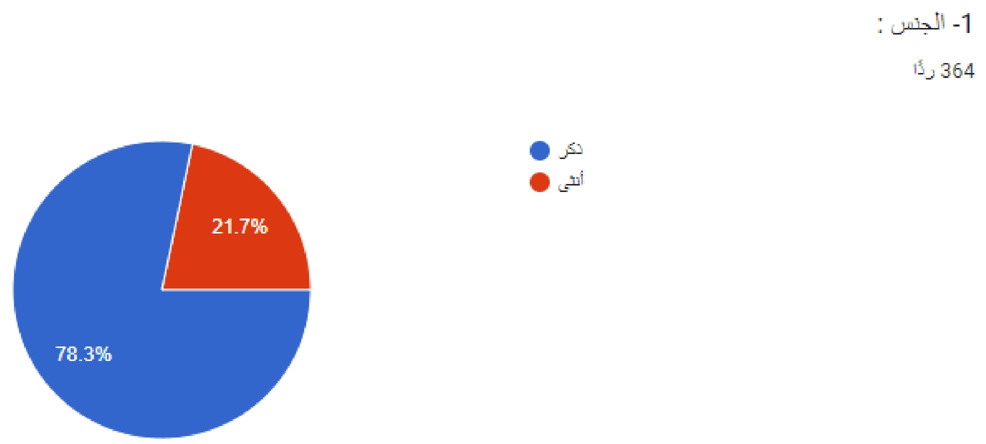

Figure 0:1 cdscsdcsdcsdv

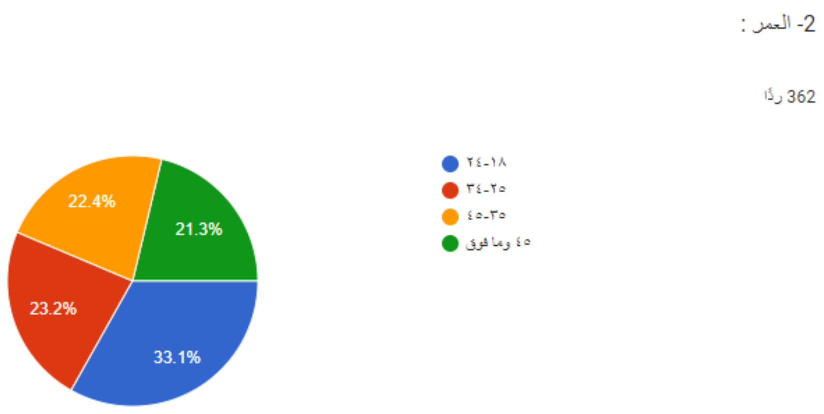

Figure 0:2 Requirement Gathering

3- هل انت مصاب بسرطان الجلد ؟

359 ردًا

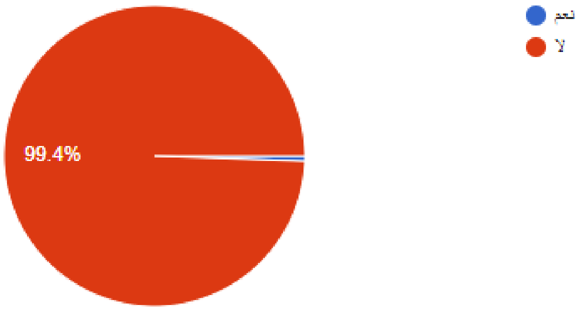

Figure 0:3 Requirement Gathering

4- هل سيساعد الذكاء الاصطناعي في التعرف على سرطان الجلد ؟

360 ردًا

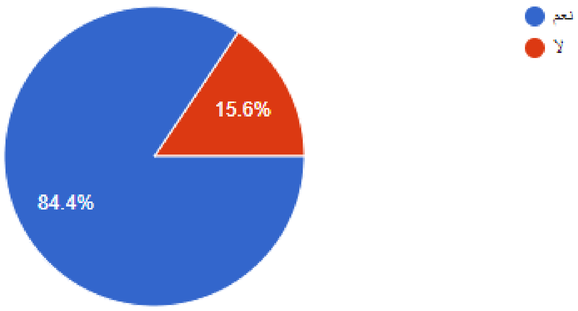

Figure 0:4 Requirement Gathering

5- هل التنبؤ بالإصابة بمرض سرطان الجلد من الممكن ان يساعد على التدارك قبل الإصابة ؟

361 ردًا

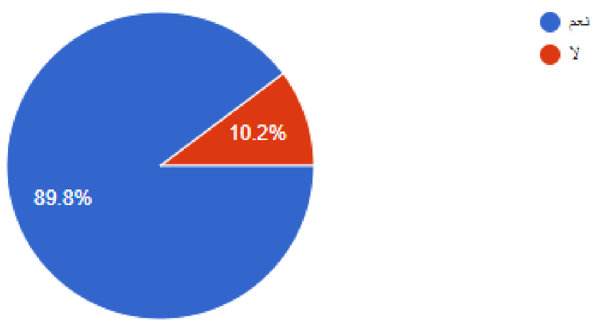

Figure 0:5 Requirement Gathering

6- هل اجريت من قبل تحليل لمعرفة هل انت مصاب بسرطان الجلد حفظنا الله وإياك ؟

361 ردًا

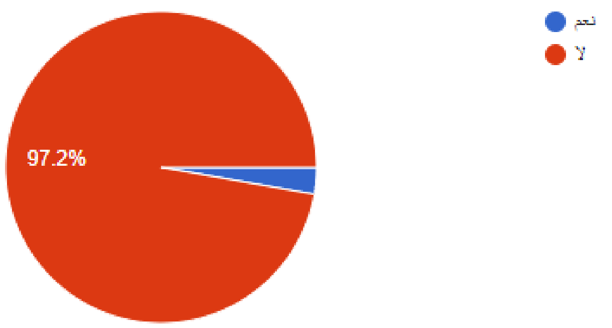

Figure 0:6 Requirement Gathering

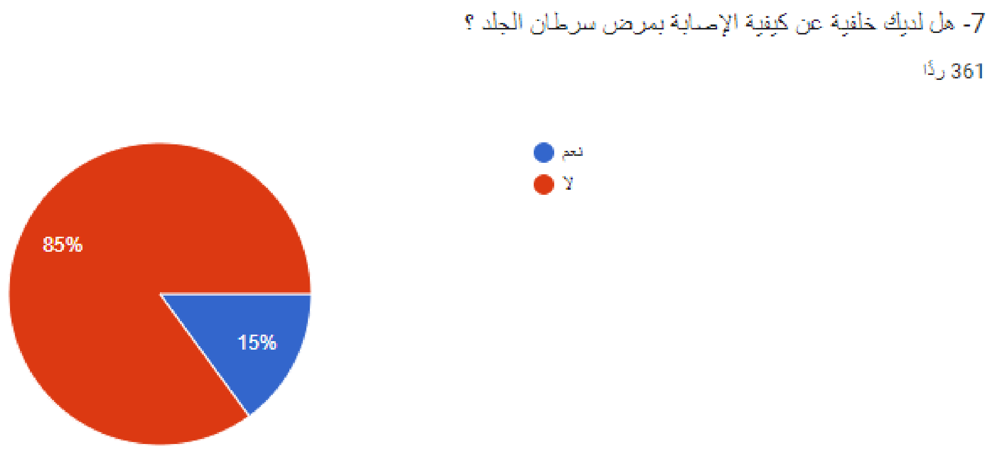

Figure 0:7 Requirement Gathering

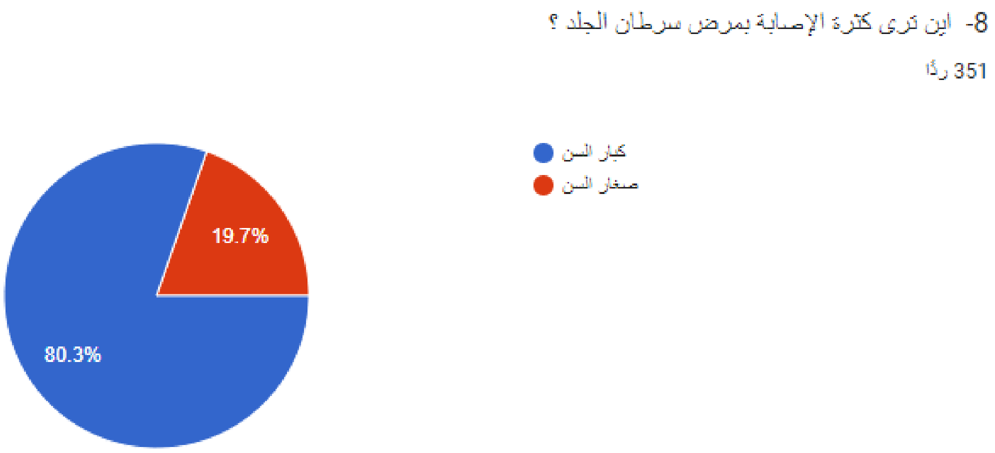

Figure 0:8 Requirement Gathering

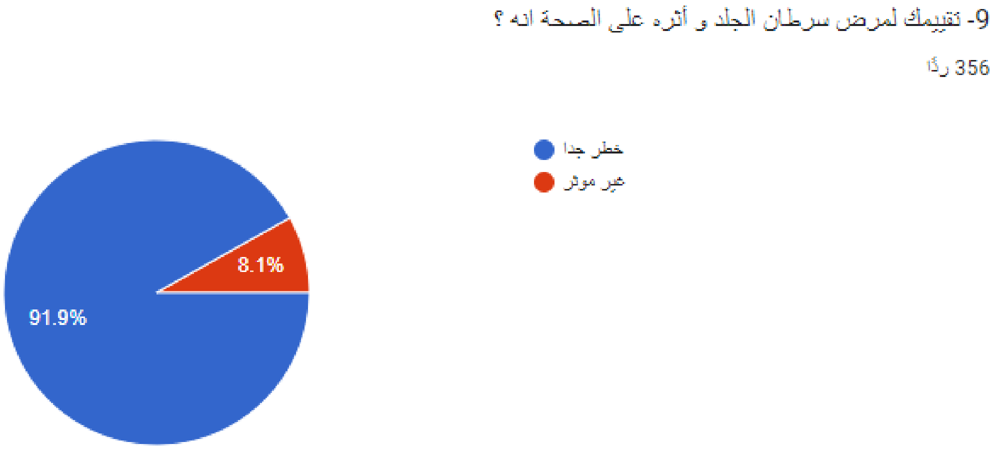

Figure 0:9 Requirement Gathering

3.2 Proposed Business Process

A business process is a collection of linked tasks that find their end in the delivery of a service or product to a client. A business process has also been defined as a set of activities and tasks that, once completed, will accomplish an organizational goal.

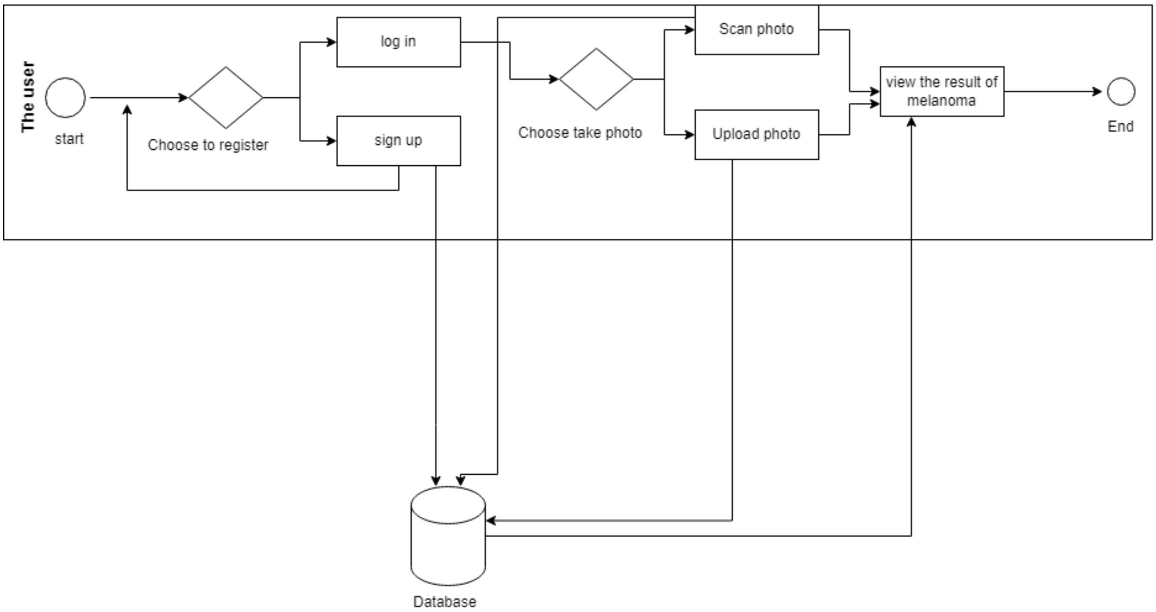

Figure 0:10 Proposed Business Process Guidelines

3.3 Functional Requirements

After gathering requirements using questionnaires and interviews functional requirements are discussed in this section. Functional Requirements are defined as “describe the behavior and information that the solution will manage. They describe capabilities the system will be able to perform in terms of behaviors or operations specific information technology application actions or responses” . From the definition the functional requirements are listed as follows:

Requirement	Requirement statement
User	sign up to create a new account.
User	log in to the application
User	upload new photos to the application.
User	scan photo using the camera
AI System	The system can detect a person's melanoma in the uploaded photo.

User	log out from the application

Table 0.1 Functional Requirements Guidelines

Based on the functional requirements we can create a use case diagram with the main requirement a use case diagram is “how a system interacts with its environment includes a diagram and a description to depict the discrete activities that the users perform” . as shown in figure (12):

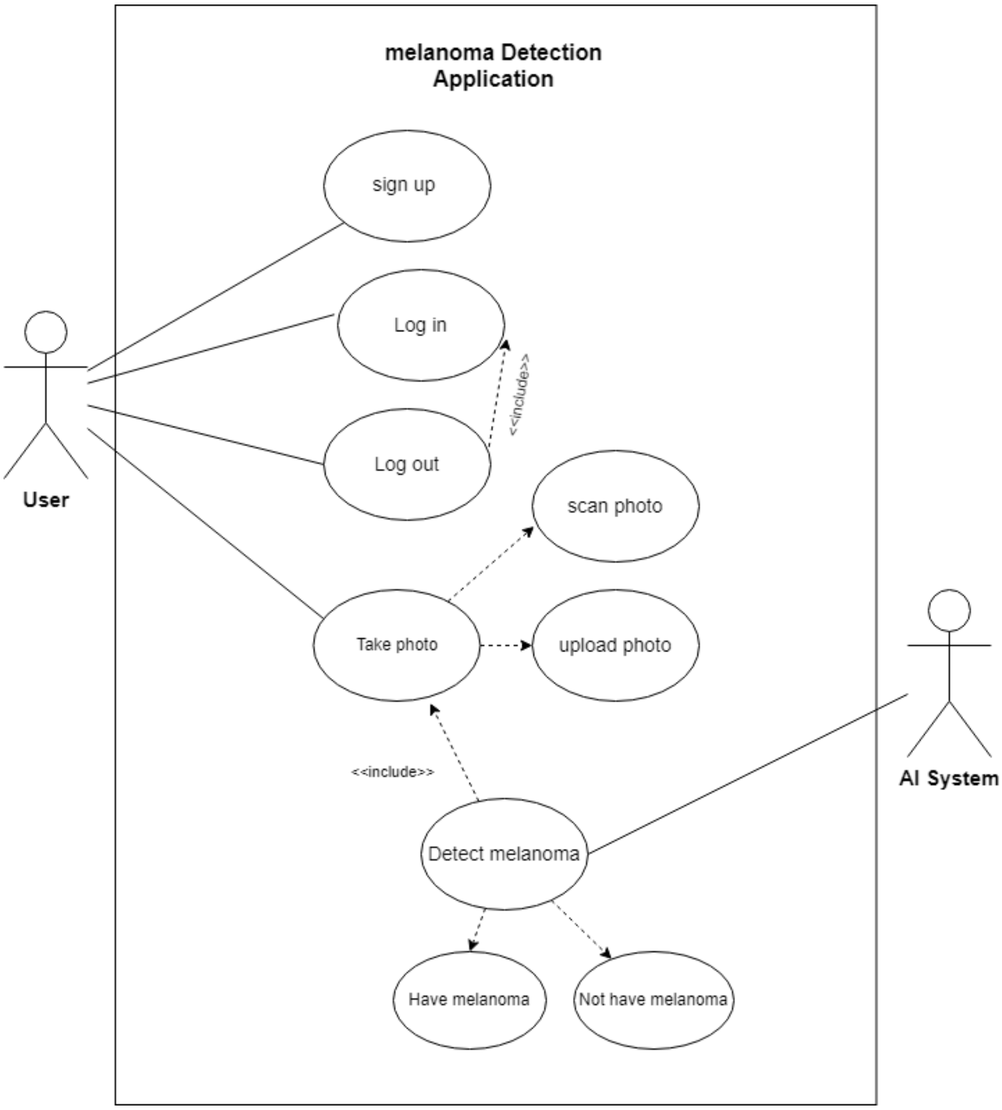

Figure 0:11 usecase diagram

3.4 Non-functional Requirements

Non-functional Requirements (NFRs) define system attributes such as security, reliability, performance, maintainability, scalability, and usability. They serve as constraints or restrictions on the design of the system across the different backlogs

Non-Functional	**Description**
Security	To guard against unauthorized access, theft, and/or disruption of the system's data and services, the database system must be secure.
Scalability	The system will initially only serve a small number of users, but it must be able to be extended to accommodate more users and transaction processing.
Robustness	The system should be able to operate and handle various types of data needed to function properly.
Extensibility	The system should be able to increase the number of services without disrupting the rest of the services offered
Traceability	The system should provide on request, details of when and where, and the transaction took place.

Table 0.2 Non-functional Requirements

3.5 User Interfaces

The user interface (UI) is the point of human-computer interaction and communication in a device. This can include display screens, keyboards, a mouse and the appearance of a desktop. It is also the way through which a user interacts with an application or a website.

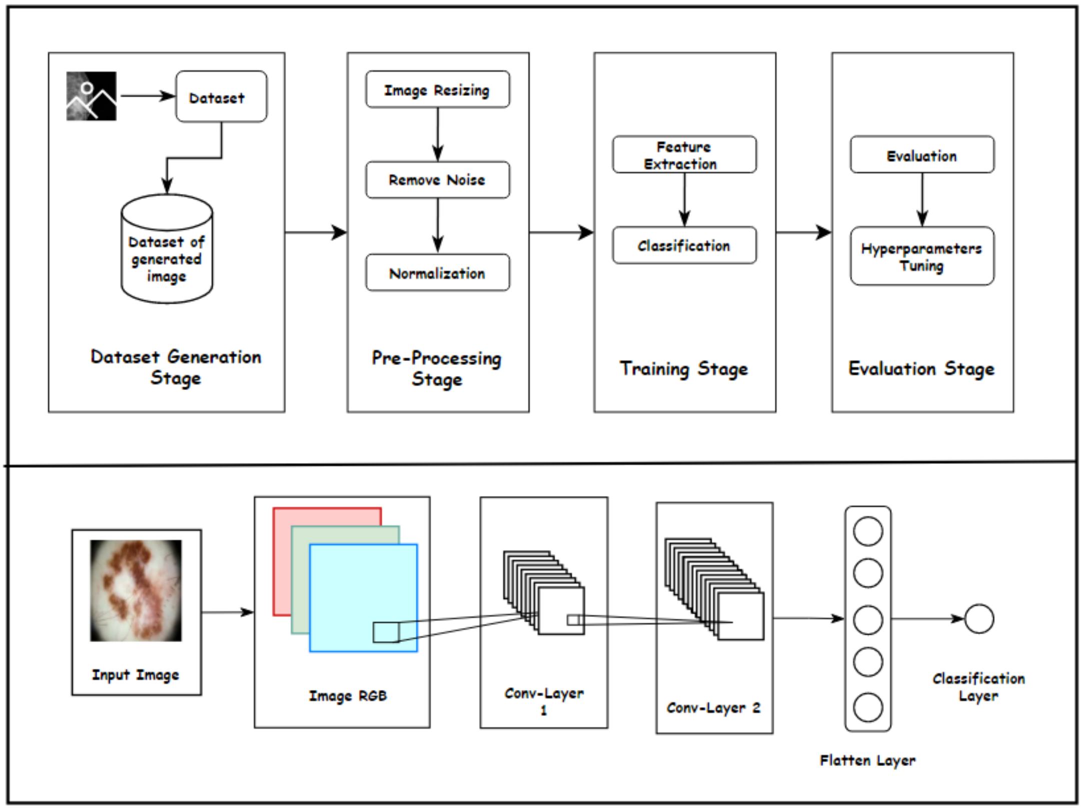

Figure 0:12 User Interfaces Guidelines

3.6 System Modelling

3.6.1 Activity Diagram

In Unified Modelling Language (UML), An activity diagram visually presents a series of actions or flow of control in a system like a flowchart or data flow diagram

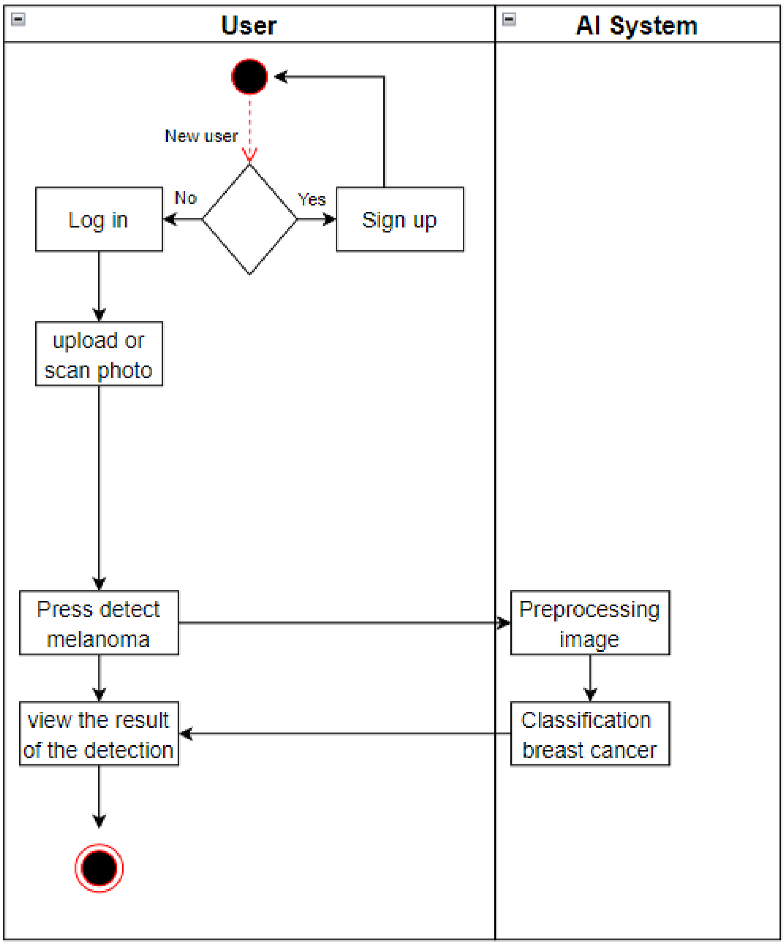

Figure 0:13 Activity Diagram

3.6.2 Class Diagram

In software engineering, a class diagram in the Unified Modelling Language (UML) is a type of static structure diagram that describes the structure of a system by showing the system's classes, their attributes, operations (or methods), and the relationships among objects

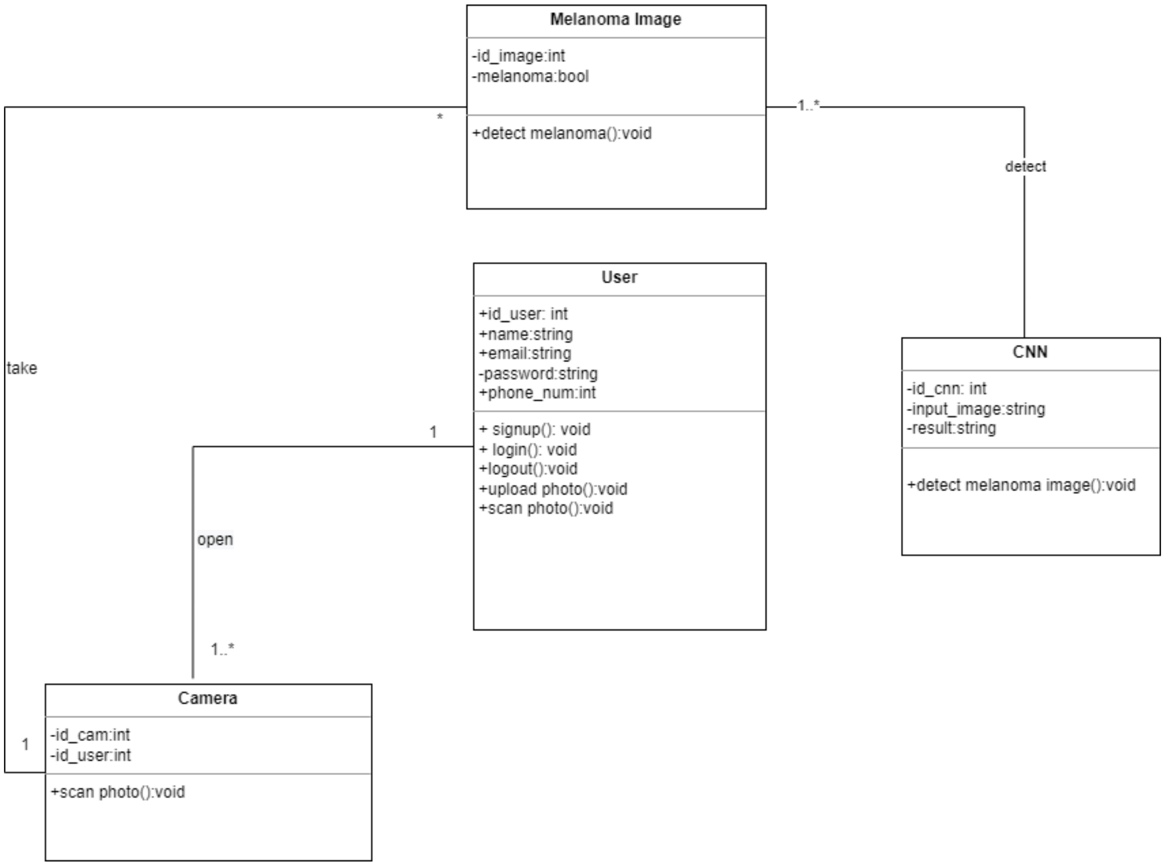

Figure 0:14 Class Diagram

3.6.3 Sequence Diagrams

Sequence diagrams, commonly used by developers, model the interactions between objects in a single use case. They illustrate how the different parts of a system interact with each other to carry out a function, and the order in which the interactions occur when a particular use case is executed.

3.6.3.1 Sequence Diagram for the user register

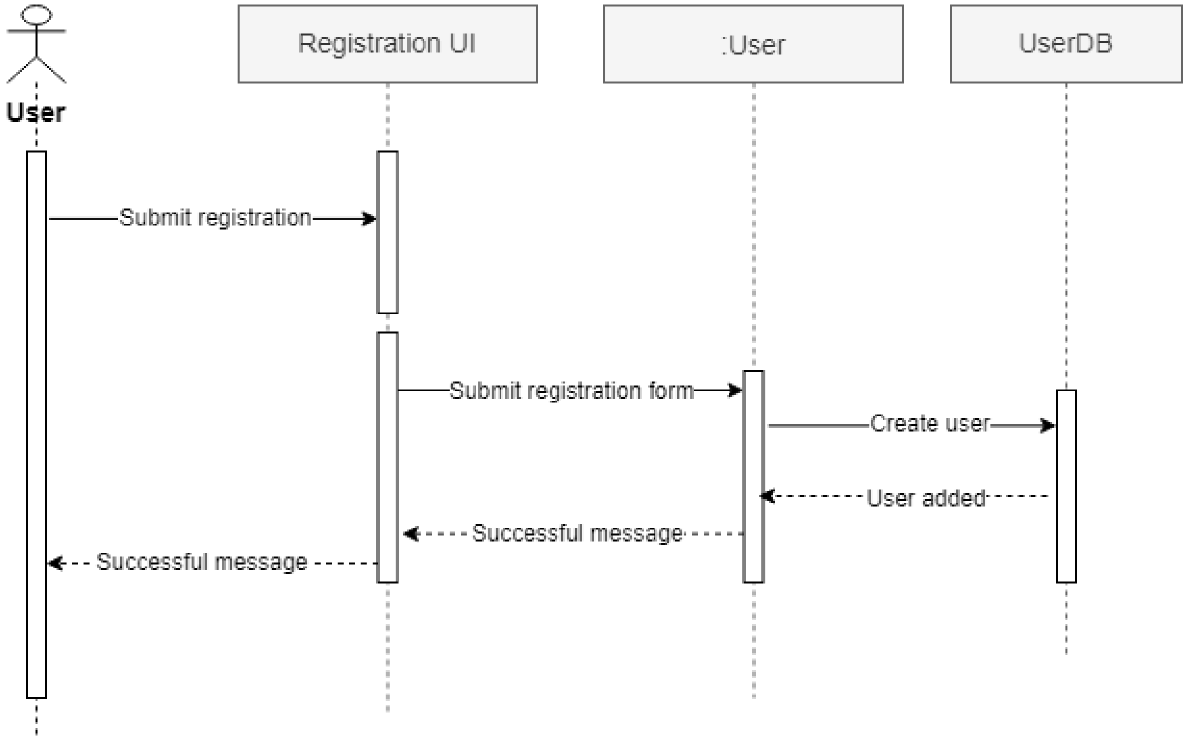

Figure 0:15 Sequence Diagram for the user register

3.6.3.2 Sequence Diagram for the user login

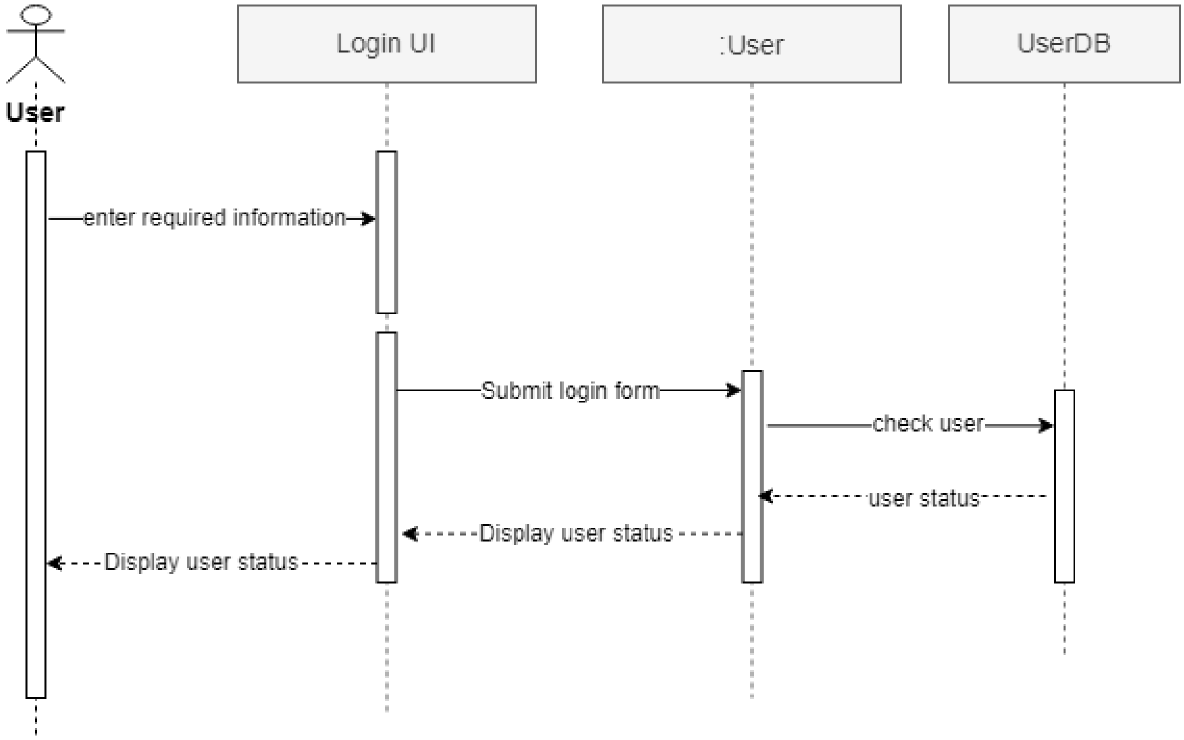

Figure 0:16 Sequence Diagram for the user login

3.6.3.3 Sequence Diagram for the user to scan photo

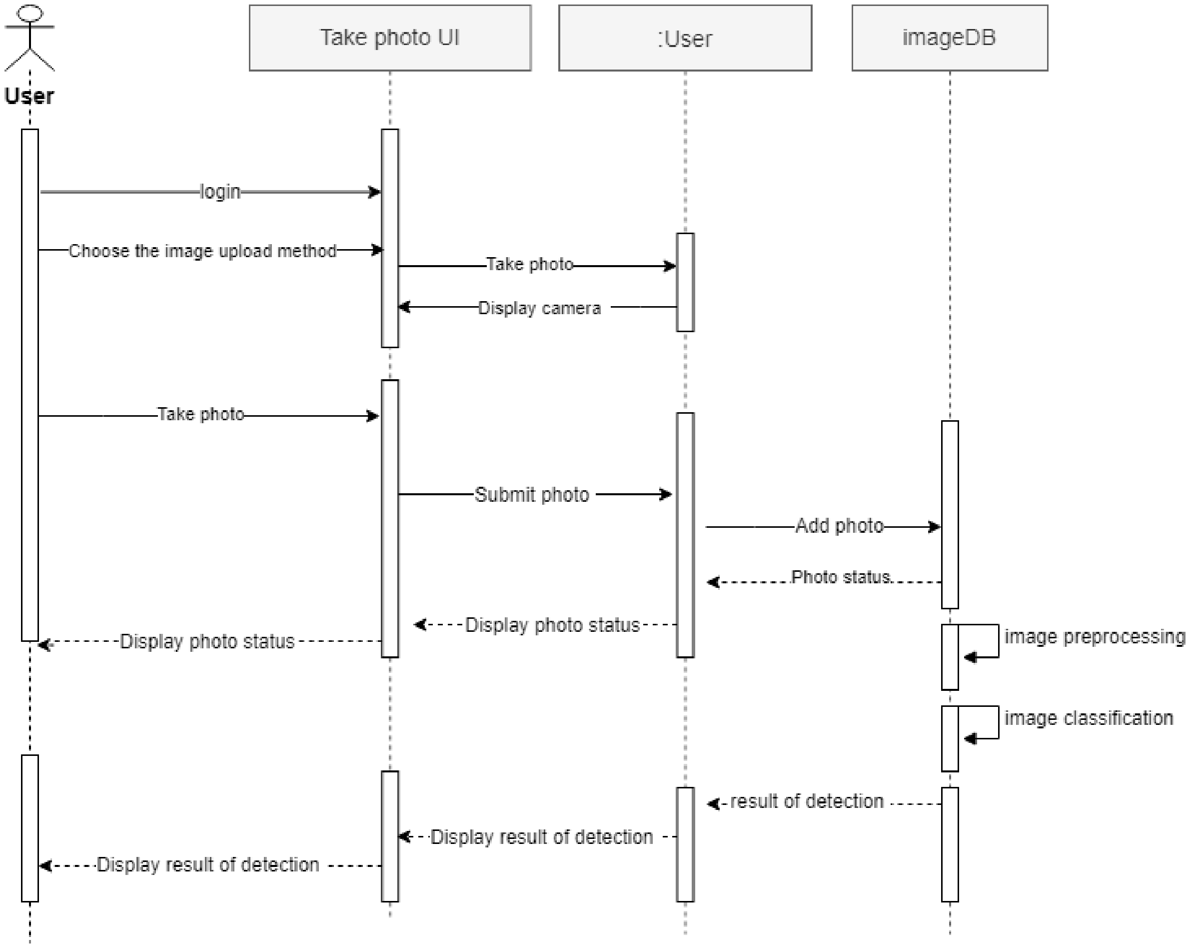

Figure 0:17 Sequence Diagram for the user to take photo

3.6.3.4 Sequence Diagram for the user to upload photo

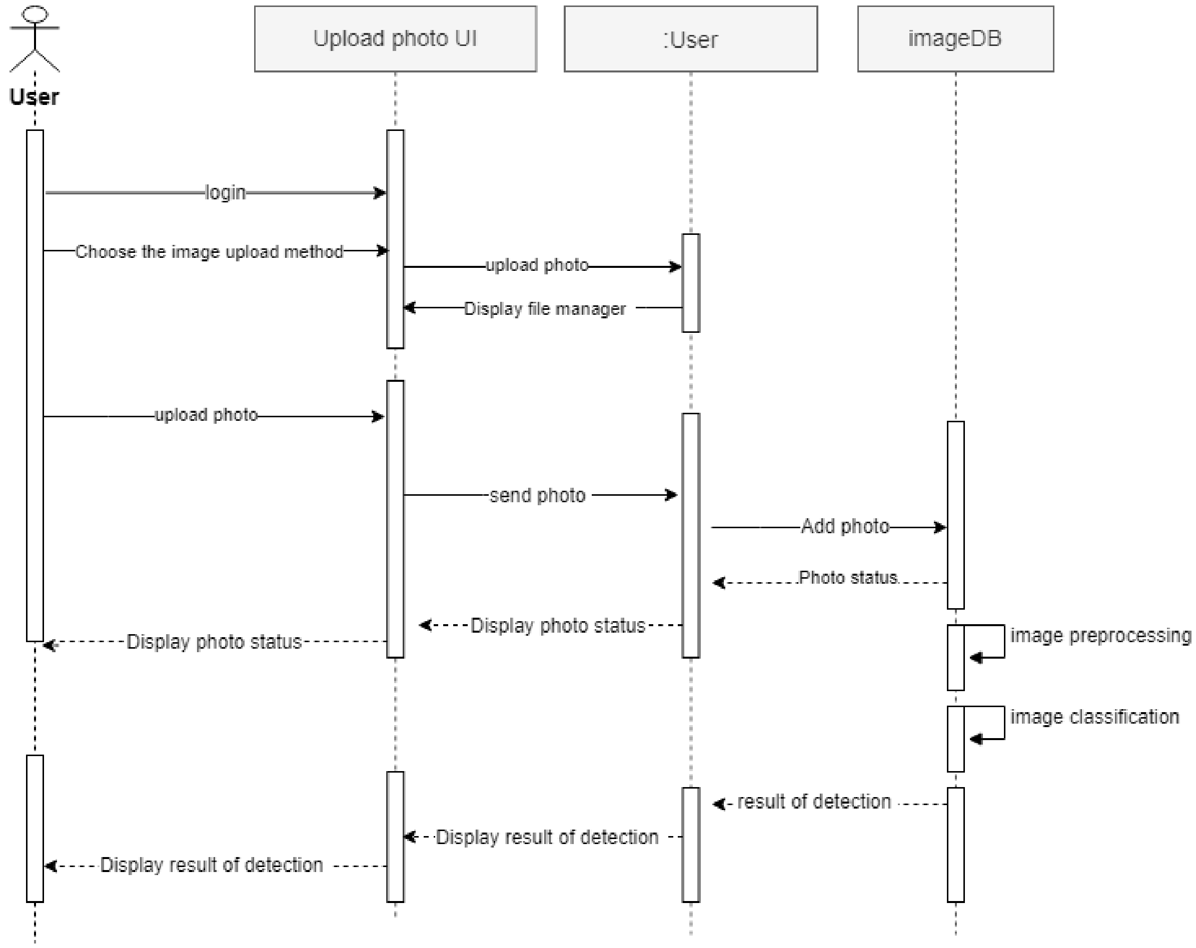

Figure 0:18 Sequence Diagram for the user to upload photo

3.7 Data Modelling

3.7.1 ER Diagram

ER is a diagram that displays the relationship of entity sets stored in a database. In other words, ER diagrams help to explain the log structure of databases

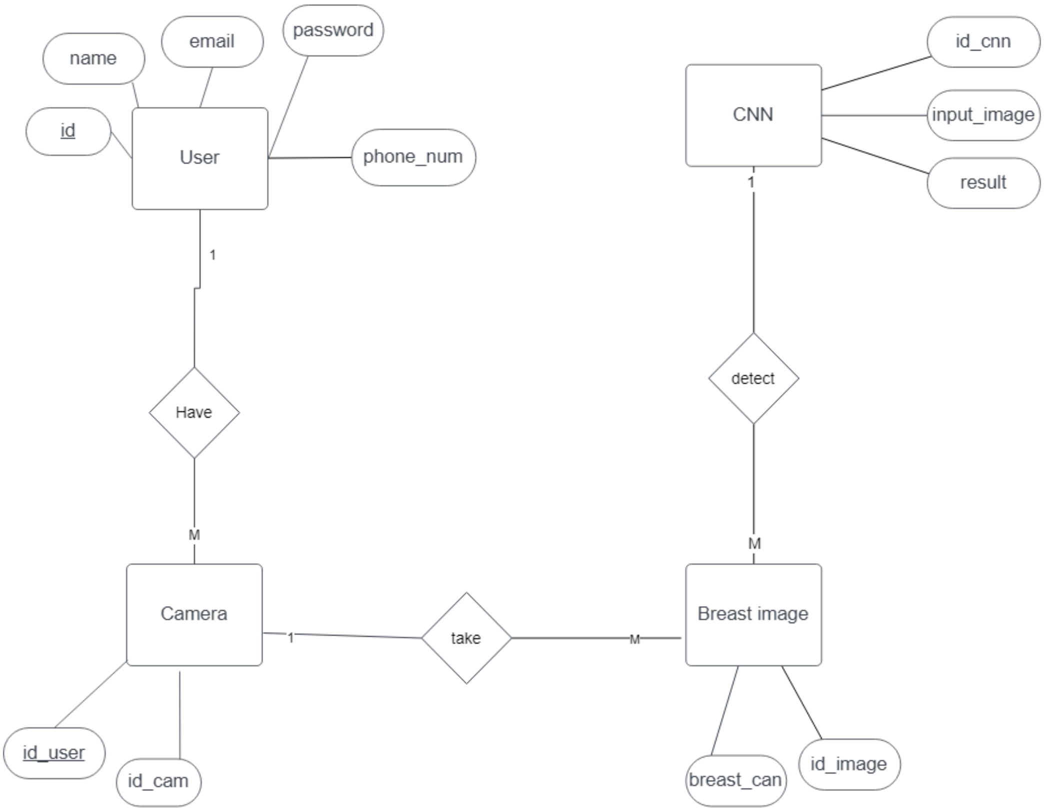

Figure 0:19 ER Diagram

3.7.2 Data Dictionary

Tables are database objects that contain all the data in a database. In tables, data is logically organized in a row-and-column format similar to a spreadsheet. Each row represents a unique record, and each column represents a field in the record. tables below show the part of from tables that are used in our system.

#	Column name	Data type	Note
1	Id_image	Int (10)	**Primary key auto increment**
2	Melanoma	Varchar(200)	**Not null**

Table 0.3 Image table

#	Column name	Data type	Notes
1	Id_cam	Int (10)	**Primary key auto increment**
2	Id_user	Int (10)	**Foreign key references user (id_user) Not null**

Table 0.4 Camera table

#	Column name	Data type	Notes
1	Id_user	Int (10)	**Primary key auto increment**
2	User_name	Varchar (200)	**Not null**
3	email	Varchar (200)	**Not null**
4	Password	Varchar (200)	**Not null**
5	Phone_num	Int(20)	**Not null**

Table 0.5 user table

#	Column name	Data type	Notes
1	Id_cnn	Int (10)	**Primary key auto increment**
2	Input_image	Varchar (200)	**Not null**
3	**output**	**Varchar (200)**	**Not null**

Table 0.6 CNN Table

3.8 Detailed Interface Design

3.8.1 Home Interface

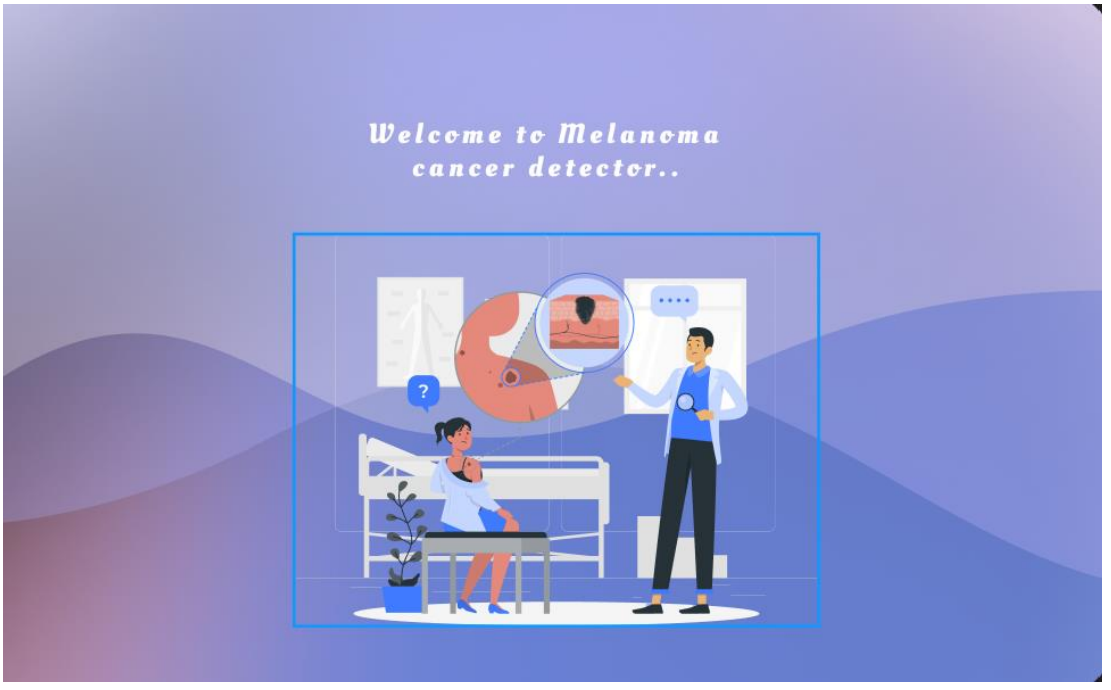

Figure 0:20 home interface

3.8.2 Sign up Interface

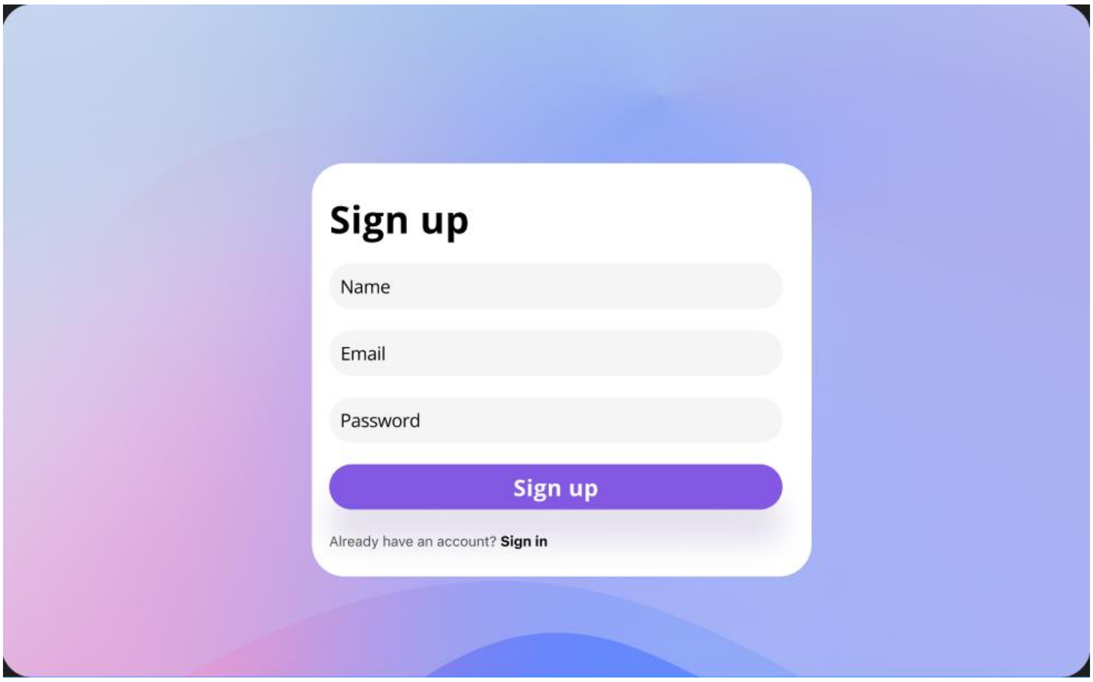

Figure 0:21 Sign up interface

3.8.3 Sign in Interface

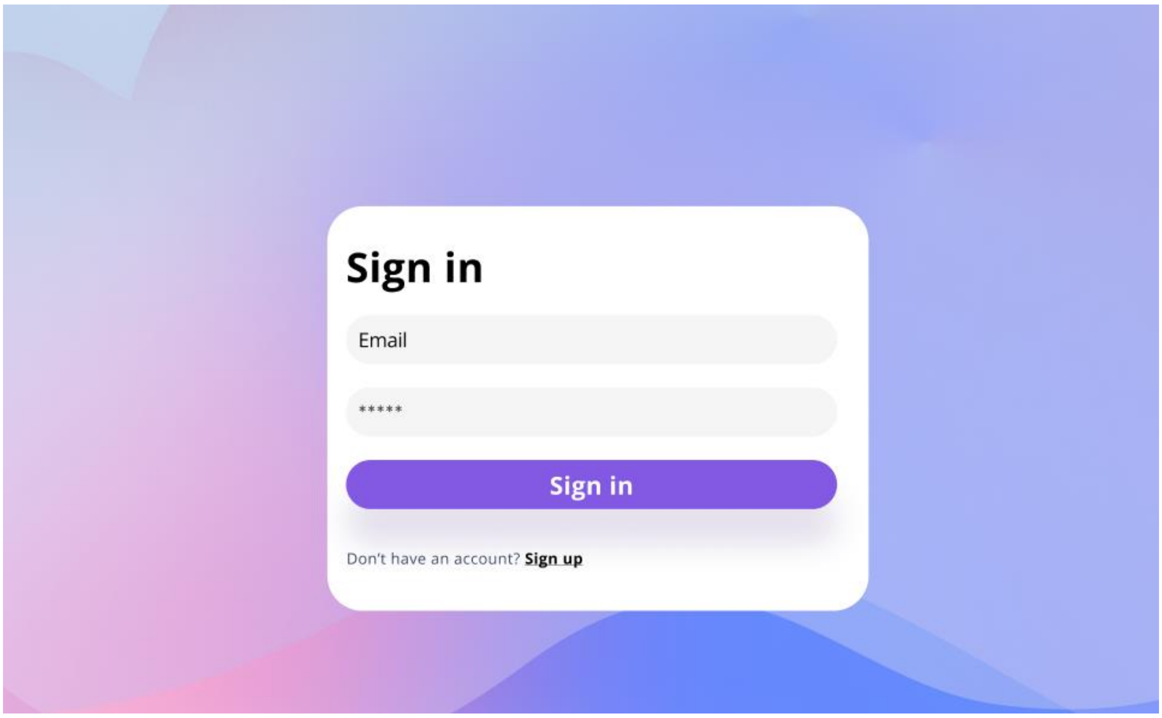

Figure 0:22 Sign in Interface

3.8.4 Scan photo Interface

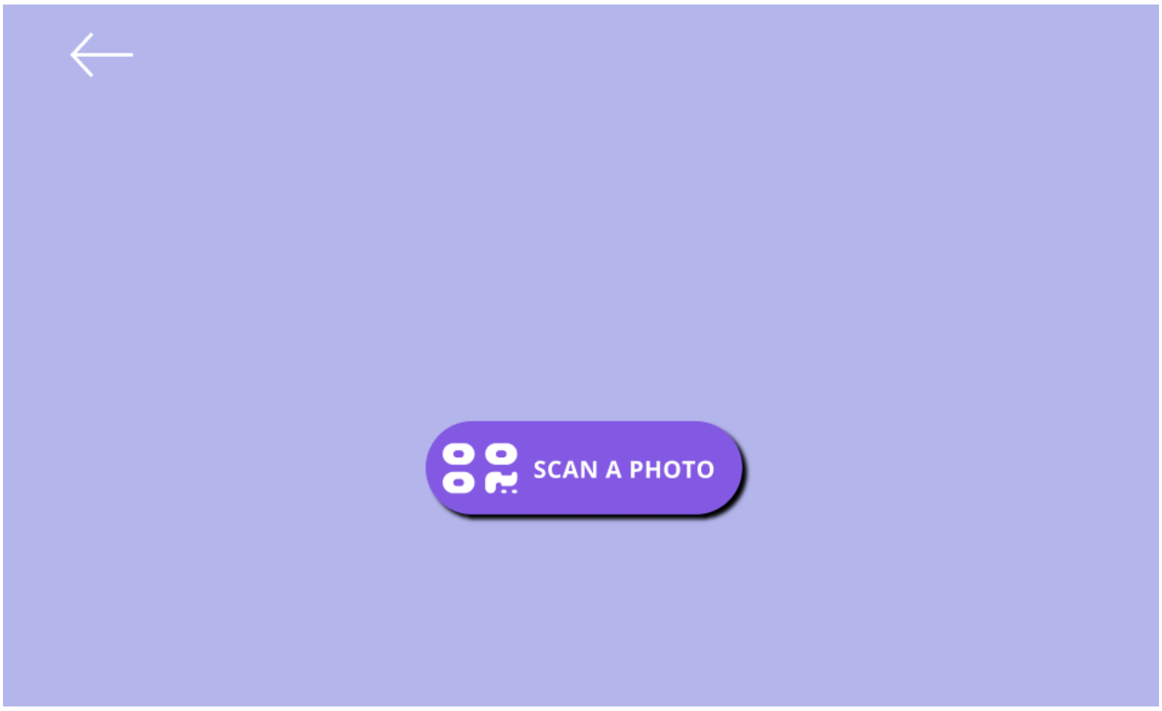

Figure 0:23 Scan photo Interface

3.8.5 Result of detection Interface

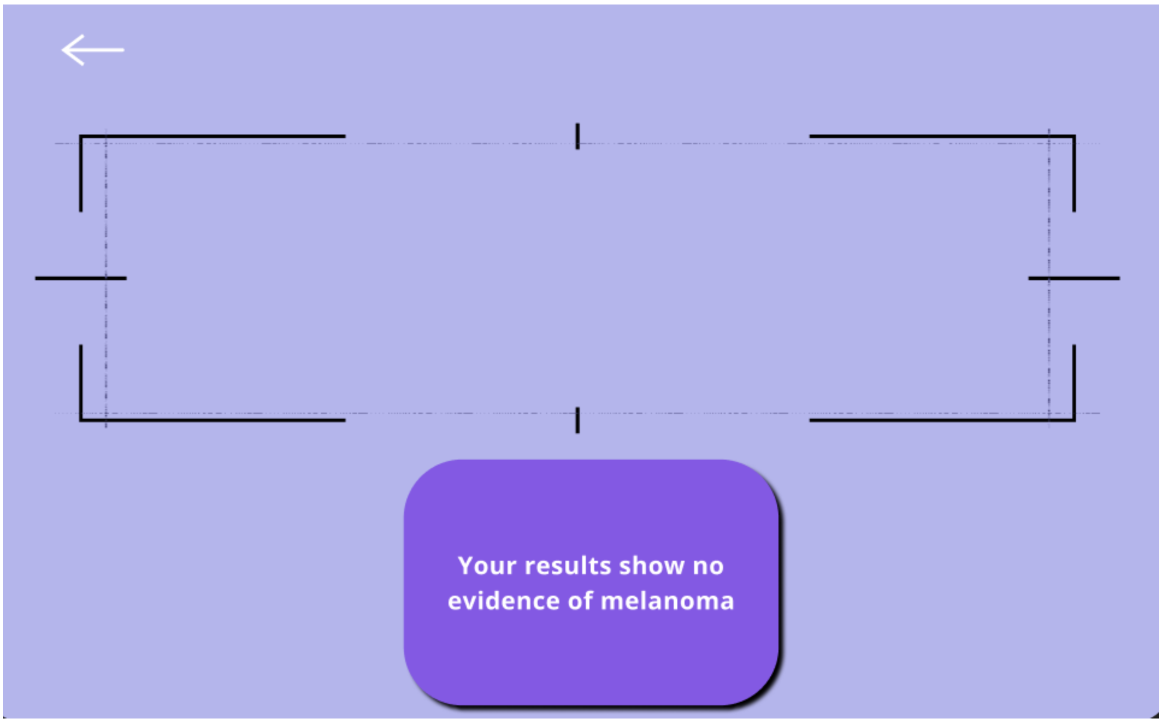

Figure 0:24 4 Result of detection Interface

3.9 Alternative Designs

The following figure shows the algorithm that will be used in building the proposed system, where we note that the inputs of the system are the proposed data set, and the outputs are the accuracy of the system in identifying skin cancer. After the dataset is entered into the system, the skin cancer must be selected and cropped from the image, ignoring the background, and then the data is pre-processed by scaling the images, cleaning them and converting them into a one-dimensional matrix to be used in the training and testing processes.The data set after processing is divided into two sets, the first is the training data set and the second is the test data set, where the training set is used to train the proposed model, while the second set is taken to test the model after training it. And to determine its accuracy in estimating true melanoma of untrained images

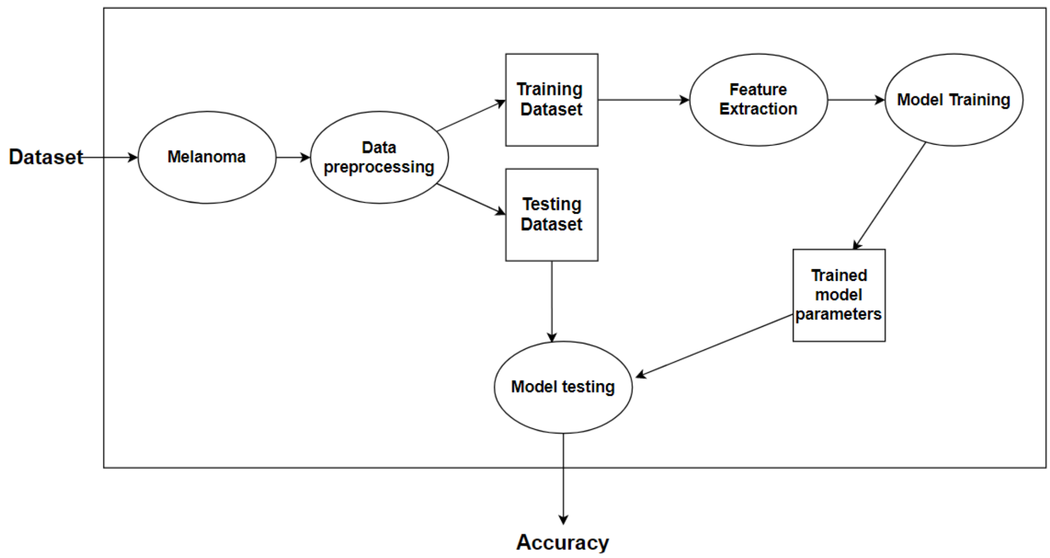

Figure 0:25 Alternative Designs

Chapter 4 : System Implementation

4.1 Introduction

This chapter will discuss how a project management system will be used in practice. System implementation refers to the process of putting a proposal system into operation. We'll discuss a variety of general subjects related to the hardware and software specifications needed to set up and operate the system.

4.2 System Specification

4.2.1 Hardware Specifications

Hardware	Requirements
Processor	Processor – i3
Hard Disk	4 GB
RAM	1GB RAM

Table 4.1 Hardware Specifications

4.2.2 Software Specifications

The specifications of any system are the most important details that everyone needs to be aware of. Software requirements are frequently referred to as the most important components we need to explain for every system.

Some instances of software standards are as follows:

Software	Role
Jupyter Notebook	To build model
Windows 10, Linux, Mac OS	Operating System Requirement
Visual Studio 2019	To build a desktop application

Table 4.2 Software Specifications

4.3 System Testing

A table describing all test cases, their objectives, inputs, anticipated results, pass/fail criteria, and test outcomes for each test individually are provided together with a description of the system aspects that have been assessed.

Case [1]: Database

```
import numpy as np
import pandas as pd
import numpy as np
import cv2
import os
import PIL
from tensorflow import keras
from keras import layers
from keras.models import Sequential
```

```
import pathlib
data_dir=pathlib.Path('data')
```

```
def laod_images_opencv_extisions(path):
    ext = [".jpg",".gif",".png",".tga",".webp"]   # Add image formats here
    files = []
    images = []
    [files.extend(data_dir.glob(path + '/*' + e)) for e in ext]
    return files
```

Figure 4:1 Loading the dataset

```
train_data_frame=pd.DataFrame(get_dataFrame(image_dir))
train_data_frame=train_data_frame.reset_index()
train_data_frame.head()
```

	index	filename	category
0	43	data\Train\actinic keratosis\ISIC_0028063.jpg	0
1	76	data\Train\actinic keratosis\ISIC_0030242.jpg	0
2	685	data\Train\melanoma\ISIC_0000469.jpg	3
3	152	data\Train\basal cell carcinoma\ISIC_0025383.jpg	1
4	27	data\Train\actinic keratosis\ISIC_0027254.jpg	0

```
test_data_frame=pd.DataFrame(get_dataFrame(test_dir))
test_data_frame=test_data_frame.reset_index()
test_data_frame.head()
```

	index	filename	category
0	18	data\Test\basal cell carcinoma\ISIC_0024345.jpg	1
1	4	data\Test\actinic keratosis\ISIC_0024511.jpg	0
2	20	data\Test\basal cell carcinoma\ISIC_0024403.jpg	1
3	22	data\Test\basal cell carcinoma\ISIC_0024431.jpg	1
4	105	data\Test\squamous cell carcinoma\ISIC_0024372...	7

+ Code + Markdown

Figure 4:2 First rows of the train and test dataset

Case [2]: Accuracy Score

```
from sklearn.metrics import classification_report,confusion_matrix
print(classification_report(ytest,p))

              precision    recall  f1-score   support

           0       1.00      0.80      0.89         5
           1       0.88      1.00      0.93         7

    accuracy                           0.92        12
   macro avg       0.94      0.90      0.91        12
weighted avg       0.93      0.92      0.91        12
```

Figure 4:3 Accuracy Score

4.3.2 Test Cases

Project Name: Melanoma Classification	
Test Case [1]	
Test Case	Database
Test Priority (Low/Medium/High):	High
Poupous of test case	Make that the database is connected properly.
Entering the wrong database into thesystem	Fail
Entering the correct database into thesystem	Pass
Input	Melanoma Database File
Expect output	The system started to work.
Test result	The system will start, and it will detect melanoma from the image entered
Pre-conditions: Verify the system's database is present.	

Table 4.3 Database test case

Project Name: Melanoma Classification	
Test Case [2]	
Test Case	Accuracy Score
Poupous of test case	Make sure the melanoma database system is accurate.
Input	Database
Expect output	percentage accuracy Score
Test result	Accuracy score: 0.94
Pre-conditions: Knowledge of Accuracy Score	

Table 4.4 Accuracy score test case

4.4 System Deployment

System deployment and use includes the processes used to plan for and manage the transition of new or evolved systems and capabilities into operational use and the transition of support responsibilities to the eventual maintenance or support organization.

4.3.1 Deployment Diagram

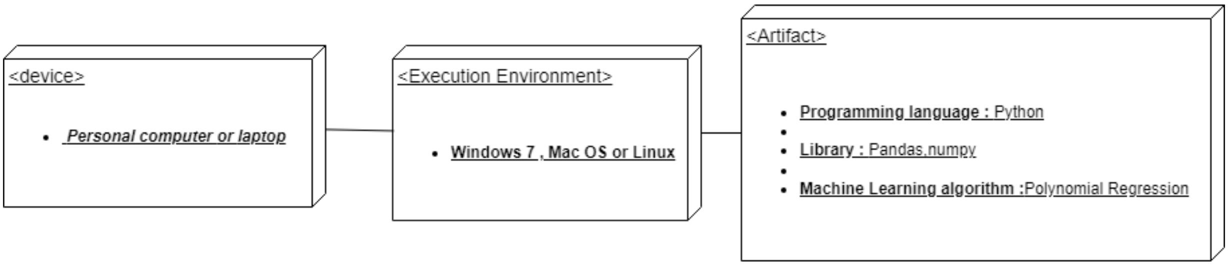

Figure 4:4 Deployment Diagram

Chapter 5 : Conclusion and Future Work

5.1 Conclusion

Skin cancer is one of the deadliest types of skin cancer because it spreads rapidly throughout the body. With the increasing prevalence and lethality of skin cancer, it is critical to develop CAD support systems to assist clinicians in the diagnosis of skin cancer. Many studies have been done over the past two decades on the rapid and reliable identification of melanoma using dermatoscopy images, with diagnostic accuracy ranging from 70% to 95% for that, so we provided An artificial intelligence system based on Python was created that is able to detect 4 types of skin cancer, namely Superficial Spreading Melanoma (SSM), Nodular Melanoma (NM), Lentigo Maligna Melanoma (LMM), Acral Lentiginous Melanoma (ALM). To help medical professionals recognize skin cancer early. In view of this great height.

5.2 Future Work

The system's potential has not been fully realized. There is constant room for development. There can be additional approaches to implementing the system. To make the system as engaging as feasible, I did my best. Because of the system's adaptable nature, changes may be made quickly and easily. There are various issues with the existing system that will probably be resolved in the future: Make a prototype of the system to see it. Developing an idea for a system and connecting it to a bigger database.

References

[1] Pillay, Pillay V., Hirasen, D., Viriri, S., & Gwetu, M. (2020). Melanoma Skin Cancer Classification Using Transfer Learning. Advances in Computational Collective Intelligence, 287–297 https://doi.org/10.1007/978-3-030-63119-2_24.

[2] Melanoma - Symptoms and causes. (2022, June 18). Mayo Clinic. Retrieved September 12, 2022, from https://www.mayoclinic.org/diseases-conditions/Melanoma/symptoms-causes/syc-20374884#:%7E:text=Melanoma%2C%20the%20most%20serious%20type,in%20your%20nose%20or%20throat.

[3] Society AC. Cancer Facts and Figures 2020. Atlanta: American Cancer Society; 2020; available from:https://www.aimatMelanoma.org/about-Melanoma/Melanoma-stats-facts .

[4] Zhang, L., Gao, H. J., Zhang, J., & Badami, B. (2019, January 1). Optimization of the Convolutional Neural Networks for Automatic Detection of Skin Cancer. Open Medicine, 15(1), 27–37. https://doi.org/10.1515/med-2020-0006.

[5] Razmjooy, N., Somayeh Mousavi, B., Soleymani, F., & Hosseini Khotbesara, M. (2012, October 6). A computer-aided diagnosis system for malignant melanomas. Neural Computing and Applications, 23(7–8), 2059–2071. https://doi.org/10.1007/s00521-012-1149-1.

[6] Li, Y. (n.d.). Skin Lesion Analysis towards Melanoma Detection Using Deep Learning Network. MDPI. Retrieved October 12, 2022, from https://www.mdpi.com/1424-8220/18/2/556.

[7] Deep Learning-Based System for Automatic Melanoma Detection. (2020). IEEE Journals & Magazine | IEEE Xplore. Retrieved October 12, 2022, from https://ieeexplore.ieee.org/abstract/document/8945133

[8] Acosta, J. M. F. (2021, January 6). Melanoma diagnosis using deep learning techniques on dermatoscopic images - BMC Medical Imaging. BioMed Central. Retrieved October 12, 2022, from https://bmcmedimaging.biomedcentral.com/articles/10.1186/s12880-020-00534-8

[9] Types of Melanoma. (2022, September 28). Memorial Sloan Kettering Cancer Center. Retrieved September 28, 2022, from https://www.mskcc.org/cancer-care/types/melanoma/types-melanoma

[10] ernesto.net. (n.d.). Intro to AI and Machine Learning – DataSciences.io. Retrieved October 2, 2022, from https://datasciences.io/course/intro-to-ai-machine-learning/

[11] Just a moment. . . (n.d.-d). Retrieved October 19, 2022, from https://www.sciencedirect.com/topics/computer-science/image-processing

[12] Pedamkar, P. (2022, May 19). Python vs Matlab. EDUCBA. Retrieved October 2, 2022, from https://www.educba.com/python-vs-matlab/

[13] Project Jupyter. (n.d.). Home. Retrieved October 2, 2022, from https://jupyter.org/.

[14] Lequan Yu, Hao Chen, Qi Dou, Jing Qin, and Pheng-Ann Heng. Automated melanoma recognition in dermoscopy images via very deep residual networks. IEEE Transactions on 234 235 Medical Imaging, 36(4):994–1004, 2017

[15] D. Gutman, N. C. F. Codella, E. Celebi, B. Helba, M. Marchetti, N. Mishra, and A. Halpern, “Skin Lesion Analysis toward Melanoma Detection: A Challenge at the International Symposium on Biomedical Imaging (ISBI) 2016, hosted by the International Skin Imaging Collaboration (ISIC),” arXiv preprint arXiv:1605.01397, 2016

[16] Do, Thanh-Toan, et al. "Accessible melanoma detection using smartphones and mobile image analysis." IEEE Transactions on Multimedia 20.10 (2018): 2849-2864

[17] Acosta, J. M. F. (2021, January 6). Melanoma diagnosis using deep learning techniques on dermatoscopic images - BMC Medical Imaging. BioMed Central. Retrieved October 12, 2022, from https://bmcmedimaging.biomedcentral.com/articles/10.1186/s12880-020-00534-8