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Early detection of colon cancer

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Graduation Project
Academic Year 2022-2023
Project Documentation

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List of Abbreviations

Word	Abbreviation
Matthews's correlation	MCC
True positives	TP
False Negatives	FN
True Negatives	TN
False Positives	FP
Mean intersection over union	Mean IOU

Abstract:

Polyps are found in nearly half of the individuals at age 50 that undergo the colonoscopy screening, and their frequency increase with age. Colorectal cancer (CRC) begins in the colon, or the rectum and it is the second most type dangerous of cancer.

The good news is that deaths from this disease have declined compared with a decade ago, and early detection is apparently one reason. If a doctor catches cancer while it's still confined to the outer lining of the colon or rectum, you can probably look forward to a full recovery. Screening is the process of looking for cancer or pre-cancer in people who have no symptoms of the disease (stage 0: stage 2). So, colonoscopy represents a very important diagnostic modality for screening colorectal cancer. we will use Kvasir dataset, which is an open-access dataset of gastrointestinal polyp images and corresponding segmentation masks, manually annotated by a medical doctor and then verified by an experienced gastroenterologist, and CVC-612 dataset which is an open-access dataset of 612 images from 31 colonoscopy sequences. It is used for medical image segmentation, in particular polyp detection in colonoscopy videos. We will demonstrate the use of our datasets with a traditional classification approach and segmentation approach with the use of modern deep learning based Convolutional Neural Network (CNN) approach.

Thus, the goal of our project is the automatic detection of more polyps at an early stage that can play a crucial role in improving both prevention of and survival from colorectal cancer by using classification and segmentation techniques. This is the main motivation behind the development of a Kvasir dataset.

Chapter 1

Introduction

1.0 Introduction

What is cancer?

Cancer is a leading cause of death worldwide, accounting for nearly 10 million deaths in 2020, or nearly one in six deaths. Cancer is the second cause of death worldwide, a total of 1.9 million new cancer cases and 609,360 deaths from cancer are expected to occur in the US in 2022, which is about 1,670 deaths a day.

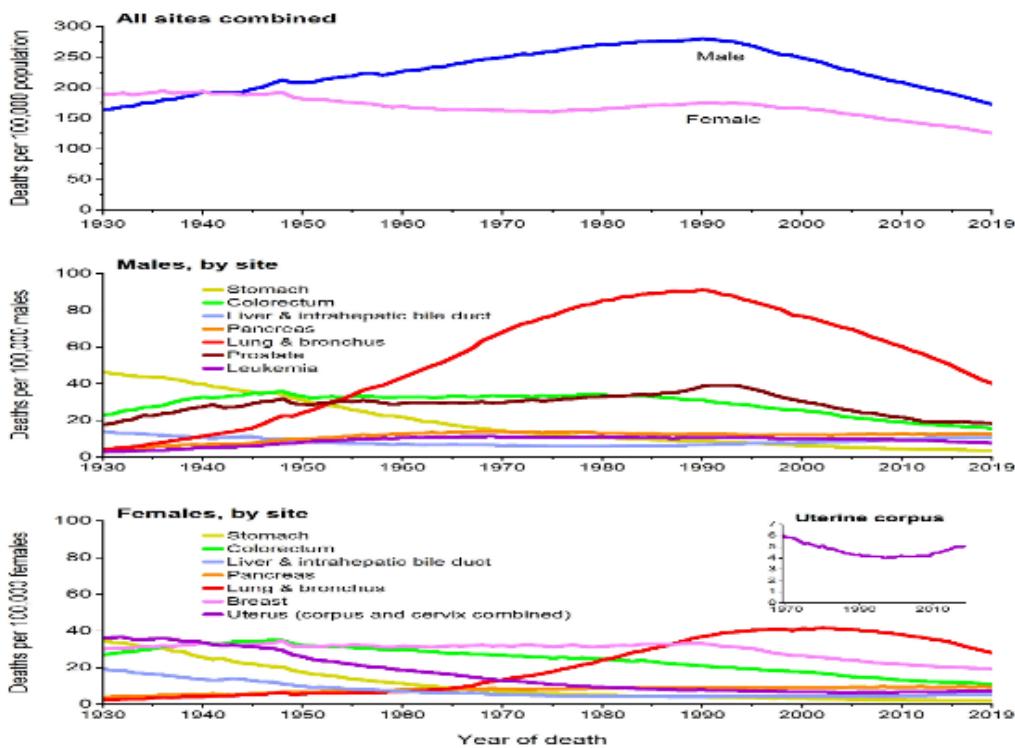


Fig. 1.1 Deaths per 100,000 population, males, and females by cancer

Cancer is a genetic disease caused by changes to genes that control the way our cell's function, especially how they grow and divide. Cancer can start almost anywhere in the human body, which is made up of trillions of cells. There are two types of tumors: Benign tumors, which are results of reproduction of slow growth cells, while Malignant tumors consist of cells which spread faster, unlike benign tumors.

According to the American Cancer Society, about 87% of all cancers in the United States are diagnosed in people 50 years of age or older, and about two-thirds of all cancer deaths occur in this age group. However,

it's important to note that cancer can occur at any age, even in children and young adults. Certain types of cancer are more strongly associated with age than others. However, it's also important to understand that cancer risk is influenced by a variety of factors, including genetics, lifestyle, and environmental exposures, and not just age alone.

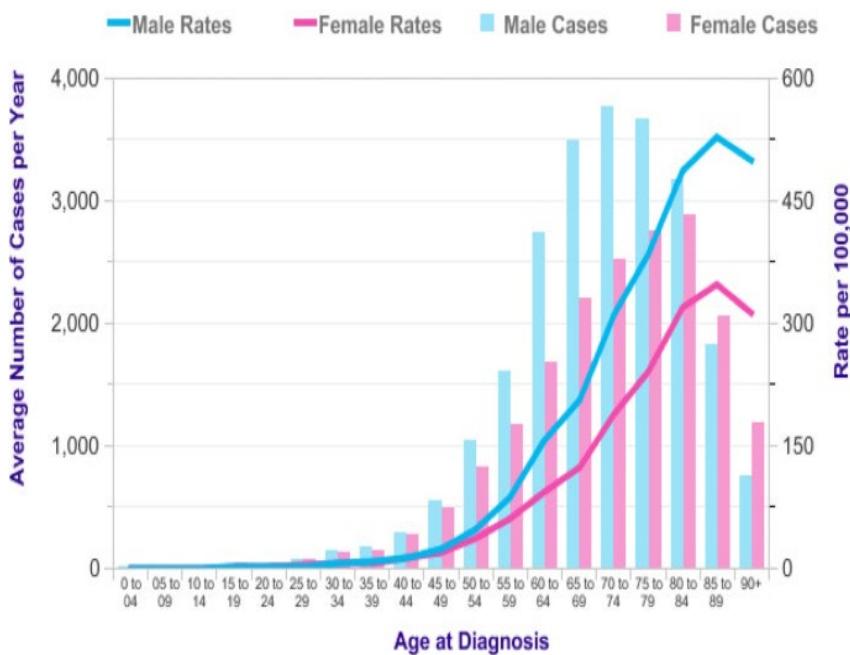


Fig. 1.2 Distribution of male rates and female rates by average number of cases per year.

What is Colon cancer?

Colon cancer is a cancer that starts in the large intestine (colon). The colon is the last section of the digestive tract. Colon cancer most commonly affects older persons, although it may strike anybody at any age. Colorectal cancer is the second most common cancer type among women and third most common among men, about one-third of all people with colon cancer and cancer in the rectum die from the disease within five years of diagnosis, if cancer spreads to the muscle of the colon or rectum, you have a 75 percent chance to live at least another five years.

Signs and symptoms of colon cancer include:

1. A persistent change in your bowel habits, including diarrhea or constipation or a change in the consistency of your stool.
2. Rectal bleeding or blood in your stool.
3. Persistent abdominal discomfort, such as cramps, gas, or pain.
4. A feeling that your bowel doesn't empty completely.
5. Weakness or fatigue.
6. Unexplained weight loss.

Polyps, which are tiny, noncancerous (benign) collections of cells that grow on the interior of the colon, are the most common starting point. Some of these polyps can develop into colon cancer over time. It starts when the process of the normal replacement of colon lining cells deviates. Healthcare professionals explained that colorectal cancer is not contagious (a person cannot catch the disease from a cancer patient). Some people are more likely to develop colorectal cancer than others.

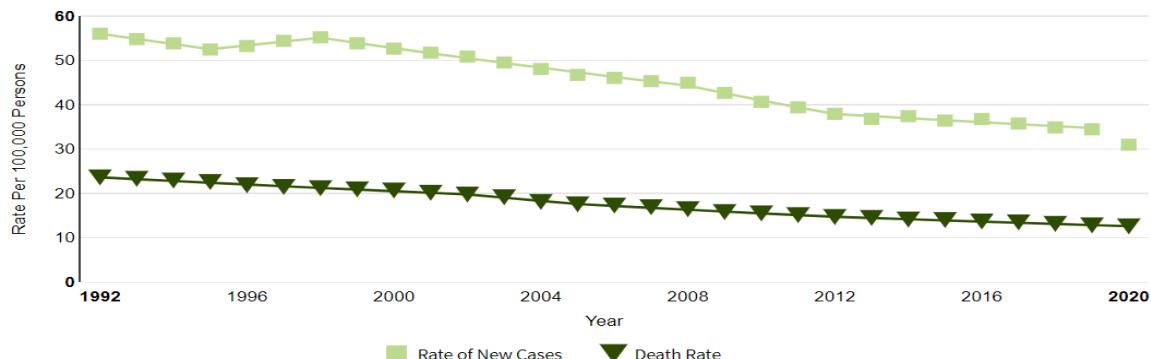


Fig. 1.3 Rate of new cases and death rate per 100,000 persons

A colonoscopy is the most effective colorectal cancer screening test available. It is the only screening test capable of detecting various types of colorectal cancer. A colonoscopy is a procedure in which your doctor examines the lining of your whole colon for polyps or cancers. If any polyps are discovered, they can be removed right away.

In a colonoscopy, the doctor looks at the entire length of the colon and rectum with a colonoscope, a flexible tube about the width of a finger with a light and small video camera on the end. It's put in through the anus and into the rectum and colon. Special instruments can be passed through the colonoscope to biopsy (take a sample) or remove any suspicious-looking areas such as polyps if needed.

Classification

Medical image classification is a type of artificial intelligence (AI) that involves using machine learning algorithms to automatically classify medical images into different categories based on their content. Medical images include X-rays, CT scans, MRI scans, ultrasound images, colonoscopy, and others.

The goal of medical image classification is to assist healthcare professionals in the diagnosis and treatment of various medical conditions. For example, a machine learning algorithm can be trained to classify colon images as either normal or abnormal.

To develop a medical image classification model, a large number of Kvasir dataset images are typically used to train the algorithm. The algorithm learns to identify patterns and features in the images that are associated with different disease states or conditions. Once the model is trained, it can be used to automatically classify new, unlabeled medical images.

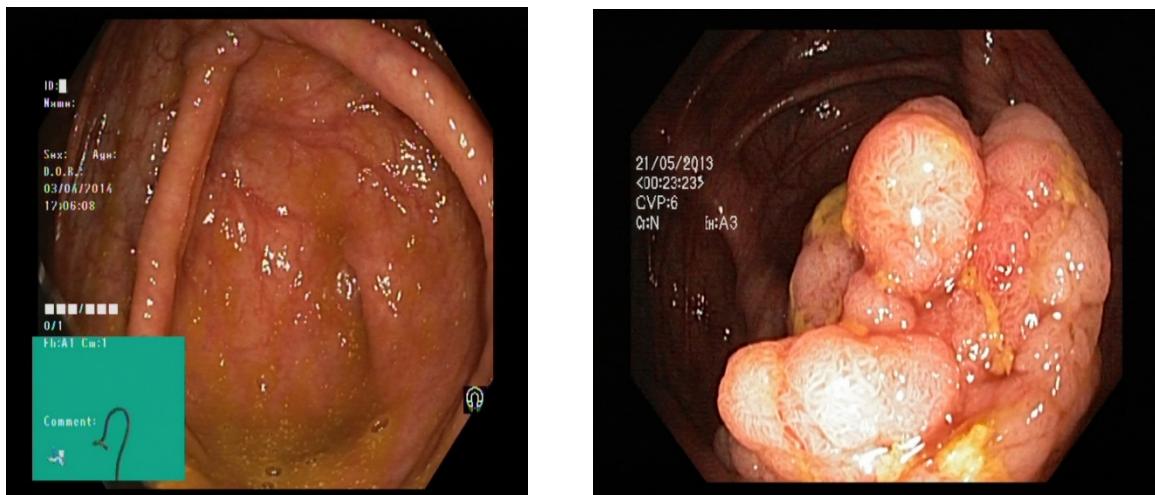


Fig. 1.4 Kvasir dataset example

Medical image classification has the potential to improve the efficiency and accuracy of medical image interpretation, reduce the workload of radiologists, and ultimately improve patient outcomes. It is an active area of research and development in the field of medical imaging and artificial intelligence.

Segmentation

Medical image segmentation is a type of image processing technique that involves dividing medical images into multiple segments or regions based on their content. The goal of medical image segmentation is to identify specific structures or regions of interest within the medical image, such as organs, tumors, blood vessels, or bones. Once these regions are identified, they can be analyzed and measured to provide valuable diagnostic information for healthcare professionals. Medical image segmentation is typically performed using computer algorithms that are trained to recognize patterns and features in the medical images that correspond to different structures or regions. There are several approaches to medical image segmentation, including thresholding, region growing, edge detection, and machine learning-based methods.

Medical image segmentation has many applications in clinical practice, including treatment planning, disease diagnosis, and monitoring of disease progression.

The current study uses semantic segmentation of the abdominal area to accomplish automatic detection of colon cancer using machine learning-based methods.

The deep residual convolutional neural network accurately segmented polyps of varied sizes from the difficult colonic areas. Colorectal cancer pictures are accurately diagnosed thanks to effective segmentation, which has overcome the inherent challenges caused by unequal stacking of leftover layers.

Overall, medical image segmentation is an important tool for healthcare professionals to better understand and diagnose various medical conditions, and it is an active area of research and development in the field of medical imaging.

In segmentation, a computer algorithm is trained using Kvasir-seg, Hyper Kvasir and CVC-612 dataset, where each image is manually segmented by a human expert and the corresponding labels are provided to the algorithm. The algorithm learns to recognize patterns and features in the labeled images and uses this knowledge to segment new, unlabeled images.

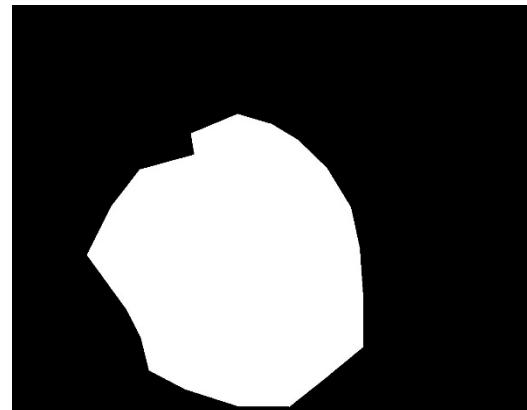
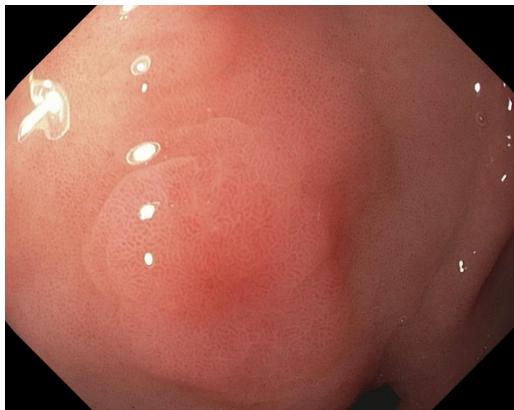


Fig. 1.5 Kvasir-seg dataset example

1.1 Motivation

1. Improved Patient Outcomes: Early detection of colon cancer can significantly improve patient outcomes by allowing for earlier treatment, which can result in a better prognosis and increased chances of survival.
2. Reduced Healthcare Costs: Late-stage colon cancer is often more difficult and expensive to treat than early-stage cancer, as it may require more aggressive treatment options and longer hospital stays. Detecting colon cancer earlier could help reduce healthcare costs by enabling earlier and less invasive treatment.

1.2 Problem Definition

The problem definition of this project is to develop an early detection system for colon cancer using classification and segmentation techniques.

Colorectal polyps and cancer can be found early by screening, which is the process of looking for cancer or pre-cancer in people who have no symptoms of the disease (stage 0: stage 2). Regular colorectal cancer screening is one of the most powerful tools against colorectal cancer.

When colorectal cancer is found at an early stage before it has spread, the 5-year relative survival rate is about 90%. When cancer has spread outside the colon or rectum, survival rates are lower.

These screening tests can be divided into 2 main groups:

- Stool-based tests: These tests check the stool (feces) for signs of cancer. These tests are less invasive and easier to do, but they need to be done more often.
- Visual (structural) exams: These tests look at the structure of the colon and rectum for any abnormal areas. This is done either with a scope (a tube-like instrument with a light and tiny video camera on the end) put into the rectum or with special imaging (x-ray) tests, such as colonoscopy that is used in our dataset.

Colonoscopy is the gold standard for the detection and assessment of these polyps with subsequent biopsy and removal of the polyps.

The specific problem we are trying to solve is the high incidence and mortality rates of colon cancer, which is one of the most common types of cancer worldwide. The current screening methods for colon cancer are not always accurate and may not detect cancer at an early stage when treatment is most effective. This can lead to delayed diagnosis and treatment, resulting in poorer patient outcomes and higher healthcare costs.

The project aims to address this problem by developing a machine learning-based system that can automatically analyze medical images of the colon and accurately detect and segment tumors, enabling earlier detection and more effective treatment. The system will use classification and segmentation techniques, specifically semantic segmentation to identify and analyze suspicious regions of the colon and provide doctors with the necessary information to make informed decisions about treatment options.

1.3 Problem objective

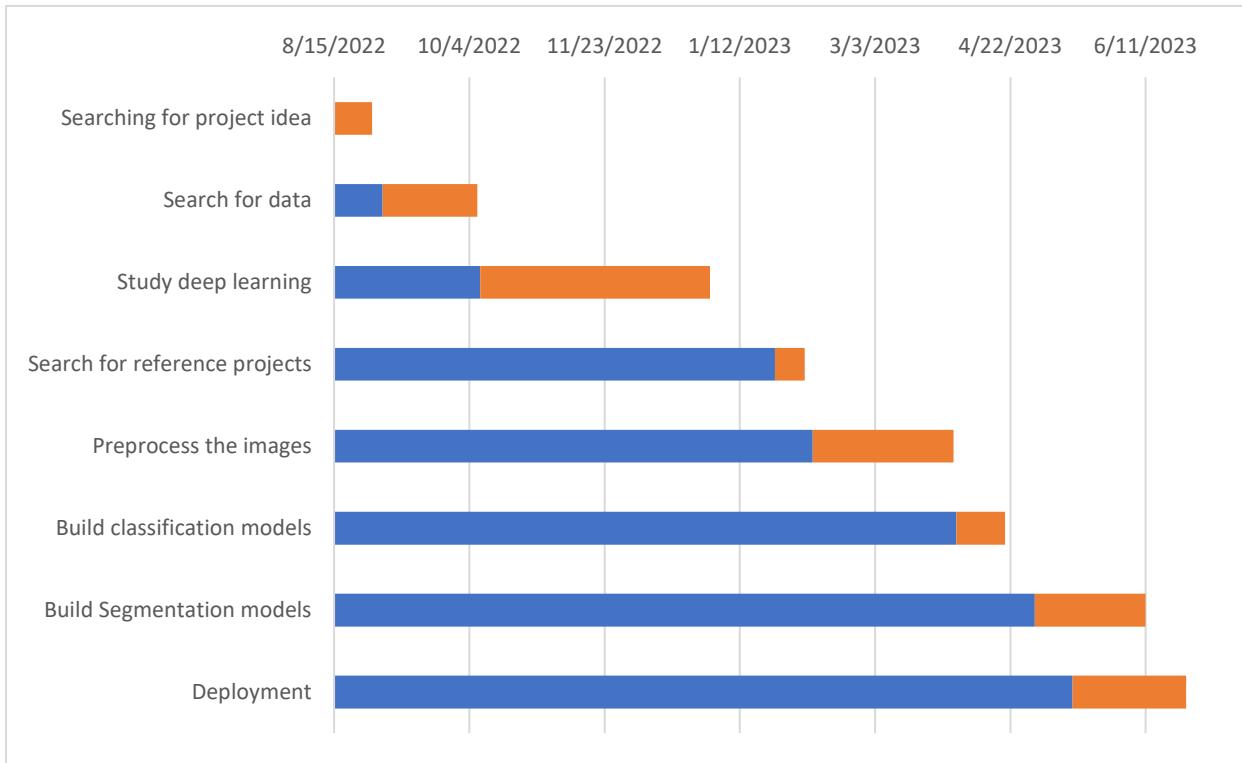
The system should be able to accurately classify medical images of the colon as either normal or polyp, and to segment any abnormal regions of the colon that may be indicative of cancer.

Specifically, the objectives of our project include:

1. Developing and training a machine learning model to accurately classify medical images of the colon as either normal or polyp.
2. Developing and implementing a segmentation algorithm to accurately segment any polyp regions of the colon that may be indicative of cancer.
3. Evaluating the performance of the classification and segmentation algorithms using a set of validation images and comparing the results with those obtained by human experts.
4. Integrating the developed algorithms into a user-friendly software system that can be used by healthcare professionals.
5. Testing the system on a large dataset of colon images to evaluate its effectiveness in detecting early-stage colon cancer.

Overall, the objective of this project is to develop a reliable and accurate system for early detection of colon cancer that can help improve patient outcomes, reduce healthcare costs, and provide healthcare professionals with a valuable tool for screening and diagnosis.

1.4 Gantt chart of project time plan



1.5 Project development methodology

- **Our problem:** Building a machine learning model that can assist doctors in detecting cancer and its location using classification and segmentation techniques. This is a critical and challenging task, as accurate and timely detection is crucial for effective cancer treatment. The model will need to analyze medical images and accurately classify regions of interest as cancerous or non-cancerous, while also providing precise segmentation information to aid in treatment planning and monitoring.

The success of this project could potentially save lives by improving the speed and accuracy of cancer diagnosis and treatment.

- **Data Collection:** Kvasir dataset and CVC-612 were used to learn our model.
- **Data preprocessing:** To optimize the performance of our machine learning model, we employed a variety of preprocessing techniques and data augmentation strategies. These techniques were aimed at improving the quality and diversity of our training data, reducing overfitting, and enhancing the generalization capability of our model.
- **Model selection:** For the classification stage of our machine learning model, we utilized two state-of-the-art convolutional neural networks (CNNs) - VGG16 and ResNet50. These models have been extensively studied and proven to be effective for a wide range of image classification tasks, including medical image analysis. By leveraging the power of these models, our classification stage is able to accurately differentiate between cancerous and non-cancerous regions in medical images, enabling more precise and efficient cancer diagnosis. For the segmentation stage, we used three cutting-edge architectures - U-Net, Res-Unet, and Res-Unet++.

These models are specifically designed for image segmentation tasks and have shown excellent performance in various medical imaging applications. By utilizing these architectures, the segmentation stage of our model is able to accurately delineate cancerous regions from surrounding healthy tissue, providing doctors with vital information for treatment planning and monitoring. The combination of both classification and segmentation techniques in our model allows for a comprehensive and effective cancer detection and localization approach.

- **Evaluation and refining the model:** Evaluating the performance of the trained model using appropriate metrics and validation techniques, and refine the model as needed to improve its accuracy, robustness, and efficiency.
 - **Deployment:** Deploy the trained model in a production environment and monitor its performance over time to ensure that it continues to meet the desired standards and requirements.
-

1.6 The used tools in the project

<i>Software tools</i>	<i>Hardware tools</i>
<ul style="list-style-type: none"> • Python • TensorFlow • Keras • Open CV • Pillow • Scikit Image • SciPy • Segmentation models • Albumentations • Scikit Learn • NumPy • Flask • HTML • CSS • Bootstrap • JavaScript • jQuery • Ajax call • Kaggle • Google Colab • Visual Studio Code • PyCharm 	<ul style="list-style-type: none"> • GPU Tesla P100 • GPU NVIDIA GTX 1050 ti • GPU NVIDIA GTX 1650 ti • GPU NVIDIA RTX 3060 • Ram 13 GB. • Ram 16 GB. • Ram 32 GB. • Intel core i7-8750H CPU • Intel core i7-12700H CPU • Intel(R) Xeon(R) CPU

Table 1.6.1 The used tools in the project

1.7 Report organization

Chapter Two: Related Work

In chapter two, we will establish other work associated with our research. We declare the authors of these methods, the classification model they use in their project, and their results.

Chapter Three: System Analysis

In chapter three, we talk about project specification. It will contain descriptions of how the program will be used from a user perspective and performance details such as usability, reliability, and stability. In addition, illustrate a use case diagram that emphasizes our program.

Chapter Four: System Design

The System Design Document describes the system requirements, operating environment, system and subsystem architecture, files and database design, input formats, output layouts, human-machine interfaces, detailed design, processing logic, and external interfaces using some diagrams. System Component Diagram, System Class Diagrams, Sequence Diagrams, Project ERD, System GUI Design

Chapter Five: Discussion & results

This phase includes an explanation of the steps we took to get the results.

Chapter six: Implementation and Testing

This phase includes screen shots of training and testing the models and screenshots of the system running and samples of the applied test cases.

Chapter 2

Related work

1. Classification papers

- **KVASIR: A Multi-Class Image Dataset for Computer Aided Gastrointestinal Disease Detection by Konstantin Pogorelov.**

- **Year:** 2017
- **Their solution:** They performed an initial multi-class detection experiment on Kvasir as a baseline for future experiments. They have experimented using various configurations of three different main approaches, i.e., classification using global features (GF), deep learning convolutional neural networks (CNN) and transfer learning in deep learning (TFL).
- **Their results:**

<i>Model</i>	<i>Accuracy</i>
6-Layers CNN	91%
3-Layers CNN	95%
Inception V3 TFL	92%
2 GF random forest	92%

Table 2.1.1 Results of paper 1

- **Work Limitation:** They focused on the use of pre-defined handcrafted features, such as JCD, Tamura, Color Layout, Edge Histogram, Auto Color Correlogram and Pyramid Histogram of Oriented Gradients. While these features have been used successfully in previous work, they may not be optimal for this particular dataset and task. Additionally, the use of these handcrafted features requires significant manual effort and may not scale well to larger datasets or more complex tasks. Another limitation is that the authors only evaluated a limited set of machine learning models, other models may perform better on this particular dataset or for different types of gastrointestinal images. Finally, the authors only evaluated the performance of their models on the KVASIR dataset and did not compare their results to those of other state-of-the-art methods on similar datasets.

- **Classification of Anomalies in Gastrointestinal Tract Using Deep Learning by John Mitchell.**

- **Year:** 2022.
- **Their solution:** Traditional image processing algorithms and a data augmentation technique are combined with an adjusted pretrained deep convolutional neural network to classify diseases in the gastrointestinal tract from wireless endoscopy images in this research. They take advantage of pretrained models VGG16, ResNet-18, and GoogLeNet, a convolutional neural network (CNN) model with adjusted fully connected and output layers.
- **Their results:**

<i>Model</i>	<i>Accuracy</i>
VGG16	96.33%
Resnet18	78.83%
GoogLeNet	91.21%

Table 2.1.2 Results of paper 2

- **Work limitation:** The study only evaluated the performance of the proposed models on one dataset. It would be beneficial to evaluate the performance of the models on additional datasets to determine the generalizability of the proposed approach across different imaging modalities and disease types.

2. Segmentation papers

- **CaraNet: Context Axial Reverse Attention Network for Segmentation of Small Medical Objects by Ange Lou.**

- **Year:** 2021
- **Their solution:** This paper proposes a Context Axial Reverse Attention Network (CaraNet) to improve the segmentation performance on small objects compared with several recent state-of-the-art models. CaraNet applies axial reserve attention (ARA) and channel-wise feature pyramid (CFP) module to dig feature information of small medical object.
- **Datasets used:** Kvasir-SEG, CVC-612.
- **Their results:**

<i>Dataset</i>	<i>Mean IOU</i>	<i>Mean Dice</i>
Kvasir-seg	86%	91%
CVC-612	88%	93%

Table 2.2.1 Results of the caraNet paper

- **Work Limitation:** They have fully considered the sizes of small objects, which can lead to poor performance in segmentation tasks. This can have a significant impact on the early detection of diseases. The proposed model, CaraNet, aims to address this limitation and improve the segmentation accuracy of small medical objects. However, without additional information, it is difficult to assess the limitations of CaraNet itself, such as its computational requirements, scalability, or generalizability to other medical imaging datasets.

- **A Comprehensive Study on Colorectal Polyp Segmentation with ResUNet++, Conditional Random Field and Test-Time Augmentation by Ibtesam M. Dheir and Samy S. Abu Naser.**

- **Year:** 2021
- **Their solution:** They demonstrate that further improvements to the overall prediction performance of the ResUNet++ architecture can be achieved by using Conditional Random Field (CRF) and Test-Time Augmentation (TTA).
- **Datasets used:** Kvasir-SEG, CVC-ClinicDB, CVC-ColonDB, ETIS-Larib PolypDB, ASU-Mayo Clinic Colonoscopy Video Database, and CVCVideoClinicDB.
- **Their results:**

<i>Model</i>	<i>Dataset</i>	<i>Mean IOU</i>	<i>Mean Dice</i>
Res-Unet++	Kvasir-seg	80%	81%
	CVC-ClinicDB	88.92%	91%
Res-Unet++ + CRF	Kvasir-seg	80%	81%
	CVC-ClinicDB	88.98%	92.03%
Res-Unet++ + TTA	Kvasir-seg	83%	84%
	CVC-ClinicDB	88%	90%
Res-Unet++ + CRF + TTA	Kvasir-seg	83.29%	85.08%
	CVC-ClinicDB	88%	90%

Table 2.2.2 Results of the Comprehensive Study paper

- **Work limitation:** It is concerning that the authors did not augment the datasets together or apply additional preprocessing steps to the data, as this may limit the generalizability and robustness of the segmentation model.

- **RUPNet: Residual upsampling network for real-time polyp segmentation by Nikhil Kumar Tomar.**

- **Year:** 2023
- **Their solution:** They propose a novel architecture, Residual Upsampling Network (RUPNet) for colon polyp segmentation that can process in real-time and show high recall and precision.
- **Dataset used:** Kvasir-seg
- **Their results**

Model	Mean IOU	Mean Dice
RUPNet	76.58%	65.53%

Table 2.2.3 Results of the RUPNET paper

- **Work limitation:** They classify images into polyp and non-polyp regions. However, they do not cover if the polyp is adenoma or non-adenoma and does not look into diagnostic classes such as hyperplastic or sessile polyps. For the algorithm to be integrated into the clinical workflow, the proposed algorithm should perform well on out-of-the-distribution datasets that are collected from different medical centers. Additionally, the algorithm should perform well in conditions such as camouflage and noise and should possess real-time processing speed .Although, they achieve real-time speed, our algorithm is trained and tested on the same distribution datasets. They have not experimented on multi-center datasets, and their algorithm shows that there are still some challenges when there is camouflage which is caused by the false positive. This is also observed through qualitative analysis. Moreover, they have not performed statistical tests for any experiments, which is also a way of interpreting the best model.

Work Differences:

1. We applied classification and segmentation techniques together to help in early detection of colon cancer.
2. We applied many augmentation techniques, and we augmented three datasets together.
3. We employed a variety of preprocessing techniques.
4. We considered the sizes of all objects.
5. We reduced the complexity of the modern deep learning based Convolutional Neural Network (CNN) models and improved its results compared to the work we found and the work that used transformers.
6. We got these results with the available computational resources which is lower than the resources the others.
7. We offer a GUI for doctors to use our model to help them detect the cancer and its location.

Chapter 3

System analysis

3.1 Project specification

- **3.1.1 System architecture**

Our System Architecture typically consists of:

1. Data collection:

This stage involves sourcing and collecting data from various sources such as datasets, APIs, web scraping and other sources. We used Kvasir datasets and CVC-612 dataset.

2. Preprocessing and feature engineering:

In this stage, data is prepared for analysis or training by applying cleaning, normalization, feature extraction and other techniques as resizing, data augmentation, enhancements, converting the segmentation masks to the appropriate format, such as a binary image. This can be achieved by thresholding or setting a specific pixel value as the cut-off. It is then necessary to remove any noise or artifacts from the mask. This could be done by smoothing, blurring or morphological operations such as erosion and dilation.

3. Modeling and training:

This stage involves building a deep learning model and then training it with the pre-processed data.

4. Evaluation:

In this stage, the trained model is evaluated based on its performance on given test sets. The metrics used was:

- Accuracy
- Precision
- Recall
- MCC
- Mean IOU
- Mean Dice

5. Deployment:

After evaluation, the model is deployed to systems that make use of it such as web applications, mobile applications and so on.

- **3.1.2 Stakeholders:**

Medical Professionals: Medical professionals such as oncologists, radiologists, and pathologists are the primary stakeholders in our project.

- **3.1.3 Functional Requirements:**

1. User Authentication: The website has a login and registration functionality, allowing doctors to create an account or login if they already have one. The website provides access to registered doctors only and doesn't allow access patients or other unauthorized users.
2. Image Upload: Once logged in, the doctor can be able to upload an image of a patient's colon for analysis.
3. Image Analysis: The website has a functionality to perform classification and segmentation techniques on the uploaded image to detect if there are any early signs of colon cancer.
4. Patient Management: The website allows the doctor to add new patients and update patient data.
5. Patient List: The website should display a list of patients that the doctor has uploaded data for, along with their current status and any relevant information about their condition.
6. Profile Management: The website allows the doctor to update their profile information, including their data, and profile image.
7. Sign out: The website has a sign out functionality to enable doctors to safely exit their account once they are done using the website.

- **Non-functional Requirements:**

1. Performance: The website is fast and responsive, with minimal load times and quick image analysis and processing times.
2. Security: The website is secure, with the doctor's password hashed in the database to prevent unauthorized access.
3. Usability: The website is easy to use and navigate, with a clear and intuitive user interface that allows doctors to quickly find the features they need.
4. Reliability: The website is reliable, with minimal errors that could impact the doctor's ability to use the website and access patient data.
5. Scalability: The website is scalable, able to handle a potentially large number of users and doctor's data without experiencing performance issues.
6. Maintainability: The website is easy to maintain and update, with clear documentation and well-organized code that allows developers to quickly make changes and fix any issues that arise.

3.2 Use case diagram

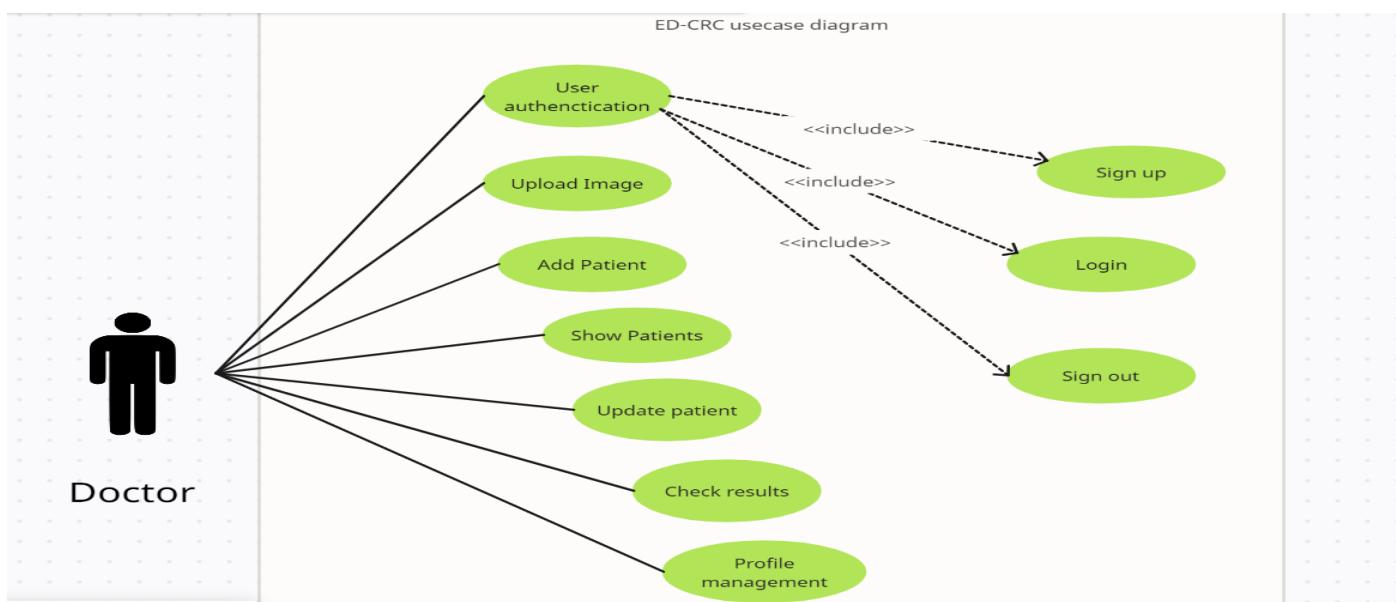


Fig 3.2.1 Use case diagram

Chapter 4

System Design

4.1 Class Diagram

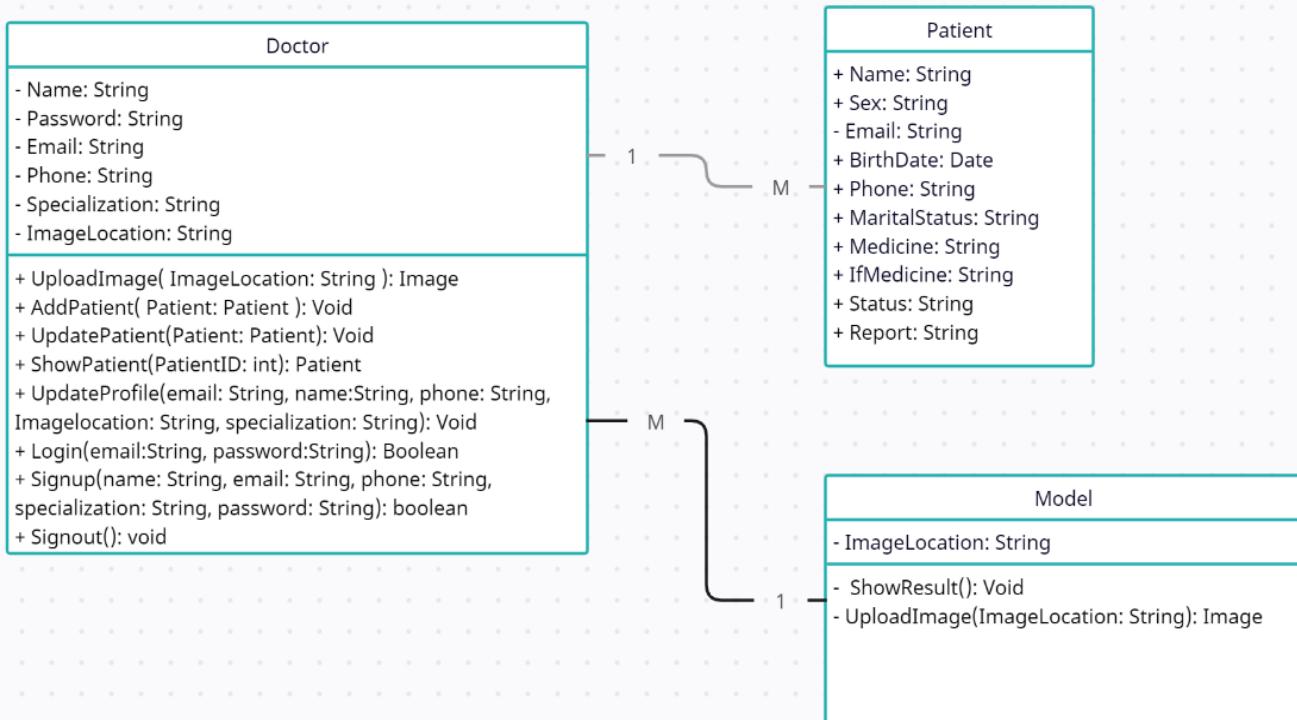


Fig 4.1 Class diagram

4.2 ERD



Fig 4.2 ERD

4.3 System component diagram

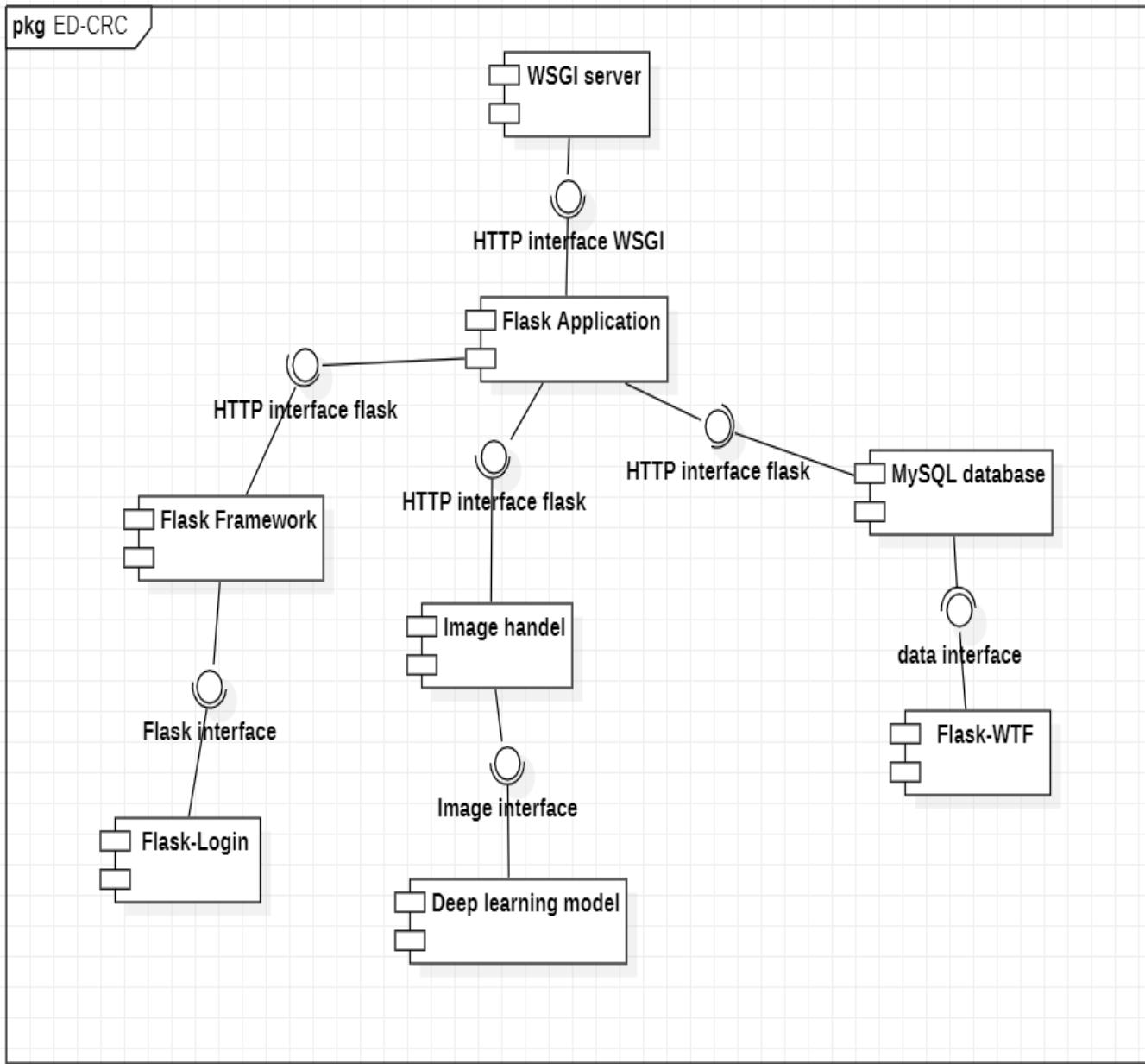


Fig 4.3 System component diagram

4.4 Sequence diagram

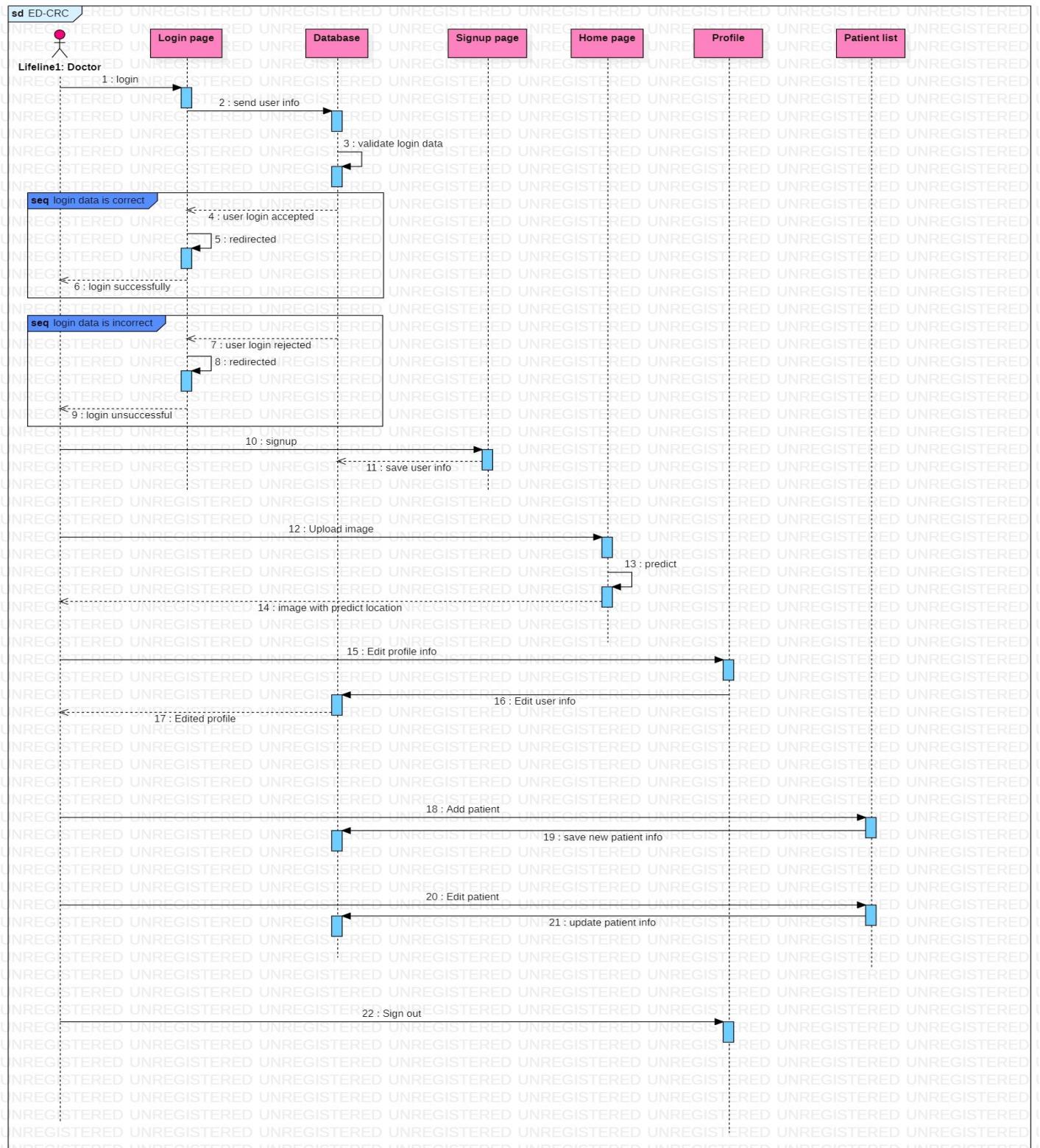


Fig 4.4 Sequence diagram

Chapter 5

Results and discussion

1. Research Objectives:

The primary objective of the study is to develop a machine learning-based system for early detection of colon cancer using medical imaging data. The specific research questions are:

1. Can a machine learning-based system accurately classify medical images of the colon as normal or polyp?
2. Can a machine learning-based system accurately segment abnormal regions of the colon that may be indicative of cancer?
3. How does the performance of the machine learning-based system compared to that of human experts?

2. Study Design:

The study will use a retrospective design, in which medical imaging data from previous colonoscopy exams will be collected and used to train and test the machine learning-based system. The study will be conducted at a single medical center.

3. Data Collection:

- The study will use **Kvasir** datasets and **CVC-612** dataset.
- For **Kvasir** datasets, it is divided into two parts, one for classification and the other for segmentation.
- The Kvasir dataset is benchmarked, it has been used by researchers and practitioners in the medical image analysis and computer-aided diagnosis fields for benchmarking various algorithms and models as Lesion detection, image segmentation, and video classification.
- The **Kvasir** dataset consists of images, annotated and verified by medical doctors (experienced endoscopists), including classes showing anatomical landmarks, pathological findings or endoscopic procedures in the GI tract, i.e., hundreds of images for each class. The number of images is sufficient to be used for different tasks,

e.g., image retrieval, machine learning, deep learning and transfer learning, etc.

- The Vestre Viken Health Trust consists of 4 hospitals and provides health care to 470.000 people. One of these hospitals (the Bærum Hospital) has a large gastroenterology department from where the data have been collected and will be provided, making the dataset larger in the future.
- The **CVC-612** dataset has been used in several research studies related to medical image analysis and computer-aided diagnosis and has become a popular benchmark for evaluating the performance of different algorithms and models on colonoscopy videos.

- **In classification part**

- There are two classes, normal or polyps with resolution 720×576 , the dataset is balanced.

<i>Normal-Cecum</i>	<i>Polyps</i>
500	500

Table 5.1 Number of images for each class of Kvasir for classification dataset

- The cecum is the most proximal part of the large bowel. Reaching cecum is the proof for a complete colonoscopy and completion rate has shown to be a valid quality indicator for colonoscopy. Therefore, recognition and documentation of the cecum is important.
 - Polyps are lesions within the bowel detectable as mucosal outgrows.
 - The data were collected from clinical examinations performed at the Haukeland University Hospital in Bergen, Norway.
 - The dataset also includes annotations for various lesions, such as polyps, ulcers, and bleeding.

- The dataset consists of images with different resolution from 720x576 up to 1920x1072 pixels and organized in a way where they are sorted in separate folders named accordingly to the content.
- Some of the included classes of images have a green picture in picture illustrating the position and configuration of the endoscope inside the bowel, by use of an electromagnetic imaging system (ScopeGuide, Olympus Europe) that may support the interpretation of the image.



Fig. 5.1 normal cecum



Fig. 5.2 polyp

- **In segmentation part**

- We used Kvasir for segmentation datasets and CVC-612 dataset.
- Kvasir is divided into three datasets (Kvasir-seg, Hyper Kvasir, and Kvasir sessile) and its corresponding masks with resolution varies from 332x487 to 1920x1072 pixels.
- The generated masks are 1-bit color depth images. The pixels depicting polyp tissue, the region of interest, are represented by the foreground (white mask), while the background (in black) does not contain positive pixels.
- Some of the original images contain the image of the endoscope position marking probe, Scope Guide TM, Olympus Tokyo Japan, located in one of the bottom corners, seen as a small green box.

- Kvasir sessile are about 196 images, but it has problems with its masks, so it used in prediction only.

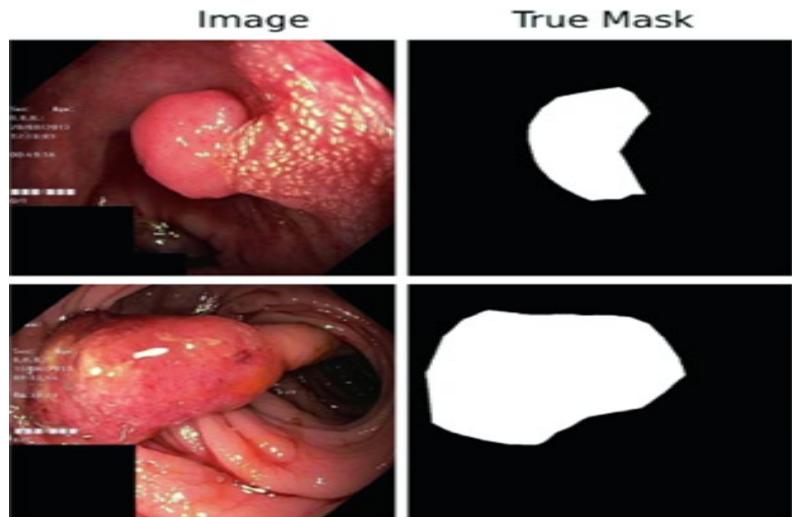


Fig. 5.3 Kvasir-seg images and their masks

- For CVC-612 datasets, it has images with a resolution of 384×288 from 31 colonoscopy sequences with its corresponding masks.

<i>Dataset</i>	<i>No. of images</i>
Kvasir-seg	1000
Hyper-Kvasir	1000
CVC-612	612

Table 5.2 Number of images for each dataset for segmentation

- The ROIs (Regions of Interests) are the pixels depicting polyp tissue. These are represented by a white foreground in the segmentation masks.
- The ROIs are generated from manual annotations verified by an experienced gastroenterologist. Manual segmentation by physicians is still the gold standard for most medical imaging modalities.
- However, manual image segmentation is tedious, time-consuming, and subject to physician's bias and inter-observer variation.

4. Data augmentation:

- a. **For classification**, we augmented the data using these methods:
- i. Rotation range.
 - ii. Width shift range.
 - iii. Height shift range.
 - iv. Horizontal flip.
 - v. Vertical flip.
 - vi. Brightness range.

<i>No. of images before augmentation for each class</i>	<i>No. of images after augmentation for each class</i>
500	1500

Table 5.3 Number of images for each class before and after augmentation

- b. **For segmentation**, we augmented the data using these methods:
- i. Augment Kvasir-seg, Hyper Kvasir and CVC-612 together, number of total images was **2612**.
 - ii. Augment the total images with these techniques:
 1. Random rotate.
 2. Horizontal flip.
 3. Vertical flip.

<i>No. of images before augmentation</i>	<i>No. of images after augmentation</i>
2612	10448

Table 5.4 Number of images before and after augmentation

5. Data Preprocessing and post processing:

1. Resizing the images and masks into **256×256**.
2. Blurring images with Median Blur to remove noise smooth out small details in the image with a kernel size of **3**.

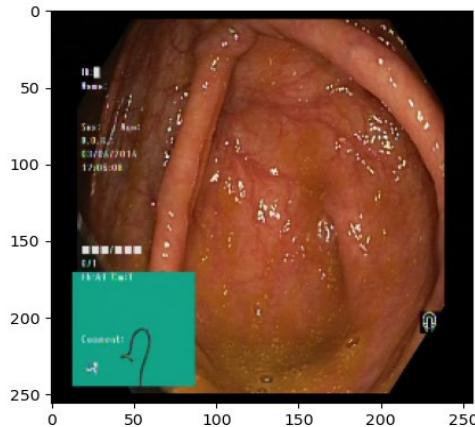


Fig. 5.4 image without blur

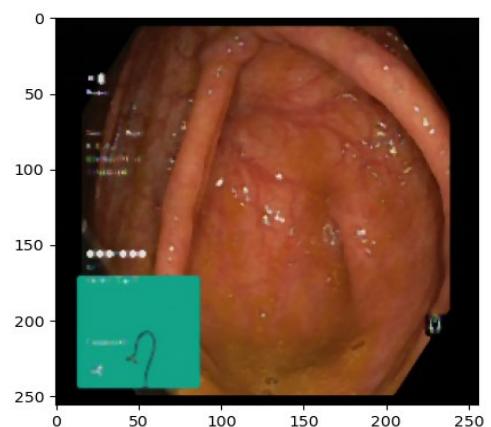


Fig. 5.5 image with blur

3. Converting the masks to grayscale as it reduces the dimensionality of the image and can simplify the segmentation process.
4. Normalizing the masks.
5. Applied binary dilation to the masks using a disk-shaped structuring element with a radius of 5 pixels to increase the size of the white regions in the mask image, which can help fill in small gaps or holes in the segmentation.



Fig. 5.6 Mask before preprocessing



Fig. 5.7 Mask after preprocessing

6. The data is split into training, validation, and testing.

Technique	Training	Validation	Testing
Classification	1680	900	420
Segmentation	5850	2508	2090

Table 5.5 Number of training, validation, and testing samples.

7. In **post processing**, we get contours of the predicted mask to draw the outer boundaries on the image.

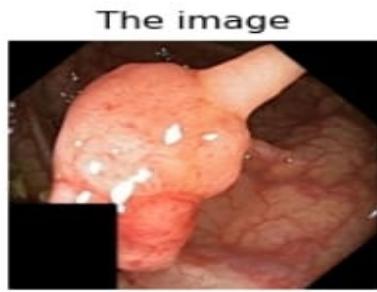


Fig 5.8 input image to be
predicted

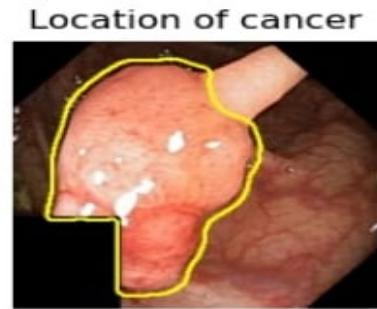


Fig 5.9 the image with the contour
of predicted mask

6. Techniques

1. Classification:

- The colon images have been classified using a Convolutional Neural Network (CNN) based classification algorithm.
- The **initial training** of the pure data without any augmentation or preprocessing yielded unsatisfactory results.
- Due to the poor accuracy achieved in the previous step, we opted for a different approach and explored various preprocessing techniques, including median blur and data augmentation, as we have mentioned earlier.
- We used transfer learning models because it is faster in training rather than the scratch one and it results in better performance on our dataset.

- We didn't use the transfer learning models' weights but trained them from scratch with addition of some layers.
- We used ***VGG16*** and ***Resnet50***:
- Both VGG16 and ResNet50 have achieved state-of-the-art performance on a wide range of computer vision tasks, including image classification, object detection, and segmentation. This is due to their deep architectures, which enable them to learn complex patterns and features from the input data and both well-established and widely used deep learning models, with many resources and tutorials available for implementation and fine-tuning.
- We intended to implement another models as inception V3 but we were out of resources.

1. VGG16:

- VGG16 is a convolutional neural network architecture that was developed by the Visual Geometry Group at the University of Oxford. It is a popular architecture for image classification tasks, particularly for its strong performance on the ImageNet dataset.
- VGG16 has a total of 16 layers, including 13 convolutional layers and 3 fully connected layers. The convolutional layers are arranged in groups of two or three, with each group followed by a max pooling layer that reduces the spatial dimensions of the feature maps. The fully connected layers are used to make the final predictions based on the features extracted by the convolutional layers.
- We added batch normalization layer to improve the training speed and stability of the network, and a Dense layer with 1024 units.

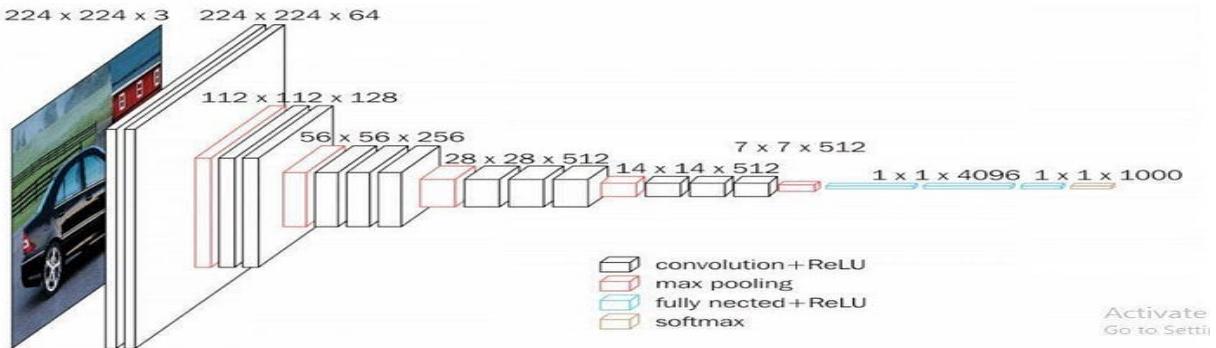


Fig. 5.10 Layers of VGG16

- **Steps taken in training:**

- We conducted multiple training sessions using different configurations.
- **In the first session**, we trained the model with the model with the pure images.
- **In the second session**, we trained the model using grayscale images and the final fully connected layer with a SoftMax activation function.
- **In the third session**, we trained the model again using grayscale images, but this time the final fully connected layer with a sigmoid activation function.
- **In the fourth session**, we trained the model using RGB images and the final fully connected layer with a SoftMax activation function.
- **In the last session**, we trained the model using RGB images and the final fully connected layer with a sigmoid activation function.
- In our training process, we utilized a batch size of **120** and trained for **50** epochs. We used **Adam** as the optimizer to train the model with a learning rate of **0.0001**. We used **binary cross entropy** loss as the loss function to train the model.

- To monitor the performance of the model during training and detect overfitting, we utilized a validation set that had been used throughout the training process.

2. Resnet50:

- ResNet50 is a deep neural network architecture that was introduced in 2015 by Microsoft Research. It was designed to address the problem of vanishing gradients in very deep neural networks, which can make training difficult. ResNet50 uses a skip connection or identity mapping to enable the gradient to flow directly through the network, even in very deep architectures.
- ResNet50 has a total of 50 layers, including convolutional, pooling, and fully connected layers. The architecture consists of a series of residual blocks, each of which contains multiple convolutional layers and a skip connection. The skip connection allows the input to be added directly to the output of the block, which helps to preserve the gradient during training.
- We added batch normalization layer to improve the training speed and stability of the network, and a Dense layer with 1024 units.

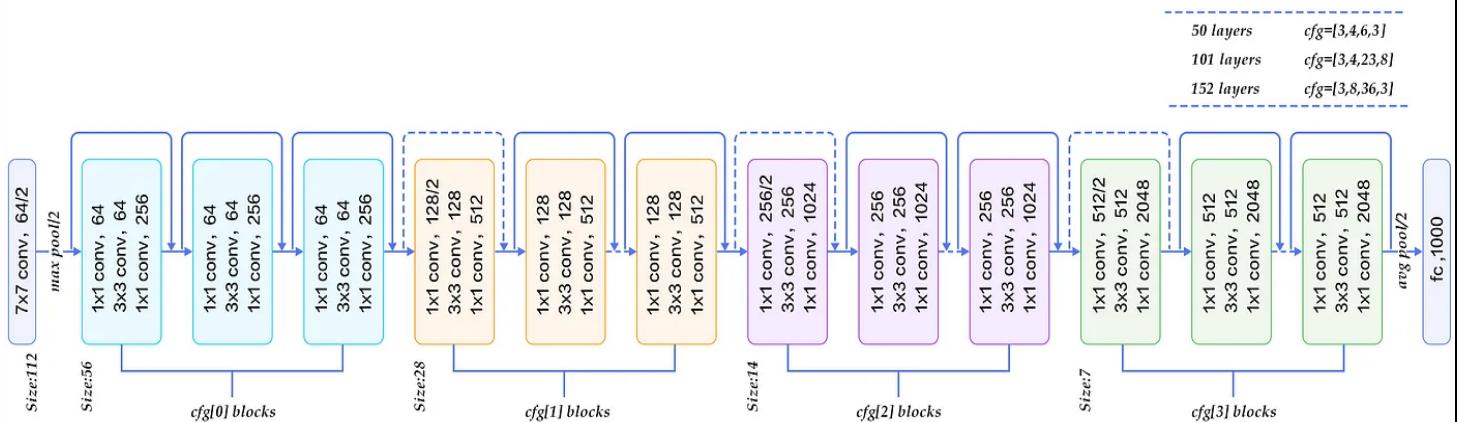


Fig. 5.11 Layers of Resnet50

- **Steps taken in training:**
 - We conducted multiple training sessions using the same configurations of VGG16.
 - In our training process, we utilized a batch size of **120** and trained for **50** epochs. We used **Adam** as the optimizer to train the model with a learning rate of **0.0001** and **SGD** optimizer with the same learning rate. We used **binary cross entropy** loss as the loss function to train the model. We utilized a validation set that had been used throughout the training process.
- **Models' Evaluation**
 - The performance of the models had been evaluated using the test data, which allowed us to determine if the model was generalizing well to new data. The evaluation will include metrics such as **accuracy**, **precision**, **recall**, and **MCC** and will be compared to the diagnoses provided by human experts.
 - **Precision** measures the proportion of true positive predictions among all positive predictions made by the model. The precision equation in the context of machine learning is:
$$\text{precision} = \text{TP} / (\text{TP} + \text{FP})$$
 - **Recall** measures the proportion of true positive predictions among all actual positive instances in the dataset. The recall equation in the context of machine learning is:
$$\text{recall} = \text{TP} / (\text{TP} + \text{FN})$$
 - **MCC** considers true positives, true negatives, false positives, and false negatives to provide a balanced measure of the model's performance. MCC ranges from -1 to 1, where 1 indicates a perfect classification, 0 indicates

a random classification, and -1 indicates a completely wrong classification. The MCC equation is:

$$\text{MCC} = \frac{(TP \times TN - FP \times FN)}{\sqrt{(TP + FP) \times (TP + FN) \times (TN + FP) \times (TN + FN)}}$$

- **Accuracy** measures the proportion of correctly classified instances over the total number of instances in the dataset. The accuracy equation in the context of machine learning is:

$$\text{accuracy} = \frac{(TP + TN)}{(TP + FP + TN + FN)}$$

- Resnet50's performance was better than VGG16's.

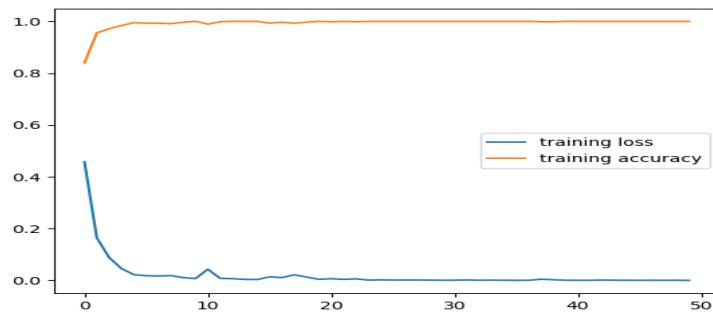


Fig.5.12 training history performance of resnet50

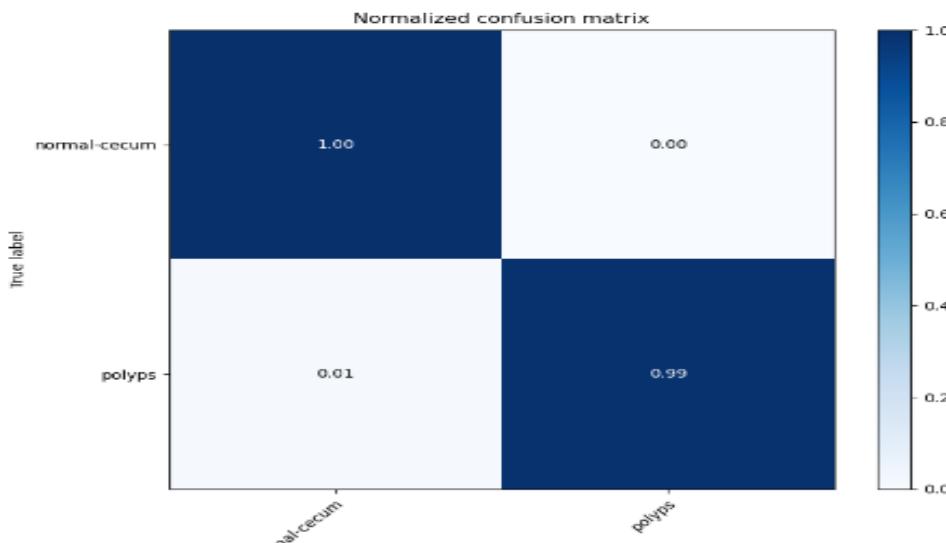


Fig. 5.13 Confusion matrix of resnet50

- The confusion matrix shows the correctness of the predictions for the two classes, the polyp class was perfectly classified 303 of 304 and the normal class was perfectly classified 296 sample of 296.
- **Results of the evaluation of the models:**

<i>Classification steps</i>	<i>Accuracy</i>	<i>Precision</i>	<i>Recall</i>	<i>MCC</i>
VGG16 + Pure dataset	73%	74%	74%	73.5%
VGG16 after preprocessing + grayscale + SoftMax	87%	88%	89%	87%
VGG16 + grayscale + sigmoid	92%	93%	93%	90%
VGG16 + RGB + SoftMax	97%	97%	98%	98%
VGG16 + RGB + sigmoid	98.5%	98.5%	99%	99%
resnet50 + RGB + SoftMax + SGD	97.5%	96.5%	98.5%	96%
resnet50 + RGB + sigmoid + Adam	99.5%	99%	99.5%	98.7%

Table 5.6 Performance of the models

<i>Paper</i>	<i>Model</i>	<i>Accuracy</i>
Konstantin Pogorelov - 2017	3-layers CNN	95%
John Mitchell - 2022	VGG16	96.33%
Our work	Resnet50	99.5%

Table 5.7 Comparison between our result and others

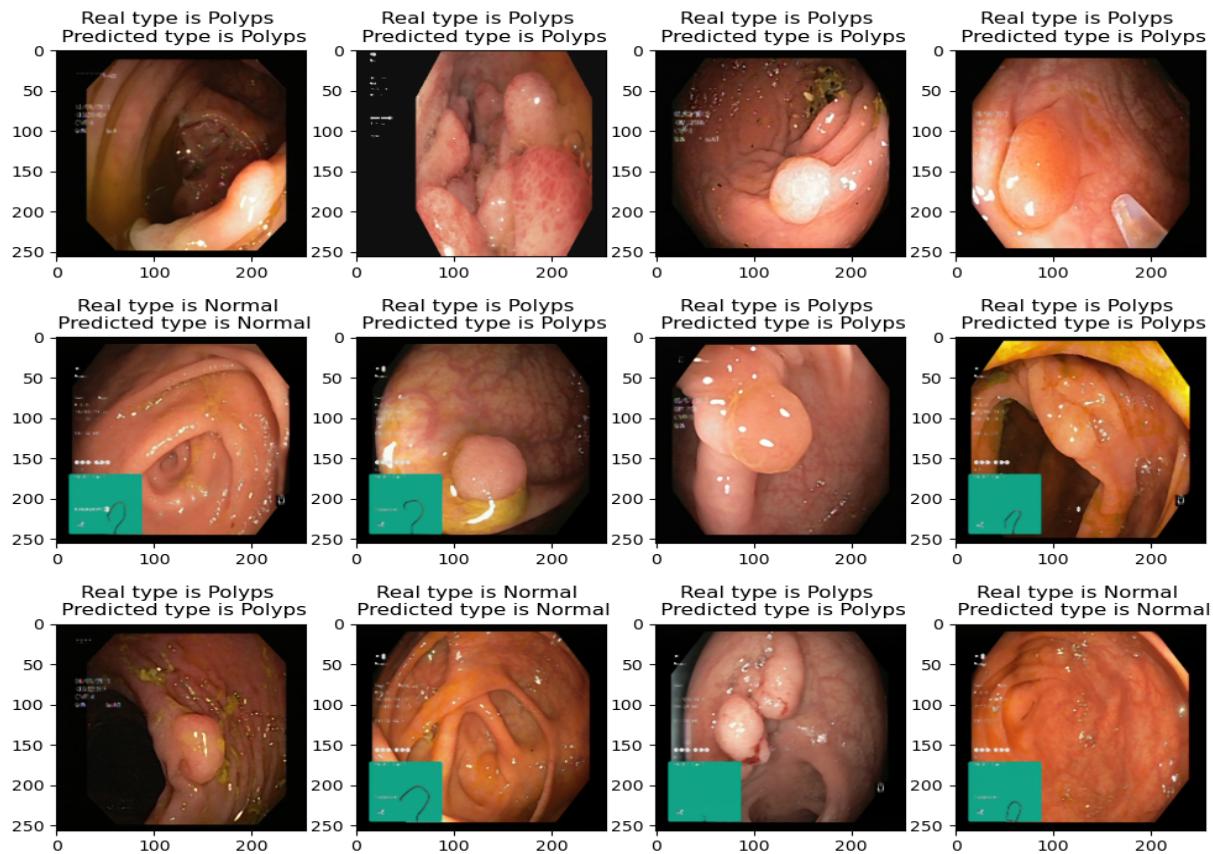


Fig. 5.14 Predictions of Resnet50 on unseen Kvasir data

2. Segmentation:

- The colon images will be segmented using a deep learning-based semantic segmentation algorithm.
- Segmentation was indeed a challenging problem due to the complexity of the anatomical structures and the variability in image quality. Additionally, developing accurate segmentation algorithms required significant computational resources and expertise in deep learning techniques.
- It is not uncommon to face conflicts with resources, complexity, and time when working on the segmentation task. This is because medical imaging data is often high-dimensional and large in size, which can require significant computational power to process.

- To overcome these challenges, planned and allocated resources, including computational power and expertise in deep learning techniques. It was also necessary to optimize the segmentation algorithm.
- We tried to train the model with the pure dataset but it gives us poor results, so we applied the preprocessing and data augmentation as I mentioned above.
- We trained using three models: U-net, Res-Unet, Res-Unet++.
- UNet, ResUNet, and ResUNet++ are designed to take advantage of the spatial information in images, which can be important for accurate segmentation. Transformers, on the other hand, are typically used for tasks that involve sequences of tokens, such as sentences or paragraphs and the features learned by UNet, ResUNet, and ResUNet++ can be transferred to other computer vision tasks beyond image segmentation, such as object detection and classification. This makes them versatile and applicable to a wide range of computer vision applications.

1. U-net:

- U-Net is a convolutional neural network (CNN) architecture that was introduced in 2015 for image segmentation tasks. U-Net is named after its U-shaped architecture, which consists of a contracting path and an expansive path.
- The contracting path of the U-Net consists of several convolutional and max-pooling layers that reduce the spatial dimension of the input image while increasing the number of feature maps. This path extracts high-level features from the input image and captures the contextual information.
- The expansive path of the U-Net consists of several convolutional and upsampling layers that increase the spatial dimension of the feature maps while decreasing the number of

feature maps. The expansive path combines the high-level features from the contracting path with the low-level features from the upsampling layers to produce a segmentation map that has the same size as the input image.

- The U-Net architecture also includes skip connections that connect the corresponding contracting and expansive path layers. These skip connections allow the low-level features from the contracting path to be directly propagated to the expansive path, which helps to preserve the spatial information and improve the segmentation accuracy.

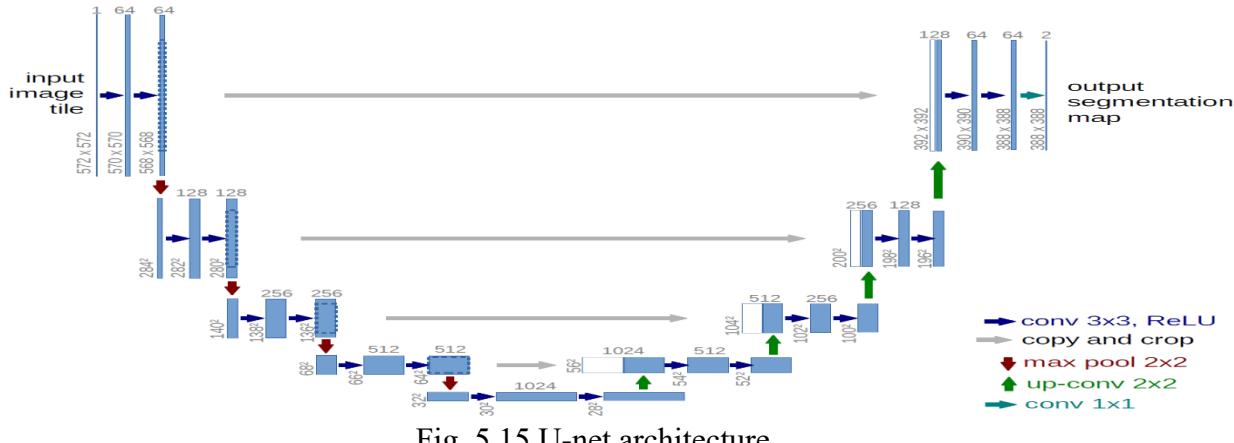


Fig. 5.15 U-net architecture

• Steps taken in training:

- We conducted multiple training sessions using different configurations.
- **In the first session**, we trained the model using the pure images.
- **In the second session**, we trained the model using the images after preprocessing but before augmentation, **32** batch size, **Adam** as optimizer with learning rate **1e-4** and **100** epochs. **Then** the weights are loaded and started another **100** epochs beginning with these weights.
- **In the last session**, we trained the model again after reducing its complexity by removing the number of contracting path layers and using the images after augmentation, trained with

16 batch size, and **Adam** as optimizer with the same learning rate and **100** epochs.

2. Res-Unet:

- Res-Unet is a modification of the U-net architecture that incorporates residual connections. Residual connections allow the network to learn residual mappings, which can help to address the problem of vanishing gradients and improve training efficiency. Res-Unet also includes batch normalization layers, which can help to reduce overfitting and improve generalization.
- The main difference between U-net and Res-Unet is the use of residual connections in Res-Unet. The residual connections in Res-Unet allow the network to learn more complex features and improve performance, especially when dealing with more challenging segmentation tasks. However, this comes at the cost of increased model complexity and computational requirements.

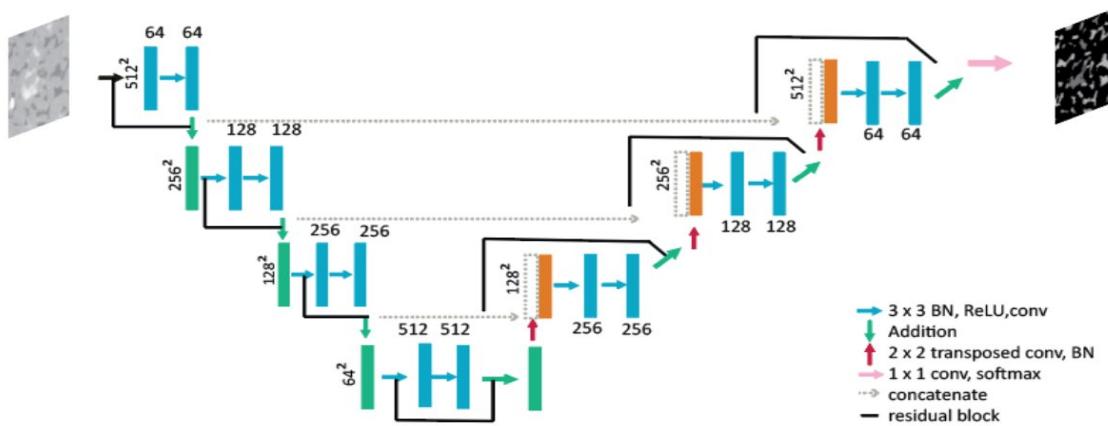


Fig. 5.16 Res-Unet architecture

- **Steps taken in training:**

- We conducted multiple training sessions using different configurations.
- **In the first session**, we trained the model using the images **after** augmentation, **8** batch size, **Adam** as optimizer with learning rate **1e-4** and **100** epochs.
- **In the second session**, we trained the model again after adding **dropout layers** and **L2 regularization** as it suffered from **overfitting** in the first session, trained with **8** batch size, and **Adam** as optimizer with the same learning rate and **100** epochs.
- **In the Last session**, we trained the model again after reducing its complexity as it suffered from **overfitting** in the second session only, trained with **8** batch size, and **Adam** as optimizer with the same learning rate and **100** epochs. **Then** the weights had been loaded and started training again beginning with it. The results were **good** at this session.

3. Res-Unet++:

- Res-Unet++ is an extension of the Res-Unet architecture that incorporates dense connections and multi-scale feature aggregation. Dense connections allow the network to learn more complex features by connecting each layer to every other layer in a feed-forward manner. This can improve feature reuse and gradient flow, which can help to mitigate the vanishing gradient problem. Multi-scale feature aggregation, on the other hand, allows the network to incorporate features at multiple scales, which can improve the accuracy of the segmentation.

- The main difference between Res-Unet ++ and Res-Unet is the inclusion of dense connections and multi-scale feature aggregation in Res-Unet ++. These additional features have been shown to improve segmentation accuracy, especially in more challenging segmentation tasks where there is a high degree of anatomical variation.

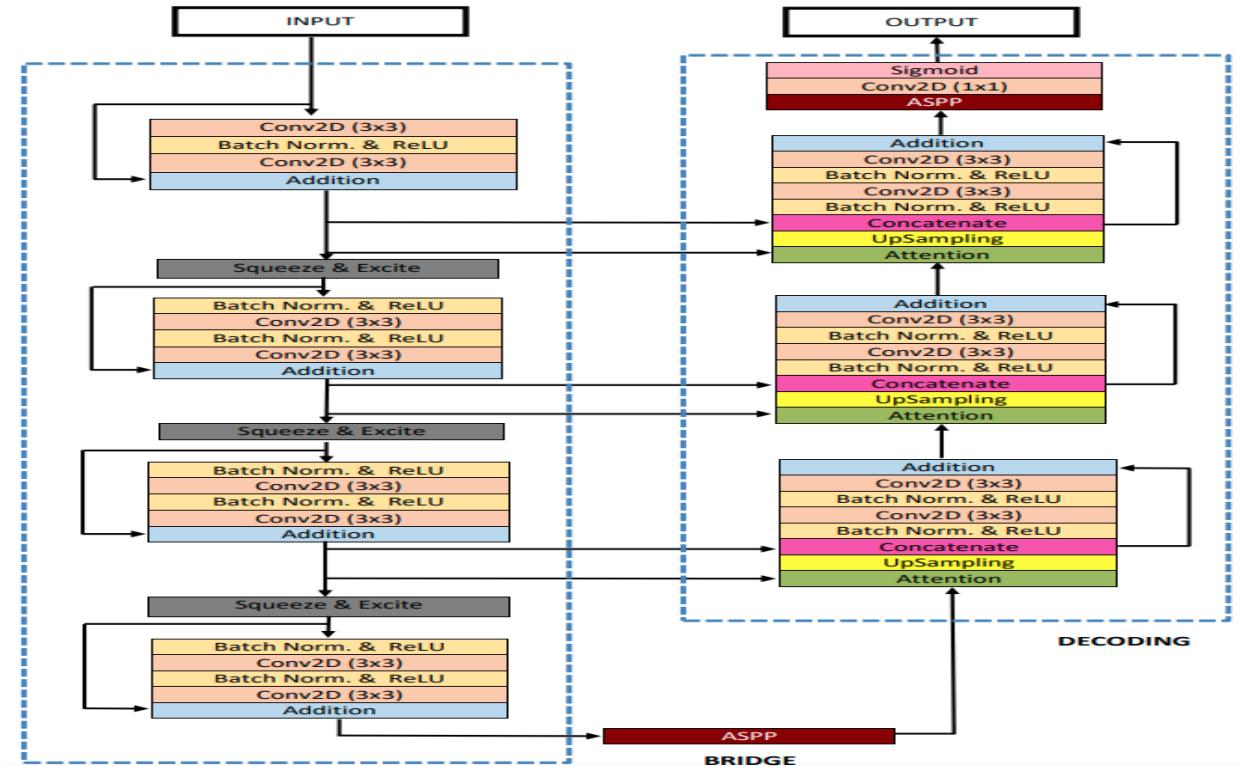


Fig. 5.17 Res-Unet++ architecture

- Steps taken in training:**

- We conducted multiple training sessions using different configurations.
- In the first session**, we trained the model using the images **after** augmentation, **16** batch size, **Adam** as optimizer with learning rate **1e-4** and **100** epochs.
- In the second session**, we trained the model again using **Nadam** as optimizer.
- In the Last session**, we trained the model again with the **weights** of the second session and started training again

beginning with it about **four** times until the model can't optimize the weights.

- The training took about **5** hours on the resources we had.
- We achieved promising results with our proposed methods when evaluated on the same data sets.
- We used **Early stopping** callback with patience of 10 to monitor the performance of the model during the training process on the validation set, and if the performance of the model on the validation set does not improve for a certain number of epochs, the training process is stopped early to prevent the model from overfitting to the training data.

- **Models' Evaluation:**

- The performance of the models had been evaluated using the test data, which allowed us to determine if the model was generalizing well to new data. Overall, these training parameters were carefully chosen to optimize the performance of the model on the given task. The evaluation will include metrics such as **accuracy**, **Mean IOU** and **Dice Coefficient**, and include losses such as **Binary cross-entropy** and **Dice loss** and will be compared to the diagnoses provided by human experts.
- **Mean IOU** measures the overlap between the predicted segmentation mask and the ground truth mask. The IOU for a single instance is calculated as the ratio of the intersection between the predicted and ground truth masks to their union:

$$\text{IOU} = \text{intersection} / \text{union}$$

- The mean IOU is the average of the IOU scores across all instances in the dataset.
- **Dice coefficient** measures the overlap between the predicted segmentation mask and the ground truth mask. The Dice

coefficient is also known as the F1 score, or the Sørensen–Dice coefficient.

- The Dice coefficient for a single instance is calculated as: **Dice coefficient = 2 * (intersection) / (predicted area + ground truth area)**, where the intersection is the number of pixels that are common to the predicted and ground truth masks, and the predicted area and ground truth area are the number of pixels in the predicted and ground truth masks, respectively.

- Res-Unet++ was the best model.

Segmentation steps	Accuracy	Mean IOU	Mean Dice	Binary cross-entropy loss	Dice loss
<i>U-net with pure data</i>	95%	65%	68%	35%	32%
U-net without augmentation	97.6%	86%	88%	13%	12%
Unet with augmentation	97.2%	83%	91%	14.47%	9%
Res-Unet with augmentation	97%	82%	90%	17.23%	10%
Res-Unet++ with augmentation and Nadam optimizer	99%	91%	95%	5%	5%

Table 5.8 Performance of the models

- Accuracy is not the best metric used for segmentation tasks because it does not consider the spatial relationship between the predicted segmentation and the ground truth segmentation.

<i>Paper</i>	<i>Model</i>	<i>Mean IOU</i>	<i>Mean Dice</i>
Ange Lou - 2021	CaraNet	88%	93%
Ibtesam M. Dheir & Samy S. Abu Naser - 2021	Res-Unet++ + CRF + TTA	83.29%	85.08%
Nikhil Kumar Tomar - 2023	RUPNet	76.58%	65.53%
Our work	Res-Unet++	91%	95%

Table 5.9 Comparison between our result and others

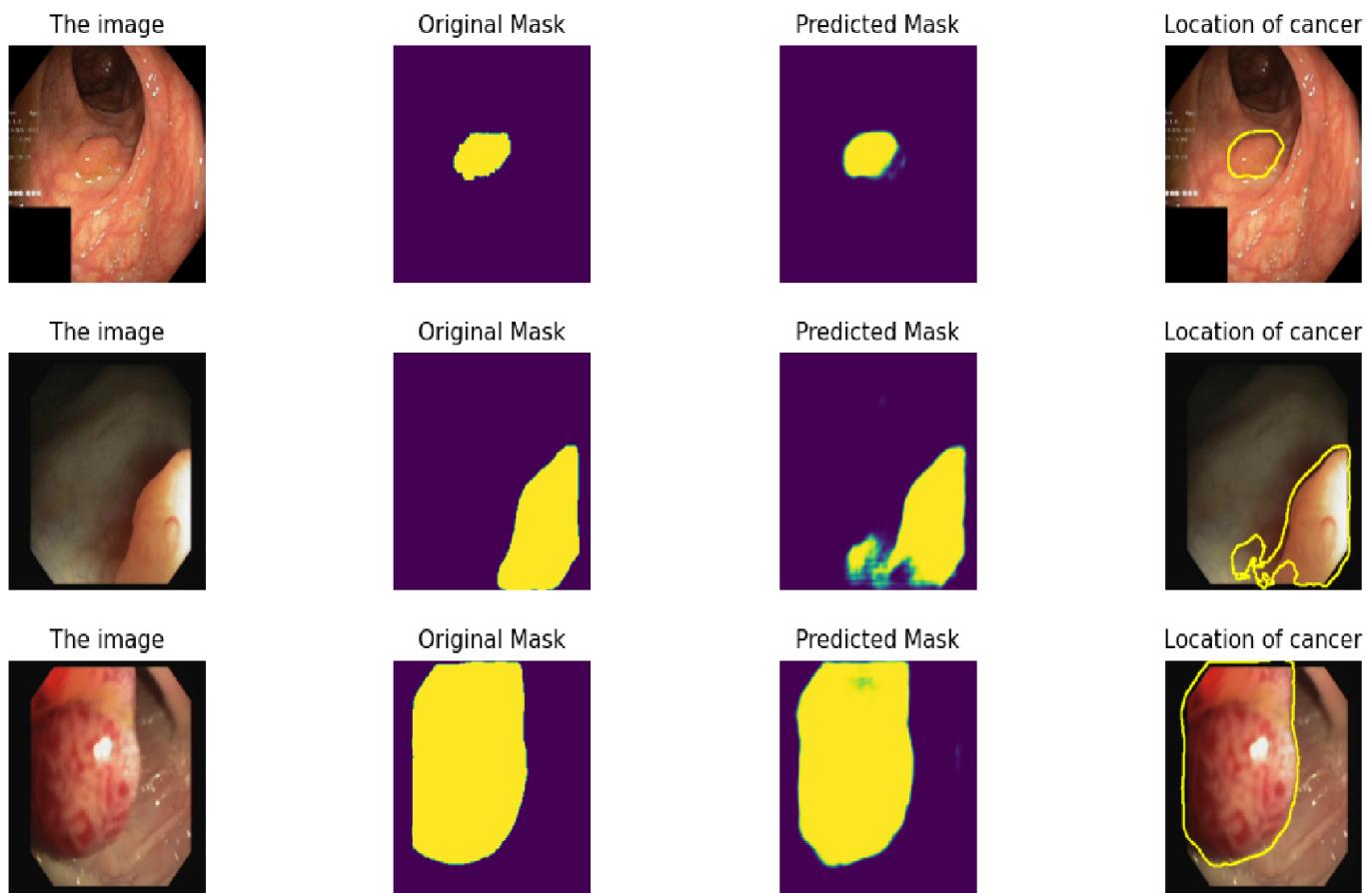


Figure 5.18 Prediction of Res-Unet++ on unseen data

Chapter 6

Implementation and testing

1. Overview of the website

- The first page the user sees is the login page, if the user doesn't have an account, he should click on **sign up**.

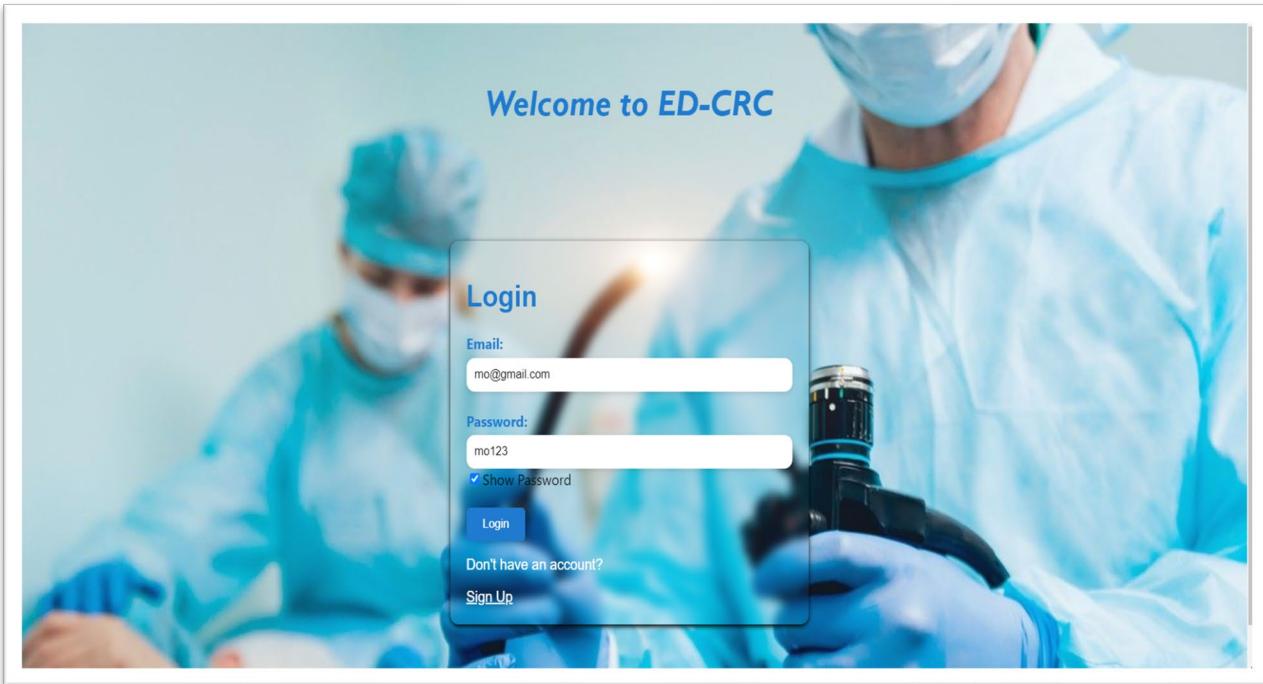


Fig 6.1 Login page

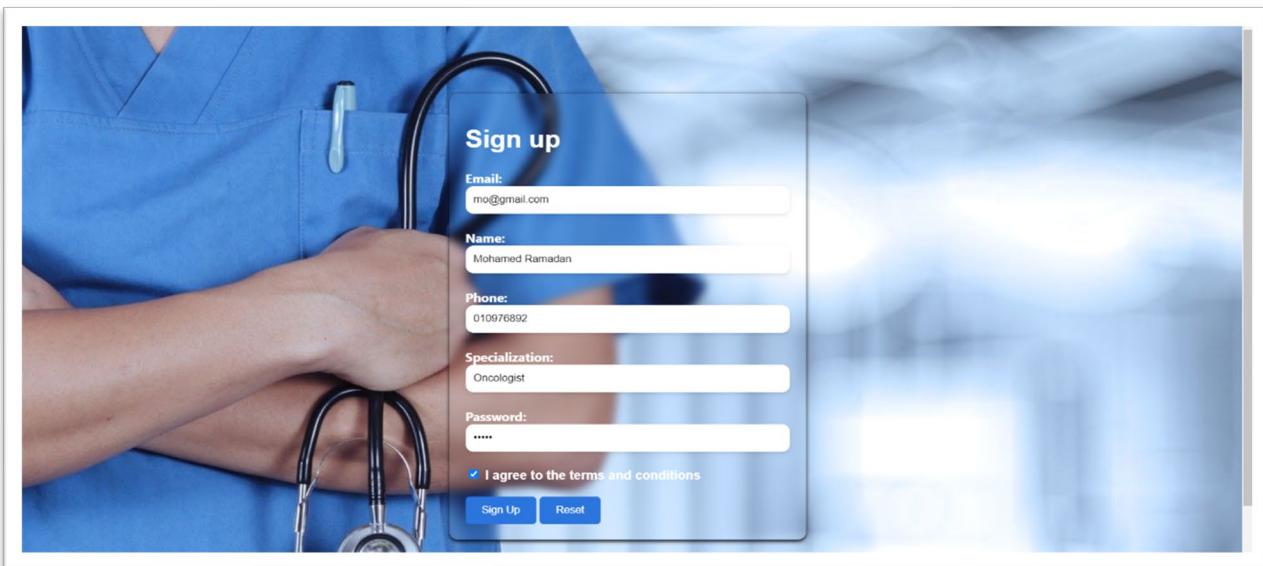


Fig 6.2 Signup page

- Our main page is divided into sections:
 - Home section.
 - About section.
 - Detect section.
 - Patients section.
 - Questions section.
 - Gallery section.

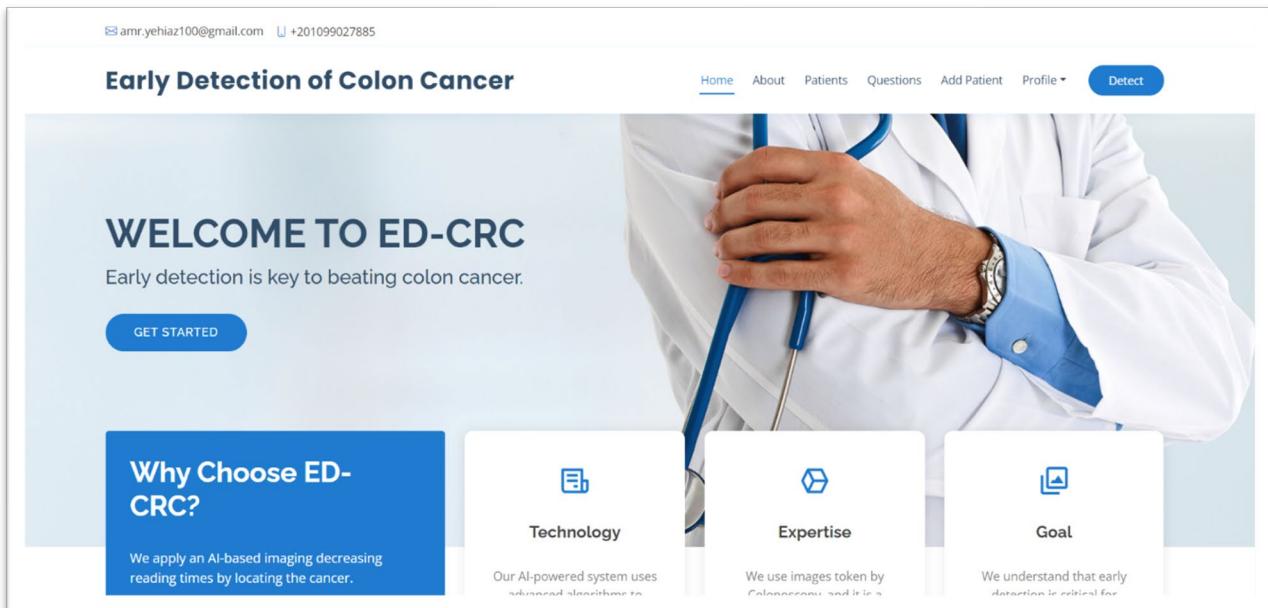


Fig 6.3 Home section

- In the home section, we define the main technology, expertise and the goal of the website.

Early Detection of Colon Cancer

Home About Patients Questions Add Patient Profile Detect

What is colon cancer ?

Colon cancer is a type of cancer that begins in the large intestine (colon). The colon is the final part of the digestive tract. Colon cancer typically affects older adults, though it can happen at any age. It usually begins as small, noncancerous (benign) clumps of cells called polyps that form on the inside of the colon. Over time some of these polyps can become colon cancers. Polyps may be small and produce few, if any, symptoms. For this reason, doctors recommend regular screening tests to help prevent colon cancer by identifying and removing polyps before they turn into cancer. If colon cancer develops, many treatments are available to help control it, including surgery, radiation therapy and drug treatments, such as chemotherapy, targeted therapy and immunotherapy. Colon cancer is sometimes called colorectal cancer, which is a term that combines colon cancer and rectal cancer, which begins in the rectum.

What could cause this type of cancer ?

- It occurs when healthy cells develop errors in their DNA
- When the cells' genetic components are mutated, they divide abnormally and accumulate in the colon to form a tumor
- With time, the abnormal cells can invade the adjacent tissues and migrate to other organs (metastasis)
- Inherited gene mutations increase the risk of developing colon cancer
- Inherited colon cancer syndromes include familial adenomatous polyposis (FAP) and hereditary nonpolyposis colorectal cancer (HNPCC). These syndromes are detected through genetic testing

Fig 6.4 About section

- In the about section, we explain what colon cancer is and its risk factors are.

Early Detection of Colon Cancer

Home About Patients Questions Add Patient Profile Detect

Upload your image to start diagnosing

Choose...

Fig 6.5 Detect section.

- In the detect section, the user should upload the image, when the image is uploaded, a **predict button** is shown. The user could get faster to the detect section by pressing on the **Detect button** in the navigation bar.

- When the user presses on **predict**, the image is passed to the model and the model starts classifying it and locating the tumor if it was abnormal image. This process takes about 3 to 5 seconds.

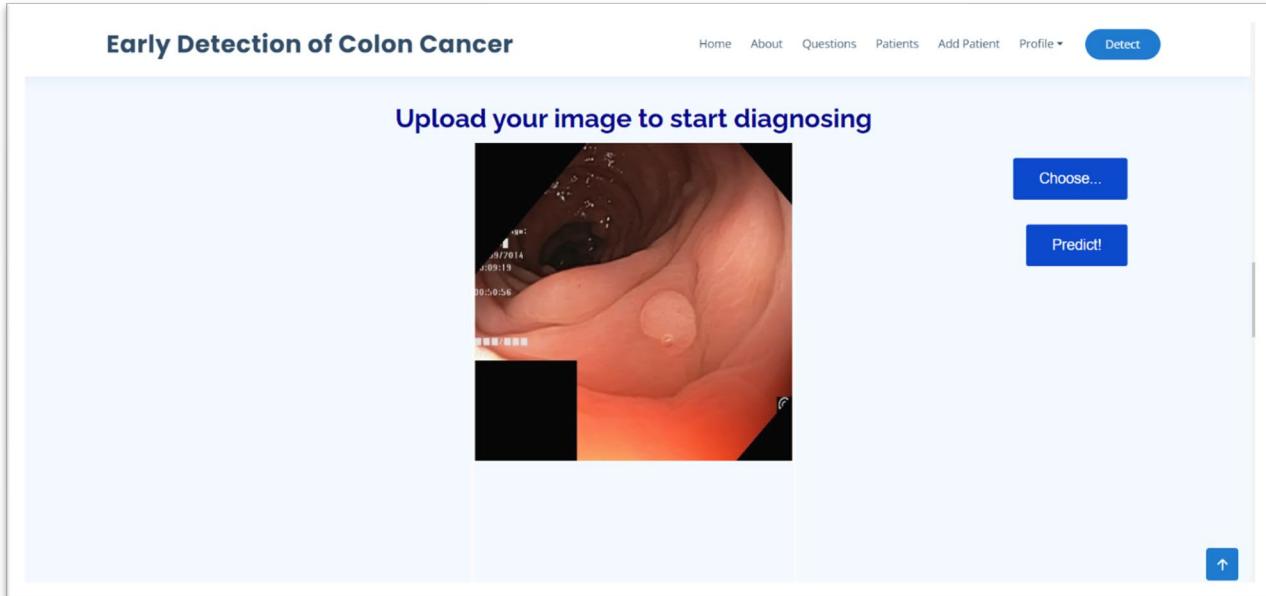


Fig 6.6 an uploaded image in the detect section.



Fig 6.7 the result of the image in the detect section.

- This is the result of the prediction, from here the user can upload another image or analyze the results and add this patient's data by clicking **Add patient** in the navigation bar.
- Here is another example with a normal image:

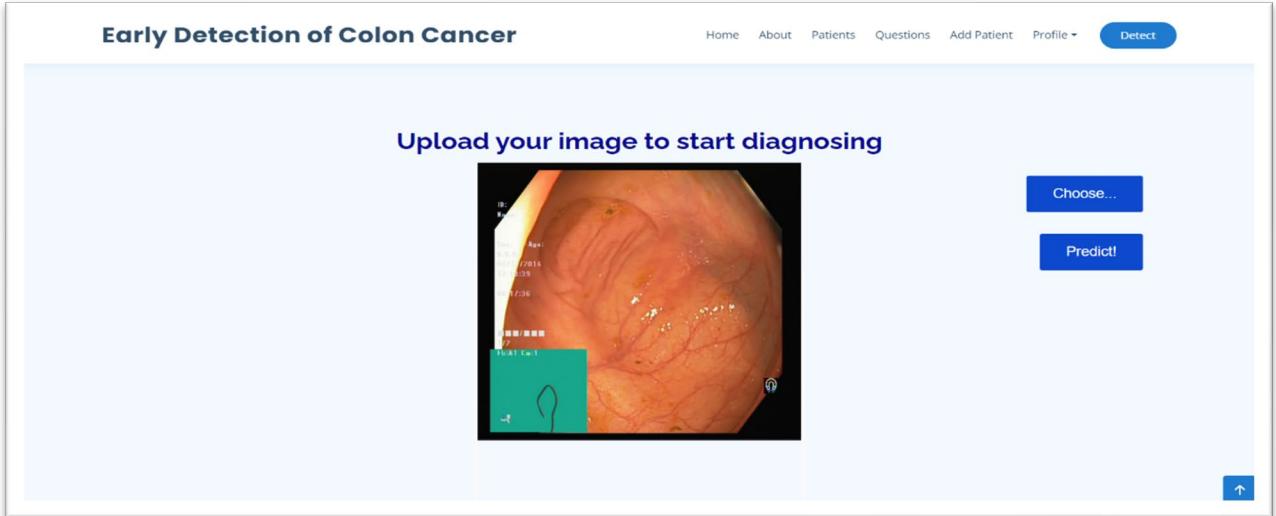


Fig 6.8 another uploaded image in the detect section.

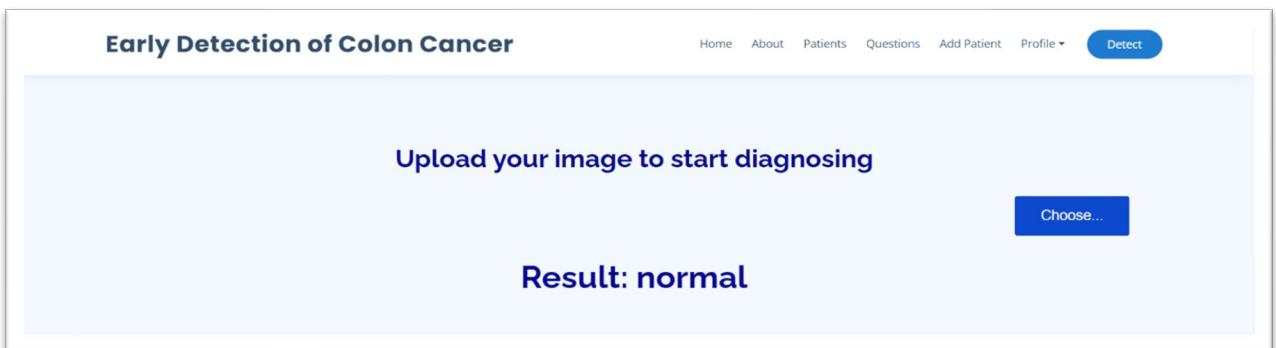


Fig 6.9 the result of the image in the detect section.

- After the result is shown, the user will be able to analyze it quickly and define the status of the patient.

- In the below figure, the user adds a patient in the **Add patient page**

Add a Patient

Name: khaled

Sex: Male

Email: k@gmail.com

Phone: 01555879888

Birth Date: 11/05/1985

Marital Status: Married

Medicine: No

Status: Abnormal

If yes, please list it:

Report: Need surgery.

Add Patient Reset Back

Fig 6.10 Add patient page.

- After adding the patient, the website redirects to the home page.
- To show patients of this user, the user can click on **Patients** in the navigation bar.

Early Detection of Colon Cancer

Home About Questions Patients Add Patient Profile Detect

Patients

#	Name	Email	Phone	Sex	Birth date	Marital status	Medicine	If medicine exist	Status	Report	Operation
1	khaled	k@gmail.com	01555879888	Male	1985-11-05	Married	No		Abnormal	Need surgery.	Update

Fig. 6.11 Patients section.

Early Detection of Colon Cancer

Home About Patients **Questions** Add Patient Profile ▾ Detect

Frequently Asked Questions

These are the most frequent questions, we try to answer them

① Does this website provide diagnoses for all types of cancer?

② **Can the input image be any type rather than Colonoscopy?**

No, It must be from colonoscopy.

③ What is the dataset used to train the models?

④ What AI techniques we used to get this results?



Fig 6.12 Questions section.

- This section answers some questions about the website, techniques used and type of data should be analyzed.

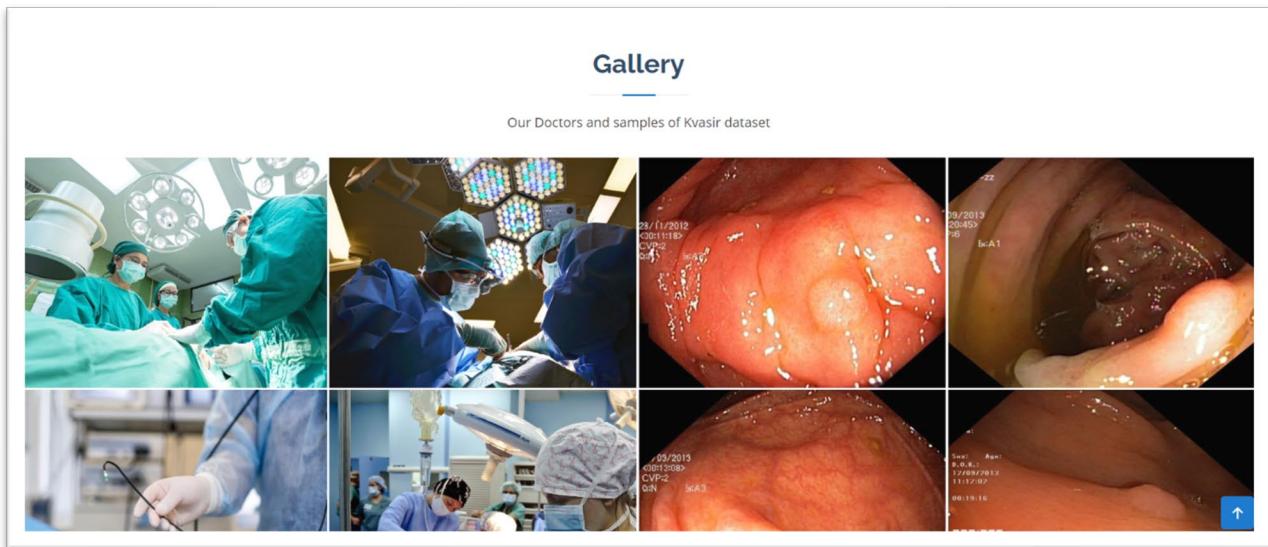


Fig 6.13 Gallery section.

- This section provides some examples of the images should be analyzed and doctors.

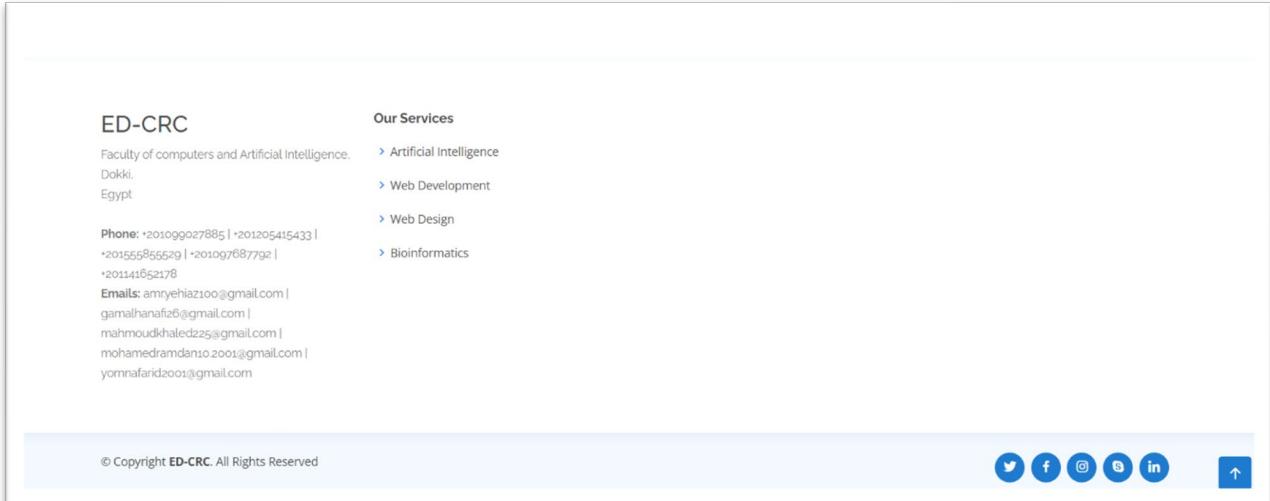


Fig 6.14 Info section.

- This section provides some information about the website's developers.



Fig. 6.15 The profile select list in the navigation bar.

- The user could sign out from the website or can show his profile if clicked on **Profile** in the navigation bar.

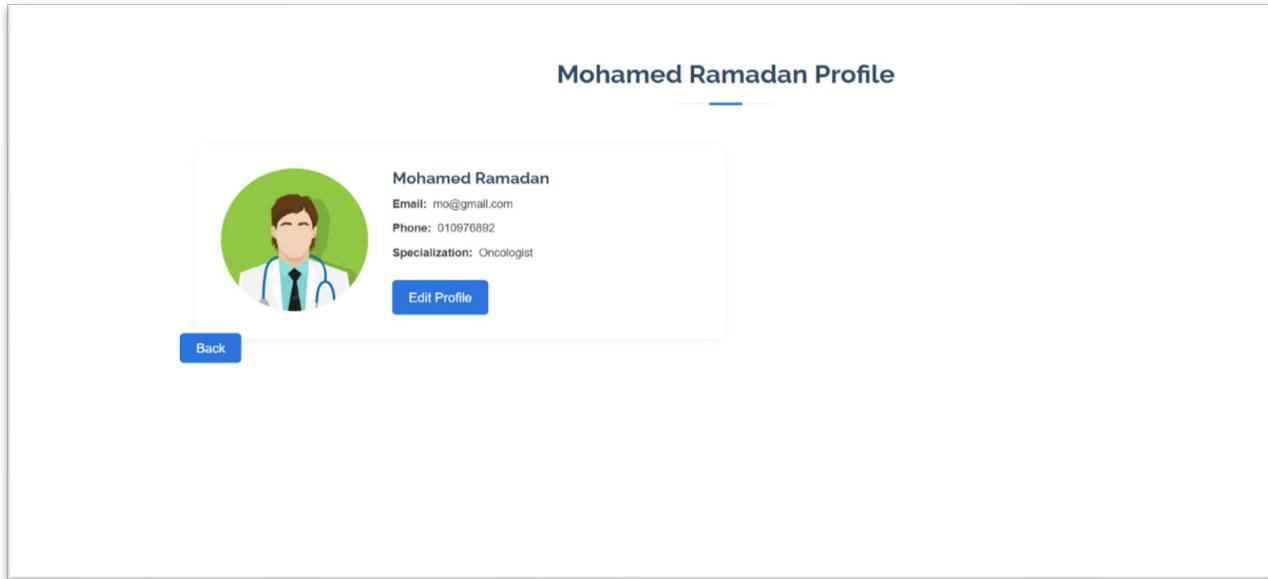


Fig 6.16 Profile page.

- If the user wants to update his profile and change the profile image, he could click on **the Edit Profile button**, after that his data will appear and an **Upload Image button**, to change his profile photo.

A screenshot of the "Edit profile" section of the application. At the top, there is a preview area showing a placeholder profile picture with a green background, the name "Mohamed Ramadan", and contact information: "Email: mo@gmail.com", "Phone: 010976892", and "Specialization: Oncologist". Below this preview area, there are four input fields: "Email" (mo@gmail.com), "Name" (Mohamed Ramadan), "Phone" (010976892), and "Specialization" (Oncologist). Underneath these fields are two buttons: "Upload Image" and "Update". At the bottom left is a blue "Back" button.

Fig 6.17 Edit profile section.

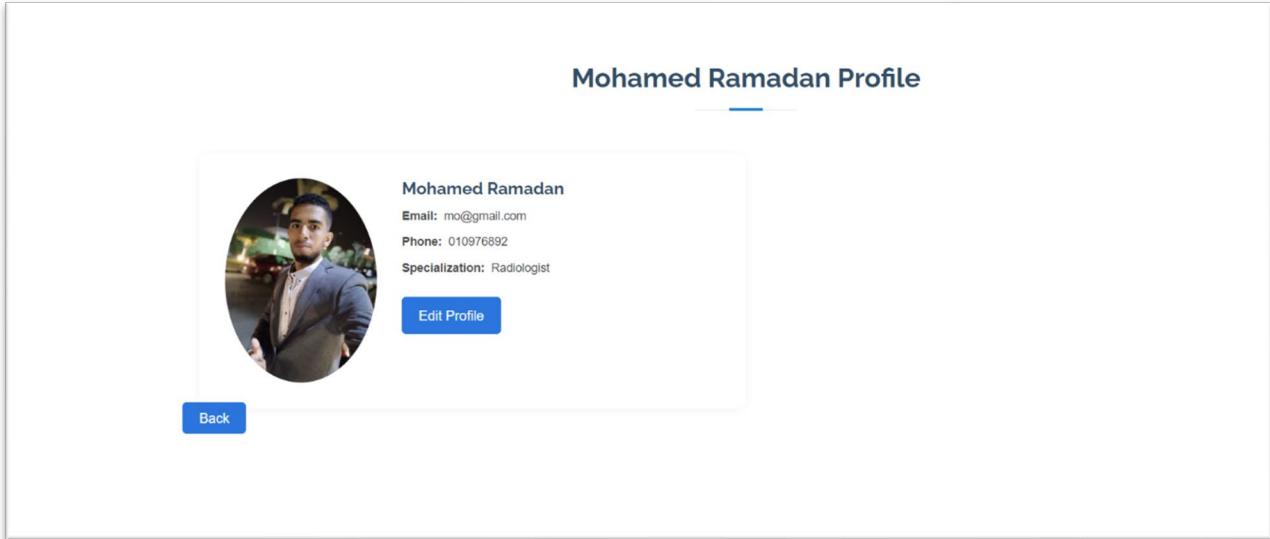


Fig 6.18 Profile page after updating the data.

2. Overview of the database

- We used MySQL database.
- Our database has two tables (Doctors table, and Patients table).

	id	name	email	phone	password	specialization	image
▶	15	Amr Yehia	amryehia@gmail.com	01125245374	eca2dd0a8612745dac92876e1317e09b6b918b...	Oncologist	photo.jpg
	16	Mohamed Ramadan	mo@gmail.com	010976892	a65accd68f911330575c6bbdca3191c895aa474...	Oncologist	NULL
◀	HULL	HULL	HULL	HULL	HULL	HULL	HULL

Fig 6.2.1 Doctors table in the database.

- We hash the password of the user in the database, to protect his account and sensitive data from unauthorized access.

	pid	pname	pemail	pphone	pstatus	id	pbirth	sex	pmarital	pmedicine	ifmedicine	report
▶	15	Mohamed	m@gmail.com	01555875878	Abnormal	15	1975-06-26	Male	Married	Yes	Blood pressure medicines	Benign, need surgery
	16	khaled	k@gmail.com	01555879888	Abnormal	16	1985-11-05	Male	Married	No	NULL	Need surgery.
◀	HULL	HULL	HULL	HULL	HULL	HULL	HULL	HULL	HULL	HULL	HULL	NULL

Fig 6.2.2 Patients table in the database.

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