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بِسْمِ اللَّهِ الرَّحْمَنِ الرَّحِيمِ

وقارب زمني علما

"The future belongs to those who believe
in the beauty of their dreams."

Eleanor Roosevelt

" The best way to predict the future is to invent it."

Alan Kay

Dedications

Praise be to Allah

We dedicate our thesis work to all those who have contributed to our education and orientation. A special feeling of gratitude to our loving **families** and dear **colleagues** who helped us a lot with their advice and their alerts according to their own experiences.

We would like to express our gratitude to all **our teachers** from whom we learned a lot during these five years on the computer science department at IBN Khaldoun University.

DERMANE Khoulood & TORCH Fatima

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Abstract

Colorectal cancer is a type of cancer that develops in the colon or rectum. It typically starts as small noncancerous clumps of cells called polyps that can become cancerous over time. In Colorectal cancer, **Histopathology images** play a critical role in the diagnosis and treatment, it is a diagnostic technique that involves the examination of tissues under a microscope to identify abnormalities in the cells and tissue architecture. In recent years, advances in digital pathology have made it possible to analyze histopathology images using artificial intelligence and machine learning algorithms. **Deep learning**, in conjunction with **convolutional neural networks** (CNNs), has emerged as a powerful and transformative approach in recent years, particularly in the **medical field**. It has made significant advancements across various domains, revolutionizing the way we analyze and interpret medical data.

In this thesis, our primary focus is on the classification of multiple tissue types within colorectal cancer (CRC) samples using a widely used database known as CRC-HE-VAL-7K, which comprises 7,000 images. For our CNN models, we explore and evaluate three distinct techniques. Firstly, we employ neural network training **from scratch**, allowing the network to learn directly from the given data. Secondly, we utilize **transfer learning** by leveraging the pre-trained VGG19 model, which has demonstrated exceptional performance in image recognition tasks. Lastly, we propose an **ensemble CNN** approach, which combines the strengths of neural network training from scratch, VGG19, ResNet50, and Inceptionv3 models. Furthermore, to achieve better results and improve overall accuracy, we incorporate two ensemble methods: the **Average** method and the **weighted averaging** method. These methods enable us to combine the predictions from multiple models in a systematic manner, taking into account their respective performance and assigning appropriate weights to the individual models.

keywords: Colon Cancer, Histopathology Images, Deep Learning, Convolutional Neural Networks, Transfer Learning, Ensemble CNN.

Résumé

Le **cancer colorectal** est un type de cancer qui se développe dans le côlon ou le rectum. Elle commence généralement par de petits amas non cancéreux de cellules appelées polypes qui peuvent devenir cancéreux au fil du temps. Dans le cancer colorectal, les **images histopathologiques** jouent un rôle critique dans le diagnostic et le traitement, c'est une technique de diagnostic qui implique l'examen des tissus sous un microscope pour identifier les anomalies dans les cellules et l'architecture tissulaire. Ces dernières années, les avancées en pathologie numérique ont permis d'analyser des images histopathologiques à l'aide d'intelligence artificielle et d'algorithmes d'apprentissage automatique. **L'apprentissage profond**, en conjonction avec **les réseaux de neurones convolutifs** (CNN), est apparu comme une approche puissante et transformatrice ces dernières années, en particulier dans le domaine médical. Il a fait d'importants progrès dans divers domaines, révolutionnant la façon dont nous analysons et interprétons les données médicales.

Dans cette thèse, nous nous concentrons principalement sur la classification de multiples types de tissus dans les échantillons de cancer colorectal (CRC) à l'aide d'une base de données largement utilisée appelée CRC-HE-VAL-7K, qui comprend 7000 images. Pour nos modèles CNN, nous explorons et évaluons trois techniques distinctes. Tout d'abord, nous utilisons la formation de réseau neuronal à partir de zéro, ce qui permet au réseau d'apprendre directement à partir des données. Deuxièmement, nous utilisons **l'apprentissage par transfert** en tirant parti du modèle VGG19 préétabli, qui a démontré des performances exceptionnelles dans les tâches de reconnaissance d'image. Enfin, nous proposons une approche **d'ensemble CNN**, qui combine les forces de la formation en réseau neuronal à partir de zéro, VGG19, ResNet50, et Inceptionv3 modèles. De plus, pour obtenir de meilleurs résultats et améliorer la précision globale, nous intégrons deux méthodes d'ensemble : la méthode moyenne et la méthode de moyenne pondérée. Ces méthodes nous permettent de combiner les prédictions de plusieurs modèles de manière systématique, en tenant compte de leurs performances respectives et en attribuant des poids appropriés aux modèles individuels.

Mots clés: cancer du côlon, images histopathologiques, apprentissage profond, réseaux de neurones convolutionnels, apprentissage par transfert, ensemble CNN.

ملخص

سرطان القولون والمستقيم هو نوع من السرطان يتطور في القولون أو المستقيم. يبدأ عادةً ككتل صغيرة غير سرطانية من الخلايا تسمى السلائل التي يمكن أن تصبح سرطانية بمرور الوقت. في سرطان القولون والمستقيم، تلعب الصور النسيجية دورًا مهمًا في التشخيص والعلاج، وهي تقنية تشخيصية تتضمن فحص الأنسجة تحت المجهر لتحديد التشوهات في بنية الخلايا والأنسجة. في السنوات الأخيرة، أتاح التقدم في علم الأمراض الرقمي تحليل صور علم الأنسجة باستخدام الذكاء الاصطناعي وخوارزميات التعلم الآلي.

ظهر التعلم العميق جنبًا إلى جنب مع الشبكات العصبية التلافيفية (CNNs)، كنهج قوي وتحويلي في السنوات الأخيرة، لا سيما في المجال الطبي. لقد أحرزت تقدمًا كبيرًا عبر مختلف المجالات، مما أحدث ثورة في الطريقة التي نحلل بها البيانات الطبية ونفسرها.

في هذه الأطروحة، ينصب تركيزنا الأساسي على تصنيف أنواع الأنسجة المتعددة داخل عينات سرطان القولون والمستقيم (CRC) باستخدام قاعدة بيانات مستخدمة على نطاق واسع تُعرف باسم CRC-HE-VAL-7K، والتي تضم 7000 صورة. بالنسبة لنماذج CNN الخاصة بنا، نستكشف ونقيم ثلاث تقنيات مميزة. أولاً، نستخدم تدريب الشبكة العصبية من الصفر، ونسمح للشبكة بالتعلم مباشرة من البيانات المعطاة. ثانيًا، نستخدم تعلم النقل من خلال الاستفادة من نموذج VGG19 المدرب مسبقًا، والذي أظهر أداءً استثنائيًا في مهام التعرف على الصور. أخيرًا، نقترح نهج مجموعة CNN، والذي يجمع بين نقاط القوة في تدريب الشبكة العصبية من الصفر، VGG19 ونماذج ResNet50, Inceptionv3. علاوة على ذلك، لتحقيق نتائج أفضل وتحسين الدقة العامة، فإننا ندمج طريقتين: طريقة المتوسط وطريقة المتوسط المرجح. تمكنا هذه الأساليب من الجمع بين التنبؤات من نماذج متعددة بطريقة منهجية، مع مراعاة أداء كل منها وتعيين الأوزان المناسبة للنماذج الفردية.

الكلمات المفتاحية: سرطان القولون، الصور النسيجية، التعلم العميق، الشبكات العصبية التلافيفية، نقل التعلم، التعلم الجماعي.

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List of abbreviations

CRC Colorectal Cancer

SSP Sessile Serrated Polyps

TSA Traditional Serrated Adenomas

GISTs Gastrointestinal Stromal Tumors

INSP The National Institute of Public Health

FAP Familial Adenomatous Polyposis

HNPCC Hereditary Non-polyposis Colorectal Cancer (Lynch syndrome)

CT Computed Tomography

MRI Magnetic Resonance Imaging

PET Positron Emission Tomography

PAs Physician Assistants

NPs Nurse Practitioners

HPV Human Papillomavirus

WSI Whole Slide Imaging

AI Artificial Intelligence

ML Machine Learning

DL Deep Learning

CNN Convolutional Neural Network

ReLU Rectified Linear Unit

ILSVRC ImageNet Large Scale Visual Recognition Challenge

VGG Visual Geometry Group

ResNet Residual Network

H Healthy Tissue

AC Adecarcinomas

TV Tubulovillous Adenomas

BH Benign Hyperplasia

IN Intraepithelial Neoplasia

Numpy Numerical Python Extension

OpenCV Open Source Computer Vision Library

GPU Graphics Processing Unit

TPU Tensor Processing Unit

H&E Hematoxylin and Eosin

GUI Graphical User Interface

TK Tkinter

General Introduction

Medical imaging research is one of the most active disciplines in the field of image processing. His recent discoveries not only allow for better diagnosis, but also open up new hope for the treatment of many conditions. Colon cancer, also known as Colorectal Cancer, is a type of Cancer that affects the colon or rectum. It is the **third** most common type of cancer in the world, with over 1.9 million new cases diagnosed each year. Early detection is critical in improving the chances of survival and reducing the morbidity of colon cancer, and since we are witnessing a revolution in the world of software which has proven effective in many fields, especially in the field of **digital medicine**. This is what motivated scientists and researchers to try to exploit computer science in medicine in order to find a solution to the proposed problem, which is the target of our research study.

AI and **deep learning** have become increasingly important in the field of medical imaging, including the detection of colon cancer. By analyzing **Histopathology images**, which are high resolution images of tissue samples obtained during colon biopsies or surgeries, doctors and researchers can identify subtle changes in tissue structure and composition that may indicate the presence of cancer, these images are used as a **database** for building machine learning models, particularly **Convolutional neural networks** (CNNs), which can analyze and interpret large amounts of data quickly and accurately.

Early detection of colon cancer is crucial for improving patient outcomes, and histopathology images are an important tool for achieving this goal.

In this thesis, our main objective is to build a model capable of classifying histopathology images for the detection of colon cancer. The focus is on constructing a robust model that can provide accurate decisions with a high percentage of correctness. To achieve our objectives, we rely on the power of deep learning, specifically convolutional neural networks (CNNs).

Research Structure

This brief consists of five chapters:

- **Chapter 1** “*Colorectal Cancer*”
In the first Chapter of our project, we developed a comprehensive overview of colon cancer, including its causes, symptoms and treatments.
- **Chapter 2** “*Medical Image Processing*”
This Chapter focused on exploring Medical Image Processing and the latest advances in diagnostic imaging used for colon cancer screening such as colonoscopy, CT scans and ultrasounds.
- **Chapter 3** “*Convolutional Neural Networks (CNN)*”
In the third Chapter, we delved into the world of artificial intelligence and deep learning, exploring concepts such as convolutional neural networks, transfer learning and ensemble learning.
- **Chapter 4** “*Stat Of Art*”
Chapter four focused on related work in the detection of colon cancer, including recent studies and research efforts aimed at improving early detection and diagnosis.
- **Chapter 5** “*Experiments and Results*”
In the final Chapter, we presented the tools used in our experiments and a brief discussion over the results. In the last we built a GUI application for colon cancer detection using our pretrained Model and Tkinter library.

Chapter I

Colorectal Cancer

Introduction

Colon cancer occurs when abnormal changes occur in the cells in the colon or rectum, leading to uncontrolled growth and tumor formation. These tumors can be benign or malignant, with the possibility of a malignant tumor spreading to other parts of the body. The development of colorectal cancer is a gradual process that may take years and is influenced by a combination of genetic and environmental factors. By exploring the underlying causes and risk factors, we can increase knowledge and develop better strategies to prevent, detect and treat this important disease.[1]

In this chapter, we will explore in depth the causes, risk factors, methods of diagnosis, available treatment options, and preventive measures related to colorectal cancer. By acquiring a comprehensive understanding of CRC, we can strive to promote early detection, effective treatment, and improved quality of life for individuals affected by this disease.

I.1 About Colorectal Cancer

I.1.1 What is a Colorectal Cancer ?

The colon and rectum are vital parts of the large intestine, responsible for absorbing nutrients and water from digested food and storing waste before elimination. Cancer is a disease characterized by the unchecked division of abnormal cells. When this type of growth occurs in the colon or rectum, it is called Colorectal Cancer (CRC).[2]

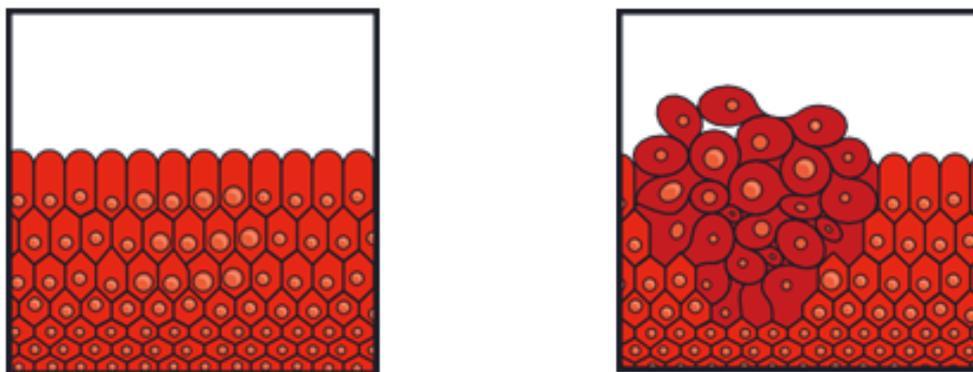


Figure I.1: Normal cells vs. cells forming a Tumor[3]

I.1.2 Anatomy

To understand Colorectal Cancer, it helps to know about the normal structure and function of the colon and rectum.

The colon is a muscular tube about 5 feet (1.5 meters) long. The parts of the colon are named by which way the food is traveling through them. The first section is called **the ascending colon**: It starts with a pouch called the cecum, where undigested food comes in from the small intestine. It continues upward on the right side of the abdomen (belly).

The second section is called **the transverse colon**: It goes across the body from the right to the left side.

The third section is called **the descending colon**: because it descends (travels down) on the left side.

The fourth section is called **the sigmoid colon**: because of its “S” shape. The sigmoid colon joins the rectum, which then connects to the anus.[4]

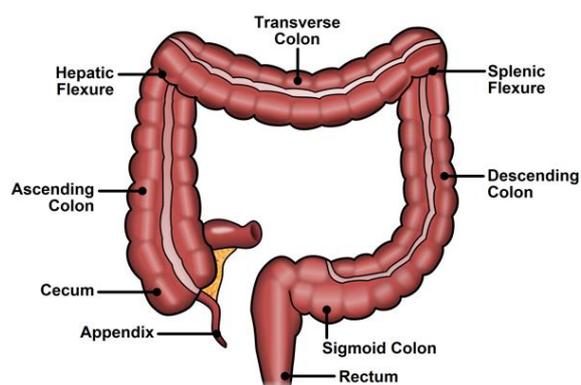


Figure I.2: Anatomy of colon [5]

I.1.3 Polyps in the Colorectal

Most colorectal cancers start as a growth on the inner lining of the colon or rectum. These growths are called polyps.

There are different types of polyps :

- **Adenomatous polyps (adenomas):** These polyps sometimes change into cancer. Because of this, adenomas are called a pre-cancerous condition. The 3 types of adenomas are tubular, villous, and tubulovillous.
- **Hyperplastic polyps and inflammatory polyps:** These polyps are more common, but in general they are not pre-cancerous. Some people with large (more than 1cm) hyperplastic polyps might need colorectal cancer screening with colonoscopy more often.
- **Sessile serrated polyps (SSP) and traditional serrated adenomas (TSA):** These polyps are often treated like adenomas because they have a higher risk of colorectal cancer.[4]

I.1.4 Types of cancer in the colon and rectum

Most colorectal cancers are adenocarcinomas, types of tumors can also start in the colon and rectum. These include:

- **Carcinoid tumors:** These start from special hormone-making cells in the intestine.
- **Gastrointestinal stromal tumors (GISTs):** start from special cells in the wall of the colon called the interstitial cells of Cajal. Some are benign (not cancer). These tumors can be found anywhere in the digestive tract, but are not common in the colon.
- **Lymphomas:** are cancers of immune system cells They mostly start in lymph nodes, but they can also start in the colon, rectum, or other organs.
- **Sarcomas:** can start in blood vessels, muscle layers, or other connective tissues in the wall of the colon and rectum. Sarcomas of the colon or rectum are rare.[4]

I.1.5 Stages

The stage is a way of describing how deep the cancer has grown into the colon or rectal wall.

T: if the cancer has spread to nearby lymph nodes.

N: if so, how many.

M: and whether the cancer has spread to other parts of the body.

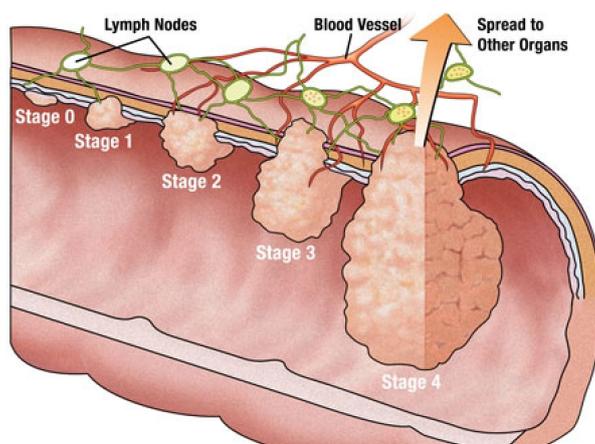


Figure I.3: Stages of colon cancer[6]

Doctors assign the stage of the cancer by combining the T, N, and M. The stage is then described using a number zero 0 through 4 (Roman numerals I through IV) and often a letter, such as A, B, or C. The stages of colorectal cancer are:

Stage 0: The cancer cells are only in the mucosa, or the inner lining.

Stage I: The cancer has grown through the mucosa and has invaded the muscular layer, it has not spread to nearby tissue or lymph nodes.

Stage IIA: The cancer has grown through the wall of the colon or rectum and has not spread to nearby tissue or to the nearby lymph nodes.

Stage IIB: The cancer has grown through the layers of the muscle to the lining of the abdomen, called the visceral peritoneum, it has not spread to nearby lymph nodes or anywhere else in the body.

Stage IIC: The tumor has spread through the wall of the colon or rectum and has grown into nearby structures, it has not spread to nearby lymph nodes or anywhere else in the body.

Stage IIIA: The cancer has grown through the inner lining or into the muscle layers of the intestine. It has spread to 1 to 3 lymph nodes or to a nodule of tumor cells in tissues around the colon or rectum that do not appear to be lymph nodes, the cancer has not spread to other parts of the body.

Stage IIIB: The cancer has grown through the bowel wall or into surrounding organs. It has spread to 1 to 3 lymph nodes or to a nodule of tumor cells in tissues around the colon or rectum that do not appear to be lymph nodes, however, the cancer has not spread to other parts of the body.

Stage IIIC: The cancer of the colon, regardless of how deep it has grown, has spread to 4 or more lymph nodes.

Stage IVA: The cancer has spread to a single distant part of the body, such as the liver or lungs.

Stage IVB: The cancer has spread to more than 1 distant part of the body.

Stage IVC: The cancer has spread to the peritoneum. It may also have spread to other sites or organs. [7]

I.2 Statistics

I.2.1 Worldwide

Globally, it is the second leading cause of cancer-related deaths and the leading cause of cancer deaths among men under the age of 50.

Overall, the researchers estimated that 153,020 cases of colorectal cancer would be diagnosed in 2023, and 52,550 individuals would die of the disease. Although most cases occur in those 65 and older, the estimates also include 19,550 new cases and 3,750 deaths among people younger than 50. [8]

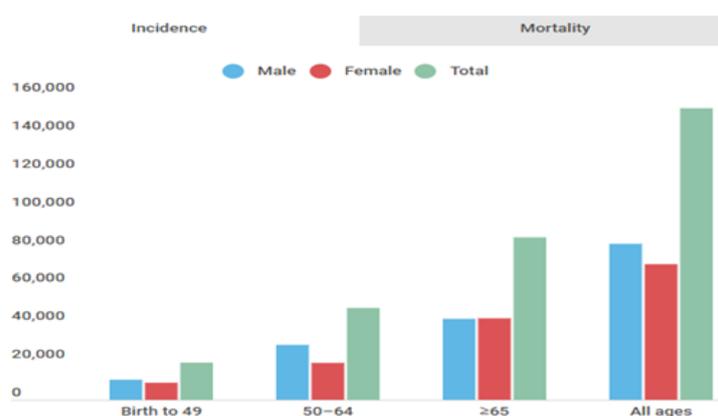


Figure I.4: Incidence estimation[8]

I.2.2 In Algeria

Algeria records nearly 6,500 new cases of colorectal cancer (CRC), including 3,500 in men and 3,000 cases in women, according to the cancer registers of the National Institute of Public Health (INSP). [9]

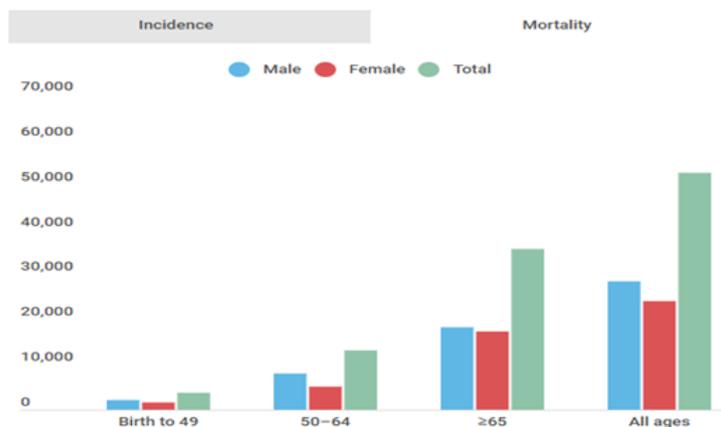


Figure I.5: Mortality estimation[8]

I.3 Causes and risk factors

The exact cause of bowel cancer is unknown, but things called risk factors can increase the chance of a person developing it.

- **Age:** Bowel cancer is more common in older people.
- **Diet:** The risk of bowel cancer may increase when consuming excessive amounts of red and processed meat, as well as fried or grilled meat. Additionally, inadequate intake of fresh fruits and vegetables may also heighten the risk.
- **Physical activity:** People who are not physically active are more likely to develop bowel cancer.
- **Body weight:** Being overweight can increase the risk of developing bowel cancer, especially in men.
- **Smoking:** Bowel cancer is more common in people who have smoked cigarettes for many years.
- **Inflammatory bowel conditions:** Having an inflammatory bowel condition, such as ulcerative colitis or Crohn's disease, can increase the risk of bowel cancer. Irritable bowel syndrome is not an inflammatory bowel condition. It does not increase the risk of getting bowel cancer.
- **Type2 diabetes:** Peoples who have type 2 diabetes, are at a slightly higher risk of getting bowel cancer.

- **Inherited (familial) conditions:** About 5 in every 100 bowel cancers (5%) are caused by an inherited faulty gene. There are two rare conditions that can run in families:
 - Familial adenomatous polyposis (FAP).
 - Lynch syndrome (also called hereditary non-polyposis colorectal cancer or HNPCC).People with either condition have a very high risk of developing bowel cancer.[3]

WHAT IS Lynch Syndrome ?

Lynch syndrome is a genetic condition that increases a person's risk for certain cancers. It is the most common inherited cause of colorectal and endometrial cancers. Many individuals with a Lynch mutation develop related cancers at very early ages, much younger than the general population. Screening should begin earlier for patients with a known Lynch mutation.[10]

I.4 Symptoms and diagnosis

Bowel screening is a way of finding bowel cancer at an early stage before it causes symptoms.

I.4.1 Symptoms

Signs and symptoms of colon cancer include:

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

Many people with colon cancer experience no symptoms in the early stages of the disease. When symptoms appear, they'll likely vary, depending on the cancer's size and location in your large intestine.[11]

I.4.2 Diagnosis

The diagnosis of colon cancer typically involves several steps including blood test, biopsy and imaging modalities, these imaging modalities include endorectal ultrasound, CT and magnetic resonance imaging (MRI). Research has also been done using positron emission tomography (PET) and contrast MRI. Validation of these newer imaging techniques may result in dramatic improvements in the management of patients with Colorectal Cancer.(**details in II.4**) This is encouraging to the advancement of the diagnosis and treatment of deadly cancers, including colorectal cancer.[12]

I.5 Treatment

I.5.1 Who treats Colorectal Cancer ?

Based on your treatment options, you might have different types of doctors on your treatment team. These doctors could include:

- **A gastroenterologist:** a doctor who treats disorders of the gastrointestinal tract.
- **A surgical oncologist(oncologic surgeon):** a doctor who uses surgery to treat cancer.
- **A colorectal surgeon:** a doctor who uses surgery to treat diseases of the colon and rectum.
- **A radiation oncologist:** a doctor who treats cancer with radiation therapy.
- **A medical oncologist:** a doctor who treats cancer with medicines such as chemotherapy or targeted therapy.

You might have many other specialists on your treatment team as well, including physician assistants (**PAs**), nurse practitioners (**NPs**), nurses, psychologists, nutritionists, social workers, and other health professionals. [13]

Different types of treatment are available for patients with colon cancer. Some treatments are standard (the currently used treatment) and some are being tested in clinical trials.[14]

I.5.2 Seven types of standard treatment are used

1. **Surgery:** is the most common treatment for all stages of colon cancer.
2. **Radio frequency ablation:** is the use of a special probe with tiny electrodes that kill cancer cells.

3. **Cryosurgery:** is a treatment that uses an instrument to freeze and destroy abnormal tissue. This type of treatment is also called **cryotherapy**.
4. **Chemotherapy:** is a cancer treatment that uses drugs to stop the growth of cancer cells, either by killing the cells or by stopping them from dividing.
5. **Radiation therapy:** is a cancer treatment that uses high-energy x-rays or other types of radiation to kill cancer cells or keep them from growing.
6. **Targeted therapy:** is a type of treatment that uses drugs or other substances to identify and attack specific cancer cells. Targeted therapies usually cause less harm to normal cells than chemotherapy or radiation therapy do.
7. **Immunotherapy:** is a treatment that uses the patient's immune system to fight cancer. Substances made by the body or made in a laboratory are used to boost, direct, or restore the body's natural defenses against cancer. This cancer treatment is a type of biologic therapy.[14]

I.6 Prevention

Modifying or avoiding the following key risk factors can help prevent cancer:

- Avoid **tobacco** use, including cigarettes and smokeless tobacco.
- maintain a healthy weight.
- Eat a **Healthy diet** with plenty of fruits and vegetables.
- Exercise regularly.
- Limit **alcohol** use.
- Get vaccinated against hepatitis B and human papillomavirus (**HPV**) reduce exposure to ultraviolet radiation.
- Prevent unnecessary ionizing radiation exposure (e.g. minimize occupational exposure, ensure safe and appropriate medical use of radiation in diagnosis and treatment).
- Avoid urban **air pollution** and indoor smoke from household use of solid fuels.
- Get regular medical care.
- Some chronic infections are also risk factors for cancer. People in low and **middle income countries** are more likely to develop cancer through chronic infections.[1]

Conclusion

In this chapter we have tried to provide a comprehensive overview of colon Cancer, we have highlighted the most important items to know, we followed an exact order to release it, we started by defining it, then moved on to mentioning its causes and risk factors that could provoke it. After that, we identified its symptoms and the most common methods of diagnosis. In the end, we referred to the ways of its treatment and made some recommendation for its prevention.

Chapter II

Medical Image Processing

Introduction

Images are an integral part of medical practice and are used extensively in various fields of medicine, including diagnosis, treatment planning, and monitoring of disease progression. Medical images are typically acquired using specialized imaging techniques that capture different aspects of the body's anatomy and function. Medical imaging techniques encompass a range of modalities, including X-ray, computed tomography (CT), magnetic resonance imaging (MRI), ultrasound, and positron emission tomography (PET). Each modality provides unique insights into different aspects of the body, allowing healthcare professionals to visualize and analyze various structures, tissues, and physiological processes. By employing these imaging technologies, medical professionals can detect and analyze abnormalities in the colon and rectum.[15]

In this chapter, our focus turns to image processing and the medical imaging and its significance in the detection of Colorectal Cancer(CRC).

II.1 Image Processing

Image processing refers to the manipulation of digital images that have been digitized and stored on a computer. Through the use of specialized software programs, these images can be modified and enhanced to make them more useful and facilitate various applications. One common application of image processing is image recognition, where algorithms and techniques are employed to analyze and identify objects or patterns within an image.[87]

We need first understand what exactly constitutes an image.

II.1.1 Understanding Image Data

An image is a two-dimensional representation of a visual subject, like a photograph, painting, or drawing. In **digital imaging**, images are stored as arrays of pixel values, where each **pixel** represents a sample of the image's brightness and color. The color of each pixel can be represented by one or multiple channels, like the red, green, and blue (**RGB**) channels in traditional color images. Let's go with an image that can be broken down into a **matrix of numbers**, where each number represents the **strength**. And this strength could be anywhere between 0 (**representing black**) and 255 (**representing white**). So, a monochromatic image can be represented by a single matrix.[16]

*But what can we do when it is a **colored image** below?*



Colour Image

Figure II.1: Color image[16]

If we have to represent an image, we will break it into three images of **three different colors**: red, green, and blue.

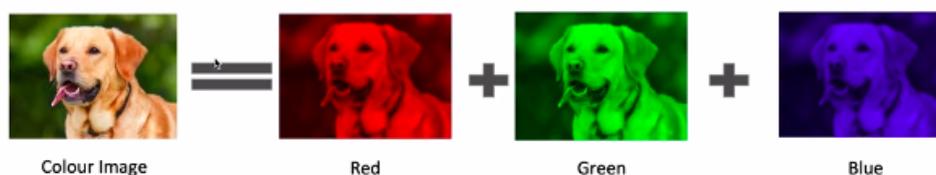


Figure II.2: RGB image[16]

The image will be broken down into three matrices: one for the red color, one for the green color, and one for the blue color so that we can represent the image in an $N * M * 3$ **matrix**.



Figure II.3: Numerical representation[16]

II.1.2 Key Concepts in Image Processing

The following table introduces some key image processing concepts and provides a brief overview of basic image properties and processing concepts:

Topic	Description
Pixel and Color Representation	Images consist of pixels, the smallest units of an image. Each pixel contains information about intensity or color. Grayscale images have one intensity value per pixel, while color images have multiple color channels per pixel (e.g., red, green, blue).
Image Resolution	Resolution refers to the number of pixels in an image. Higher resolution means more pixels, resulting in finer details and clearer images. Resolution is typically expressed as the total number of pixels in the width and height dimensions.
Image Formats	Different file formats are used to store and represent images. Each format has its own characteristics and compression methods. Common formats include JPEG, PNG, GIF, and TIFF.
Histograms	Histograms provide a graphical representation of the distribution of pixel intensities in an image. They can be used to analyze contrast and brightness.
Luminance	Luminance refers to the brightness or intensity of light in an image. It represents the perceived brightness levels of different pixels and plays a crucial role in image perception and analysis.

Noise	Noise refers to random variations or unwanted disturbances in image data. It can be caused by various factors, such as sensor limitations, transmission interference, or environmental factors. Understanding and mitigating noise is important for image quality and analysis.
Dimension	Dimension refers to the size or spatial extent of an image. It is typically measured in terms of width and height. Understanding the dimension of an image helps in determining the visual size or aspect ratio of the image.

Table II.1: Fundamental Image Characteristics

II.1.3 Phases of Image Processing

- **Image Acquisition:**

Image acquisition is the initial step in image processing where the image is retrieved from a hardware based source or input device.

- **Image Enhancement:**

Image enhancement aims to improve the quality and highlight specific features of interest in an image. Techniques like adjusting brightness, contrast, and sharpness are used in this step.

- **Image Restoration:**

Image restoration involves improving the appearance of an image using mathematical or probabilistic models. It focuses on removing noise, artifacts, or other distortions that may have occurred during acquisition or storage.

- **Color Image Processing:**

Color image processing deals with various techniques for modeling and processing color information in digital images. It has gained significance due to the widespread use of digital images, especially on the internet.

- **Wavelets and Multiresolution Processing:**

Wavelets are employed to represent images at different resolutions. This technique involves subdividing images into smaller regions called wavelets, enabling efficient data compression and pyramidal representation.

- **Compression:**

Compression is employed to reduce the storage space required for image storage or the

bandwidth needed for image transmission. This is particularly useful for images intended for internet use.

- **Morphological Processing:**

Morphological processing applies a set of operations to alter images based on their shapes. These operations involve dilation, erosion, opening, and closing to modify and extract features.

- **Segmentation:**

Segmentation is a challenging step in image processing, involving the partitioning of an image into meaningful parts or objects. It enables the identification and separation of different regions within an image.

- **Representation and Description:**

After segmentation, regions are represented and described in a form suitable for further computer processing. Representation focuses on capturing the characteristics and properties of the regions, while description involves extracting quantitative information to differentiate different classes of objects.

- **Recognition:**

Recognition assigns labels or identifies objects based on their descriptions. This step utilizes the extracted information to classify or identify objects present in the image.[87]

II.1.4 Advantages of Image Processing

- **Enhanced image quality:** Algorithms improve image clarity, sharpness, and information, aiding interpretation and analysis.
- **Automation of tasks:** Object recognition, pattern detection, and measurement can be automated, saving time and effort in various industries.
- **Increased efficiency:** Algorithms process images faster than humans, enabling quick analysis of large data sets.
- **Improved accuracy:** Precise measurements and quantitative analysis are performed more accurately, eliminating human errors and subjectivity.
- **Extraction of valuable information:** Textures, edges, shapes, and patterns are extracted, facilitating medical diagnosis, industrial inspection, and object recognition.

- Integration with other technologies: Image processing combines with AI and machine learning, enabling advanced applications like facial recognition, autonomous vehicles, and augmented reality.[88]

II.1.5 Disadvantages of Image Processing

- High computational cost: Some algorithms require significant computational resources, leading to increased processing time and resource requirements.
- Limited interpretability: Complex algorithms may produce results that are difficult for humans to interpret or understand.
- Dependence on input quality: The quality of output is heavily reliant on the quality of the input images.
- Algorithmic limitations: Algorithms may struggle in certain scenarios, such as recognizing objects in cluttered or poorly lit scenes.
- Dependence on training data: Performance relies on the quality and diversity of the training data used to develop the algorithms.
- Ethical and privacy concerns: image processing raises concerns related to privacy infringement, biases, and unauthorized use of personal data.[88]

II.1.6 Applications of Image Processing

Image processing has a wide range of applications in various fields:

- Medical Image: Image processing aids in the early detection and accurate diagnosis of diseases through algorithms that analyze medical images.
- Traffic Sensing Technologies: Image processing systems, like Video Image Processing Systems (VIPS), are used for traffic monitoring and management. They can detect vehicles, record license plates, monitor speeds, and optimize traffic flow.
- Image Reconstruction: Image processing can be used to reconstruct and fill in missing or damaged parts of images, restoring old or damaged photos.
- Face Detection: Image processing algorithms trained with deep learning can detect and recognize human faces. It is used in security systems, biometrics, and social media filters.[87]

II.2 Medical Imaging

The internal organs and bones of our body are covered by skin and other tissue barriers, and are therefore not visible to the naked eye. The term **‘medical imaging’** is used to refer to techniques that allow us to view the interior of the body.

Medical imaging refers to the use of various **imaging techniques** to create visual representations of the body’s internal structures and functions. Medical imaging plays a critical role in the diagnosis, treatment, and monitoring of various medical conditions, and it has become an essential component of modern healthcare.[17]

II.3 Diagnostic Medical Imaging

Diagnostic imaging is a medical imaging technique that is used by physicians to look inside your body for diagnostic purposes and to determine proper treatment. Many imaging tests are **noninvasive, easy and painless**.[18]

Some machines and methods can produce pictures of the activities and structures inside your body, your doctor will decide which medical imaging tests they’ll need to use based on the body part they’re evaluating and your symptoms.[19]



Figure II.4: Diagnostic Imaging[20]

II.4 Diagnostic Medical Imaging Techniques Of Colorectal Cancer

Recently, other medical imaging modalities have been employed to help aid in the diagnosis and treatment of Colorectal cancer. The diagnosis techniques are listed below:[21]

II.4.1 Colonoscopy

A colonoscopy is a medical procedure that allows doctors to examine the inside of your large intestine, including your colon, rectum, and anus. It is performed using an **endoscope**, which is a thin, flexible tube with a camera and light on the end. The endoscope is inserted through the anus and guided through the colon while the camera sends images to a monitor. This allows the doctor to look for any abnormalities, such as polyps or tumors, and to take tissue samples if necessary.[22]

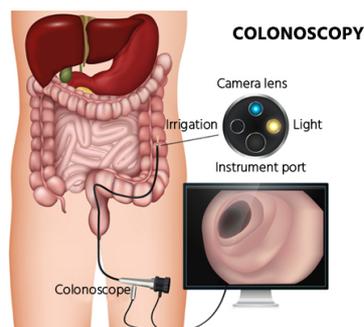


Figure II.5: Colonoscopy[23]

II.4.2 Computed tomography (CT or CAT) scan

Computed tomography scan is a useful diagnostic tool for detecting diseases and injuries. It uses a series of **X-rays** and a computer to produce a **3D image** of soft tissues and bones. CT is a painless, noninvasive way for your healthcare provider to diagnose conditions.[22]



Figure II.6: CT scan[25]

II.4.3 Magnetic resonance imaging (MRI)

It is based on the **magnetic field** that produces relevant pictures of the body and is used to calculate the size of a tumor. Contrast medium, which is a special dye, is provided to the patient before the scan in order to produce a clear image and is also incorporated into the patients' veins.[24]

II.4.4 Ultrasound

Ultrasound is a diagnostic test that uses **high frequency sound waves** to produce images of the body's internal organs. It is commonly used to check if cancer has spread to nearby organs. Endorectal ultrasound is often used to determine the depth of rectal cancer and to plan treatment accordingly. However, this test is not very effective in detecting cancer that has spread beyond the pelvis or nearby lymph nodes.[25]

II.4.5 Positron emission tomography (PET) or PET-CT scan

Positron emission tomography: is normally combined with a CT check and sometimes additionally with a PET-CT filter. A PET output consists of images of cells that are present internally in the body. To obtain these, a limited quantity of a radioactive material is infused into the body. At that point, a scanner can distinguish liquid to deliver internal images of the human body.[24]

II.5 Histology

Histology is the microscopic study of the **normal tissues** of the body. The procedures adopted for the preparation of material for such studies are known as histologic or histopathologic techniques. The tissues are usually obtained during surgery, biopsy, or autopsy, they are used to diagnose diseases and conditions, including cancer. [26]

II.5.1 What is Histopathology?

To understand histopathology, let's break down the name: "**Histo**" stands for "*tissue*" while "**pathology**" is the study of disease. When you put it together, *histopathology* means exactly what it describes: the study of **diseased tissues**.

In Colorectal cancer, histopathology images of tissue samples taken during a biopsy can provide important information about the presence, **type**, and **stage** of the cancer. The examination of

these images under a microscope can help to determine the characteristics of the cancer cells and the surrounding tissue, which can then be used to guide treatment decisions. [27]

II.5.2 What is Biopsy?

In some cases, your doctor may decide that he or she needs a sample of your tissue or your cells to help diagnose an illness or identify a cancer. The removal of tissue or cells for analysis is called a biopsy.[28]

A biopsy is the removal of a small amount of tissue for examination under a **microscope**. Other tests can suggest that cancer is present, but only a biopsy can make a definite diagnosis of Colorectal cancer. A pathologist¹ then analyzes the sample(s).

A biopsy may be performed during a colonoscopy, or it may be done on any tissue that is removed during surgery.[27]

II.5.3 What is the difference between Biopsy and Histopathology?

Many medical professionals use the terms “**Biopsy**” and “**Histopathology**” interchangeably. A biopsy involves taking a tissue sample to evaluate it for a typical cells. Sound familiar? That’s because histopathology involves looking at those cell samples.

If you want to get technical, a biopsy is a procedure for **gathering the tissues**, while histopathology is a **study** of the sample itself. Also, histopathology can involve looking at samples from entire organs, which technically isn’t a biopsy.[27]

II.6 Digital pathology

Traditionally, pathology has been studied through the use of a microscope to examine tissues and organs from patients. This process is called histology.

However, the advancement in technology brought **digitized images** to pathology, propelling histology to a new level, now referred to as digital pathology. It involves using **computers** and **imaging software** to examine images of tissue and organs for abnormalities. As a result, it is becoming an increasingly important tool for diagnosing and treating diseases.

There are many applications of digital pathology including: diagnosis, treatment, research and education.[28]

¹is a doctor who specializes in interpreting laboratory tests and evaluating cells, tissues, and organs to diagnose disease.

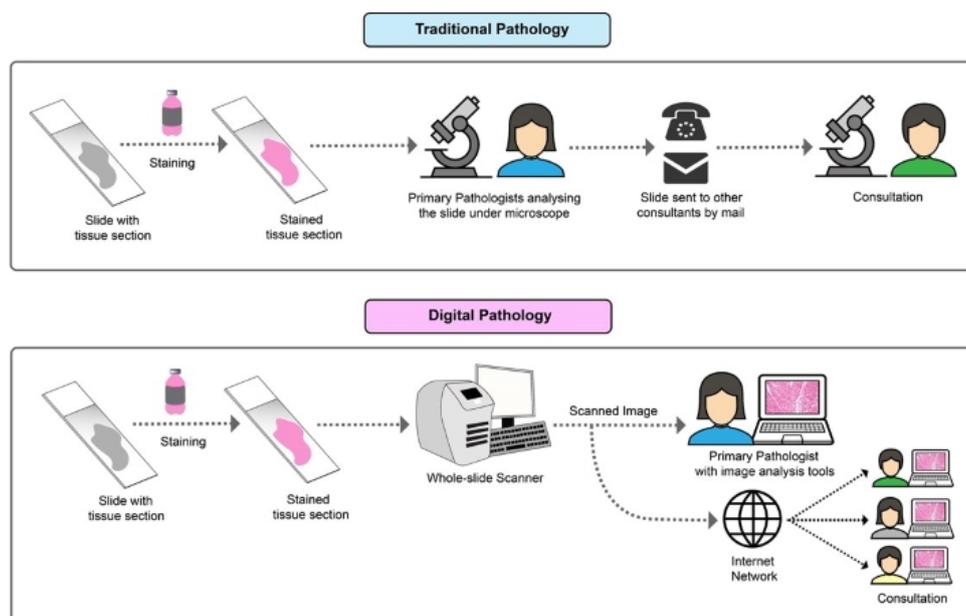


Figure II.7: Comparison between the workflow of traditional and digital pathology[29]

Conclusion

The key developments and enhancements of CRC have been widely applied in medical imaging as we shown in this chapter. As technology advances, there's an increasing need to understand more about AI's role in pathology.

Therefore, in the next chapter we will explore AI field and its application.

Chapter III

Convolutional Neural Networks (CNN)

Introduction

Artificial Intelligence is one of the rapidly emerging technologies deployed in almost every industry for maximum favorable outputs. When you hear the term Artificial intelligence, you might associate it with robots or those typical sci-fi movies depicting the rise of AI technology. But in reality, AI is present everywhere around you these days. Whether you interact with a smart assistant like *SIRI* by Apple and *Alexa* by Amazon, or commute in a self driven car, refer to Google or Apple maps, use a smartphone, get targeted by personalized ads on social media. In recent years, advances in digital pathology have made it possible to analyze histopathology images using **artificial intelligence** and **machine learning** algorithms. Artificial intelligence (AI) and machine learning (ML) are likely to play a larger role in digital pathology, this approach can help pathologists to more accurately and efficiently diagnose cancer and other diseases. The AI automatically classifies cells into different cell groups and identifies patterns and cell conditions using **deep learning** to diagnose the patients. The developers are training AI programs with image analysis algorithms to diagnose problems using deep learning and big data from healthcare industry.[30] First, we need to define clearly what we're talking about when we mention AI. What does artificial intelligence mean, machine learning, and deep learning (see Figure III.1)? How do they relate to each other ? [31]

III.1 Artificial Intelligence

“(AI) is a science devoted to making machines think and act like humans.”

The idea of AI emerged in the 1950s when a group of computer science pioneers began questioning whether computers could be programmed to display human like intelligence. Some

believed that by crafting complex sets of explicit rules, programmers could achieve human level intelligence in machines, a method known as **symbolic AI** in the 1950s to the late of 1980s. Although symbolic AI has demonstrated its effectiveness in solving well defined, logical problems, it has proven to be challenging to determine explicit rules for tackling more complex, ambiguous problems like image classification, speech recognition, and language translation. As a result, a new approach has emerged to replace symbolic AI, known as **machine learning**. [32]

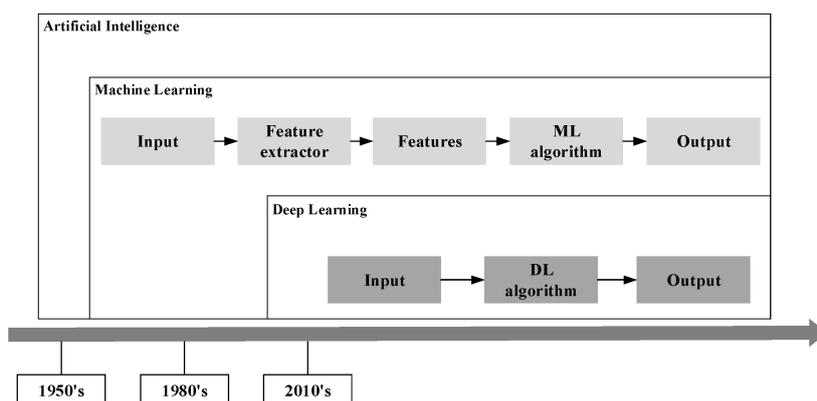


Figure III.1: The relationship between AI and Deep Learning [33]

III.2 Machine Learning

“Focusing on enabling computers to perform tasks without the need for explicit programming.”

A subset of artificial intelligence (AI), machine learning (ML) deals with the study and use of data and algorithms that mimic how humans learn. This helps machines gradually improve their **accuracy**. ML allows software applications to improve their prediction accuracy without being specifically programmed to do so. It estimates new output values by using historical data as input. Machine learning is fundamental to the operations of many of today’s biggest organisations like *Facebook* and *Google*. For many businesses across the world, it has become a crucial competitive differentiator. [34]

III.2.1 Machine Learning Models

Supervised learning is a type of machine learning in which a dataset includes the **desired outputs** or **labels**. The goal is to create a **function** that can calculate an error for a given prediction by comparing it to the desired output. The function is then altered based on the error

produced, and the model learns **the mapping** between inputs and outputs, the function is trained using a **training** dataset, and then applied to unseen data to make predictions. The aim is to build a function that can generalize well over new data it has never seen before, making accurate predictions based on the patterns it has learned from the training data. [35]

In **Unsupervised learning**, the dataset does not have any desired outputs or labels. Therefore, there is no way to supervise the function. Instead, the function attempts to **segment the data** into groups or "classes" based on common features within the data. The goal is to build a mapping function that can categorize the data into groups or clusters based on patterns and features hidden within the data.[35]

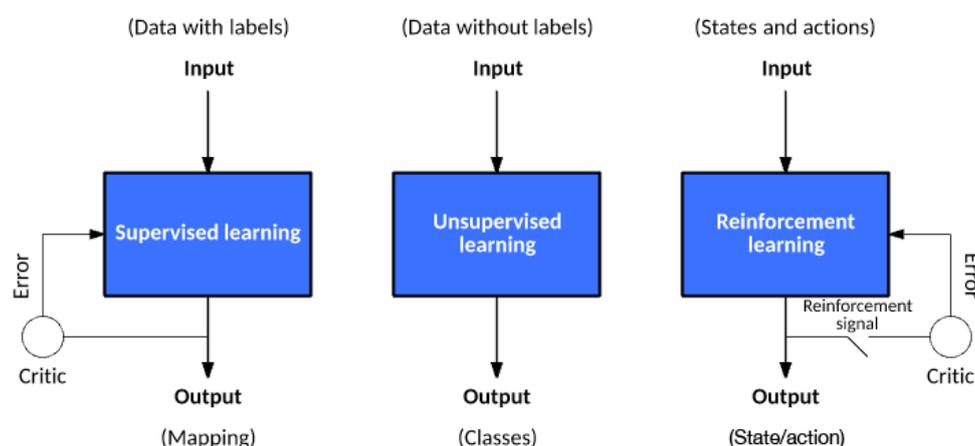


Figure III.2: Three Learning Models for ML[35]

Finally, **Reinforcement learning** based on rewarding desired behaviors and/or punishing undesired ones. An error is provided not after each example (as is the case for supervised learning) but instead on receipt of a **reinforcement signal** (such as reaching the goal state). In general, a reinforcement learning agent is able to perceive and interpret its environment, take actions and learn through trial and error.[36]

III.3 Deep Learning

“A subset of machine Learning based on artificial neural networks“

Deep Learning neural networks, or artificial neural networks, attempts to mimic the human brain through a combination of data **inputs**, **weights**, and **bias**. These elements work together to accurately recognize, classify, and describe objects within the data.[37]

The neural network is composed of the input layer, hidden layer, and output layer:

Input layer — the first layer that loads data into a model and passes it without any computation.

Hidden layers — multiple interconnected layers that perform mathematical operations on data

and extract features.

Output layer — the final layer that provides the result by taking inputs from preceding hidden layers.[38]

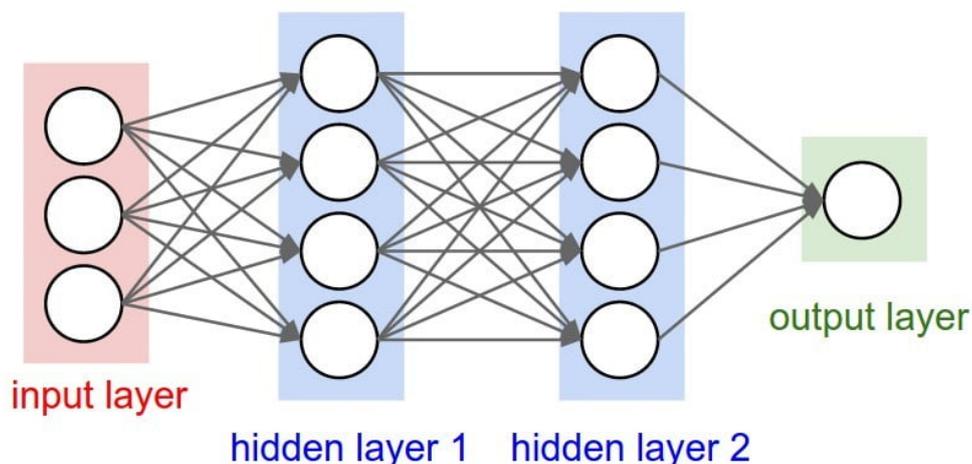


Figure III.3: Deep neural network[39]

There are different types of Deep Learning architectures, including:

- **Deep Neural Networks:** these are multi-layered networks that are used for supervised learning tasks such as image or speech recognition.
- **Recurrent Neural Networks:** these networks are used for tasks that involve sequential data, such as natural language processing or speech recognition.
- **Convolutional Neural Networks:** these are networks that are commonly used for image and video recognition tasks, where the network is able to learn features from the image or video input.[40]

Each Deep Learning architecture has its own unique **strengths** and **weaknesses**, and the choice of architecture depends on the specific task at hand.

III.3.1 Machine Learning vs. Deep Learning

Here are five main differences between machine learning and deep learning:

1. **Human Involvement:** Machine learning often requires more human intervention to achieve results, while deep learning requires more complex initial setup but then requires minimal intervention.

2. **Hardware:** Machine learning programs can often run on standard computers and require less powerful hardware than deep learning algorithms, which require high-performance resources and often utilize GPUs due to their high memory bandwidth and ability to handle multiple operations simultaneously.
3. **Time:** Machine learning systems can be set up and run quickly, but may have limitations in their capabilities. Deep learning systems take longer to set up but can generate results instantly, with the quality expected to improve over time as more data is processed.
4. **Approach:** Machine learning relies on structured data and traditional algorithms such as linear regression, while deep learning uses neural networks and is better suited for handling large amounts of unstructured data.
5. **Applications:** Machine learning is already used in everyday applications like email, banking, and healthcare, while deep learning enables more complex and autonomous programs such as self-driving cars and robots for advanced surgery.[41]

DL models have been regarded as superior to ML based techniques in the presence of large amounts of data and have been popular in multiple disciplines, including the diagnosis and prognosis of cancer in digital pathology.[42]

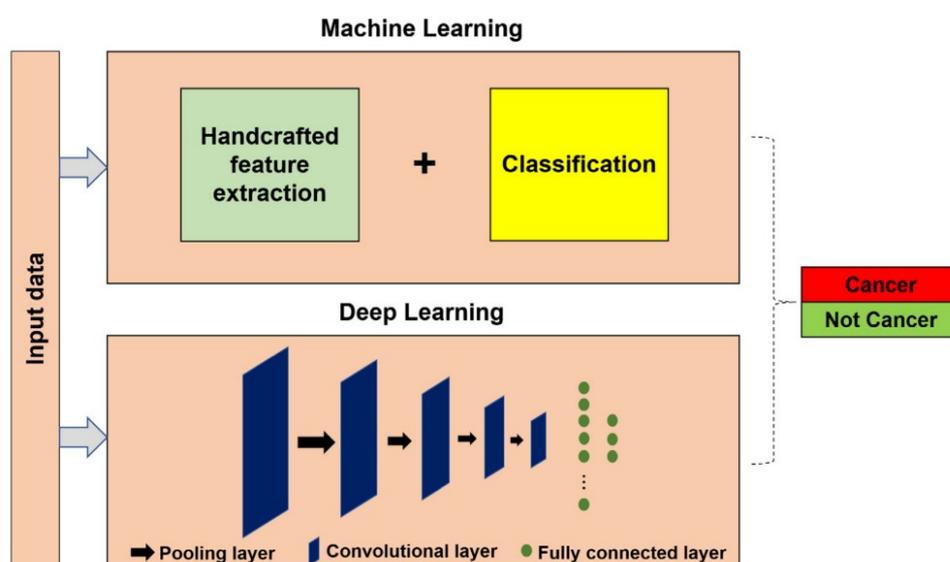


Figure III.4: Machine Learning & Deep Learning[42]

III.3.2 The Neuron

The foundational unit of the human brain is the neuron. A tiny piece of the brain, about the size of grain of rice, contains over 10,000 neurons, each of which forms an average of 6,000 connections with other neurons. The neuron is specifically designed to **receive** information, **process** it uniquely, and **send** it to other cells. [43]

III.3.3 Artificial Neuron

We can translate this functional understanding of the neurons in our brain into an artificial model that we can represent on our computer. Just as in biological neurons, our artificial neuron takes inputs (x_1, x_2, \dots, x_n) , multiplies each input by a weight (w_1, w_2, \dots, w_n) and then **sums** these weighted inputs together to produce **the logit** (z) of the neuron. In many cases, the logit also includes a bias (b) , which is a constant. This sum is then passed through an activation function f to generate the output (y) . This output can be transmitted to other neurons (view figure III.5) [43].

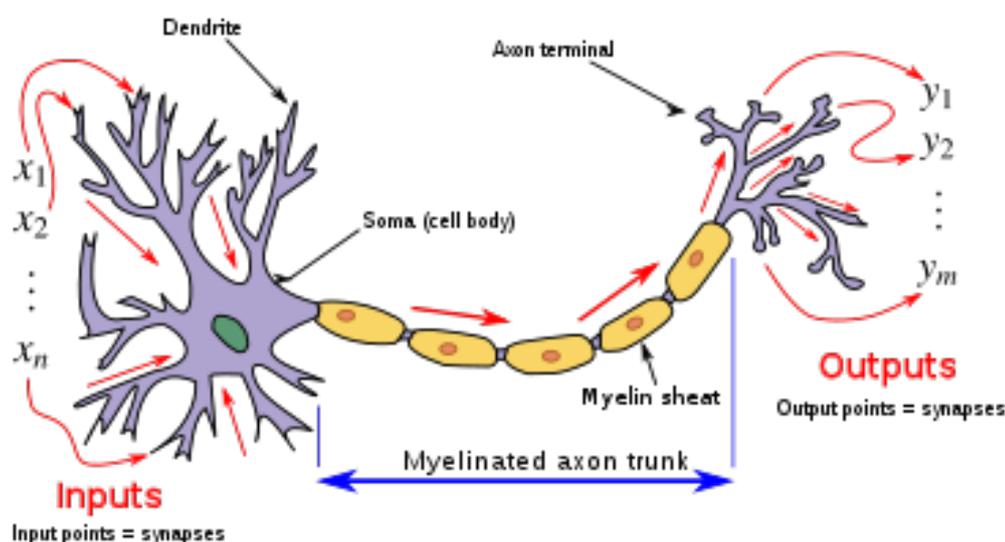


Figure III.5: Illustration of an artificial neuron[44]

III.3.4 Biological Neuron vs. Artificial Neuron

The biological neuron is analogous to artificial neurons in the following terms: [45]

Biological neuron	Artificial neuron
Cell Nucleus (Soma)	Node
Dendrites	Input
Synapse	Weights or interconnections
Axon	Output

Table III.1: Biological & Artificial Neuron

III.3.5 The Perceptron Model

The most commonly used term in Artificial Intelligence and Machine Learning is Perceptron. It is the beginning step of learning coding and Deep Learning. We can also consider it a single-layer neural network with four main parameters: input values¹, weights² and Bias³, and an activation function. [45]

III.3.6 Activate Functions

Activation functions are mathematical equations that determine the output of a neural network used at the end of a hidden. It is also known as **Transfer Function**. [46]

The Activation Functions can be basically divided into 2 types:

1. Linear Activation Function:

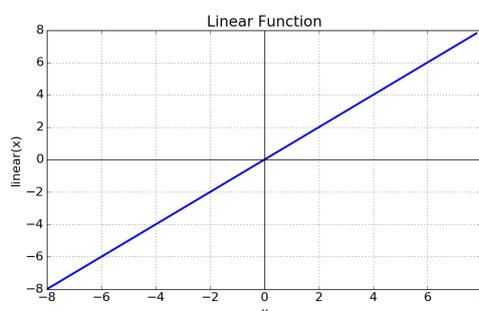


Figure III.6: Linear Activation Function [46]

¹Consists of one or more input neurons, which receive input signals from the external world or from other layers of the neural network. [45]

²Each input neuron is associated with a weight, which represents the strength of the connection between the input neuron and the output neuron. [45]

³A bias term is added to the input layer to provide the perceptron with additional flexibility in modeling complex patterns in the input data. [45]

2. **Non-Linear Activation Functions:** Here are the most common ones:

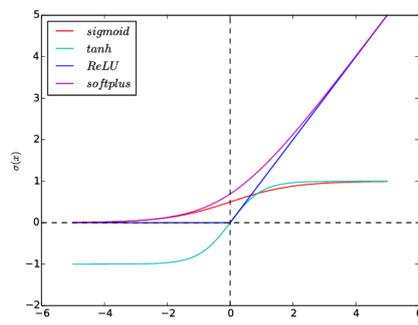


Figure III.7: Common Non-Linear Activation Functions[47]

III.4 Convolutional Networks

Similar to traditional neural networks, Convolutional networks use **mathematical operations** to process and transform data. However, unlike general neural networks, which treat input data as a flat vector. Convolutional networks have proven to be particularly effective in image recognition and classification tasks, where they can automatically learn to identify complex patterns and features in images[48]. CNN is one of the best Deep Learning algorithms that is used in analyzing medical images, since it maintains the spatial relationships after filtering the input images. These relationships are extremely significant in the field of medical analysis.[49]

III.4.1 Architecture of CNN

A basic CNN consists of an input layer, output layer, and hidden layers, including Convolution layers, ReLU, pooling layers, and fully connected layers III.8: [49]

- **Input Layer**

This is the first layer in the neural network. It takes input signals (values) and passes them on to the next layer of the network, which is typically a convolutional layer. It doesn't apply any operations on the input signals (values) and has no weights and biases values associated. [50]

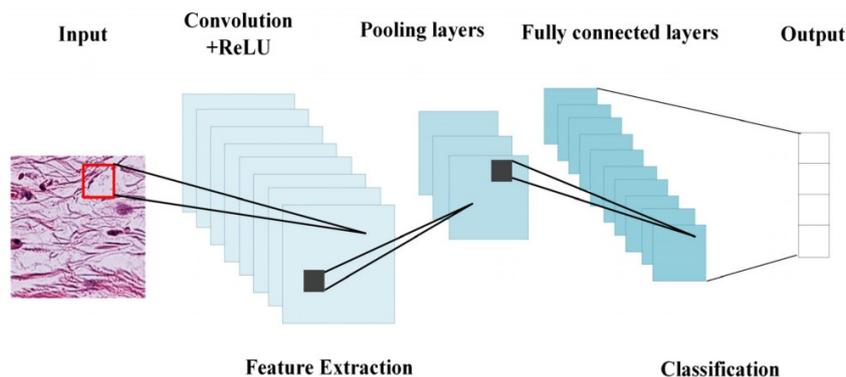


Figure III.8: Convolutional Neural Network Architecture[49]

• **Convolution layer**

The Convolutional layer is a crucial element in the Convolutional neural network. This layer generates **feature maps**⁴ by using multidimensional filters on the input data. Typically, models containing multiple Convolutional layers allow the emergence of different features, while also reducing the received data based on the size of the filter. A new image is obtained by removing more characteristic features in the image.[51]

Consider the following 5x5 image. There’s also a filter matrix with a dimension of 3x3. Slide the filter matrix over the image and compute the dot product to get **the Convolved feature matrix** (output).

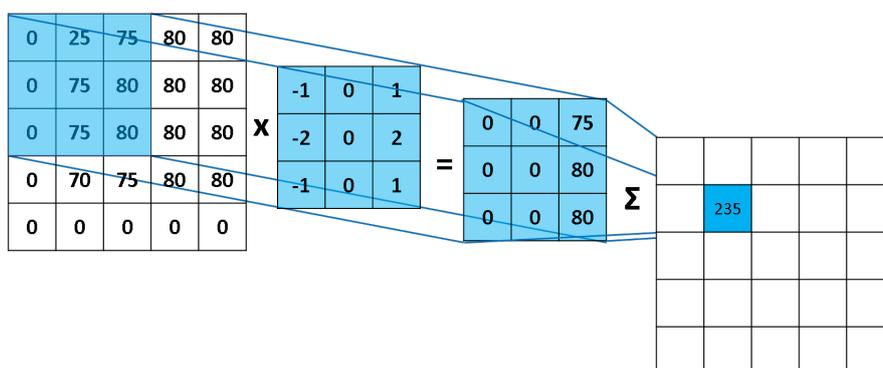


Figure III.9: Example of Convolutional Operation[52]

⁴refers to the output of a particular layer in the network determined by the dimensions of the input data, the filter/kernel size, and the padding and stride used in the convolution operation.

• **ReLU layer**

(Rectified Linear Unit) is a popular activation function proposed in 2010 that maps any number to zero if it is negative and otherwise maps it to itself that is shown in Figure III.10.

The ReLU activation was first used in *AlexNet*.

The ReLU function has been found to be very good for networks with many layers because it can prevent vanishing gradients when training deep networks. [53]



Figure III.10: ReLU Layer [54]

• **Pooling Layer**

Pooling layers section helps to reduce the number of parameters and computation required in the subsequent layers this preventing **Overfitting**⁵ and improving the network’s efficiency. Pooling can be done in various ways, such as:

Max Pooling

Average Pooling

Max pooling takes the largest element from the rectified feature map. Taking the largest element could also take the average pooling.

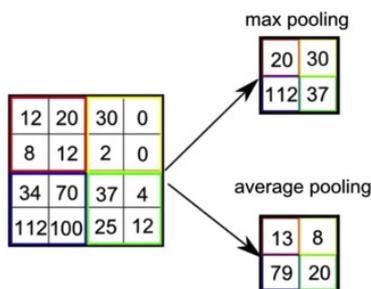


Figure III.11: Max Pooling and Average Polling [55]

⁵is a phenomenon that occurs when a machine learning model learns the training data too well to the extent that it starts to perform poorly on unseen or new data.

However, too much pooling can result in a **loss** of information, so it is important to choose the appropriate pooling size and stride based on the problem at hand.[56]

- **Fully connected**

In the last layer, we flattened our matrix into **vector** and feed it into a fully connected layer like a neural network layers use feature information to obtain a final class label. There exist n nodes (n is equal to the number of classes). Nodes in the last layer of fully connected layers usually have a special activation function. This activation function is usually a *softmax* function or in the case of binary classification, a *sigmoid* function. [56]

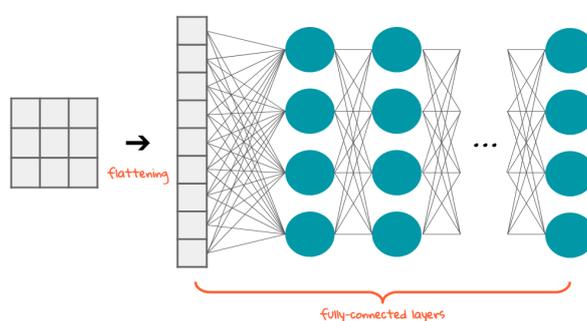


Figure III.12: FC Layer[57]

- **Output layer**

The output layer is the final layer in a neural network, where the network produces its predictions or classifications. With this layer we can get desired number of values and in a desired range. [50]

III.4.2 Popular CNN Architectures

ImageNet dataset

The IMAGENET dataset was first developed for visual object recognition built with WordNet which is a lexical database for the English language. A total of 1000 classes are presented by over 14 million images. Since 2010, an annual IMAGENET Large Scale Visual Recognition Challenge (ILSVRC) has been taking place. It is a competition where research teams evaluate their algorithms on the given dataset, and compete to achieve **higher accuracy** on several visual recognition tasks.

It's fair to say that IMAGENET has played an important role in the advancement of computer vision, it has been used to train many popular computer vision models.[58]

Here are the five common deep neural networks based on CNN model:

1. LeNet5

LeNet-5 is a convolutional neural network that was developed in 1998. It is a seven-layer network that was designed to classify **handwritten digits**. It has been used by several banks for recognizing hand-written numbers on checks.

As computational hardware started improving in capability, CNNs started becoming popular as an effective learning approach in the computer vision and machine learning communities and laid the foundation for many of the modern deep learning architectures that are used today. [53]

2. AlexNet

AlexNet is a Convolutional neural network that was developed in 2012. It was the winning entry in the ImageNet Large Scale Visual Recognition Challenge, which was a competition to classify images into 1000 categories.

One of the key innovations of *AlexNet* was the use of **data augmentation** techniques, such as horizontal, flipping and random cropping, also introduced the use of **graphics processing units** (GPUs) to accelerate the training process. Its success demonstrated the potential of deep learning achieve a competitive performance in classification compared to other kinds of networks.[53]

3. VGGNet

Developed by researchers at the Visual Geometry Group (VGG) from the University of Oxford in 2014. It achieved a top-5 error rate of 7.3%, which was the second best result in the competition. The main contribution of *VGGNET* is that it shows that the **depth** of a network is a critical component to achieve better recognition or classification accuracy in CNNs. The VGG architecture consists of two Convolutional layers both of which use the *ReLU* activation function, which is followed by a single max pooling layer and several fully connected layers, which also use the *ReLU* activation function. The final layer of the *VGGNet* model is a *Softmax* layer for classification.[49]

4. ResNet

Short for *Residual Network* is a deep Convolutional neural network architecture proposed by researchers at Microsoft Research in 2015. It achieves a top-5 error rate of 3.6% which beats human-level performance on this dataset.

ResNet is developed with many different numbers of layers: 34, 50,101, 152, and even 1202. The popular *ResNet50* contained 49 convolution layers and 1 fully connected layer at the end of the network.[53]

5. DenseNet

DenseNet proposed in 2017 which consists of densely connected CNN layers, it consists of several dense blocks and transition blocks which are placed between two adjacent dense blocks, it has achieved state-of-the-art performance on a wide range of computer vision tasks including image classification, object detection, and semantic segmentation. It has been used in various real world applications such as medical imaging, facial recognition and autonomous vehicles.[53]

III.5 Transfer Learning

Transferring knowledge from one expert to another is known as transfer learning. In deep learning techniques, this approach is utilized where the CNN is trained on the base dataset (source domain), which has a large number of samples (e.g ImageNet). Then, the weights of the convolutional layers are **transferred** to the new small dataset (target domain). Using pre-trained models for classification tasks can be divided into two main scenarios: freezing the layers of the **pretrained** model and **fine-tuning** the models. [59]

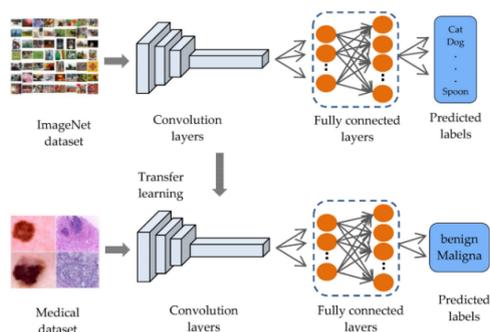


Figure III.13: Transfer learning from ImageNet[60]

III.6 Ensemble Learning

Ensemble can be considered a cooperation of the group of models to solve a problem. Process of problem modeling is quite challenging as includes many entities that cooperate between themselves. One of the main challenges is permanently changing states of entities. They can become as part of the collaboration or leave it, as they can change their state and adapt to new conditions.

Although there are different methods that can be used for ensemble modeling, it is essential to **combine** them to achieve better results. [61]

We can categories the ensemble methods as Simple ensemble methods and advanced ensemble methods [62]:

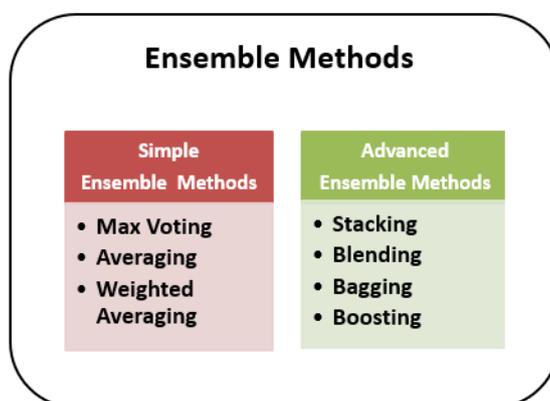


Figure III.14: Ensemble Methods[62]

Conclusion

In this chapter, we have discussed of basic notions such as AI, machine learning and deep learning. Specifically, we provided an overview of convolutional neural networks (CNNs), which are commonly used for image recognition and processing tasks. We examined the fundamental architectures of CNNs, including convolutional layers, pooling layers, and fully connected layers. In addition, we discussed two important machine learning concepts: transfer learning and ensemble learning.

Chapter IV

Stat Of the Art

Introduction

Deep learning, particularly CNN models has made remarkable strides in the field of image classification, histopathology images have become a significant resource for scientists and research teams worldwide in the diagnosis of colorectal cancer (CRC), sparking interest among researchers to integrate these models into specialized medical applications, such as the early detection of colon cancer. The utilization of such models empowers doctors with improved abilities to diagnose, detect, and treat this condition.

Given the critical importance of the subject, it has garnered significant attention in scientific research. A multitude of studies have been conducted, and this chapter specifically highlights relevant previous research that addresses the state-of-the-art advancements pertaining to the issue presented in our research document.

IV.1 Related Work

The use of deep learning models, in particular Convolutional Neural Network (CNN) models, is driven primarily by their demonstrated efficacy in image categorization, in particular in addressing the difficulties faced by doctors in the identification of colon cancer. We conducted a thorough examination and analysis of prior research, with a particular emphasis on deep learning methods, to solve this issue.

IV.1.1 Hawraa et al. (2017)

“Classifications of Multispectral Colorectal Cancer Tissues Using convolution Neural Network”

In this study [86], the authors proposed the use of CNNs to model the progression of CRC tissues based on multi spectral microscopy images. Firstly they acquired a Multispectral CRC biopsy images and used an optical microscope system with a charge-coupled device (CDD) camera a liquid crystal tunable filter (LCTF), then they used These images as input to the CNN classifier, both for training the model and classifying the tissue type of a new images, They used a semi-automatic segmentation technique based on the active contour algorithm, which can accurately delineate the boundaries of irregularly shapes and has been shown to perform well for tissue segmentation. They obtained the Histological CRC data from an atomical pathology at the CHU Nancy Brabois Hospital, the size of Multispectral images is 512x512 Pixels were then they acquired using a CCD camera and integrated there with a LCTF in an optical microscopy system, for each tissue sample, they used LCTF to provide 16 multi spectral images, they used three pathological tissue types which are BH Benign hyperplasia (10 Samples), IN Intraepithelial neoplasia (10 Samples) and CA Carcinoma (10 Samples). The approach achieved a 99.17% accuracy rate.

IV.1.2 Francesco et al. (2019)

“Colorectal Cancer Classification using Deep Convolutional Networks”

In this study [64], authors proposed a transfer learning approach based on VGG16 as a pre-trained model which is a pretrained CNN with fine-tuning of the stages after POOL3 block (fine-tune CNN), For the purpose of adapt the pretrained VGG16: they initialized all weights of the network to the ones determined on the ImageNet Dataset, they continued the backpropagation on CRC Dataset, they kept the weights of the first blocks of the net frozen (Froze all the weights up-to the most discriminative Pooling Layer (POOL3), all the computational power can be devoted to the training of top most layers, which are expected to learn high-level task specific features for CRC Images Classification. They used a public CRC Tissue Images for researchers, This dataset contains 13500 image. The size of each image is 1089x1089 pixels, classified into three classes such as Healthy tissue, Adenocarcinoma, Tubulovillous adenoma. The use of fine-tune CNN achieved 96.82% accuracy rate and consume 2 hours as a training time, the use of full-train CNN achieved 90.37% accuracy rate and consume 8 hours as a training time.

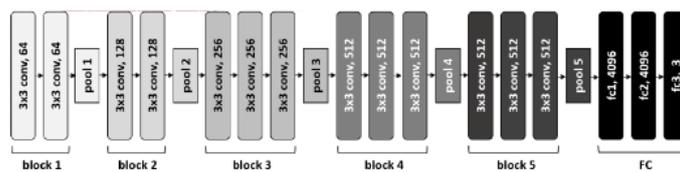


Figure IV.1: CNN architecture[64]

IV.1.3 Amina et al. (2021)

“Deep learning for colon cancer histopathological images analyses”

In this study [85], authors proposed a Patch-level classification of colon cancer histopathological images: the purpose of this task is to ensure accurate classification of histopathological images relying on recent DL models, and a pixel-level segmentation of colon cancer histopathological images, they used both of UNET and SEGNET models as a deep semantic segmentation networks, the purpose of the use of SEGNET and UNET is to generate a binary mask that highlights the colon cancer regions in the slides. SEGNET is an architecture relies on the idea of “reflecting” a fully connected network (FCN), in other words, it creates a mirror of each layer and each kernel. UNET is an architecture relies on the skip connections for image segmentation. They used four datasets in this research which is AiCOLO-8, AiCOLO-2, CRC-5000 [91] and CRC-100k [94], the main dataset utilized is AiCOLO-8 contains 396 slides, the size of each image is 224x224 pixels, classified into eight classes such as Tumour, Necrosis, Immune, Stroma, Fat, Tissue, Trash, and Background. The AiCOLO-2 is the same dataset the only difference is in segmentation of the classes, this data has only two classes which is Tumour and Non-Tumour. The accuracy of UNET and SEGNET strategies with the use of AiCOLO-2 dataset in the from scratch are 76.18%, 81.22% respectively and in the fine-tuning are 32.17%, 46.23% respectively.

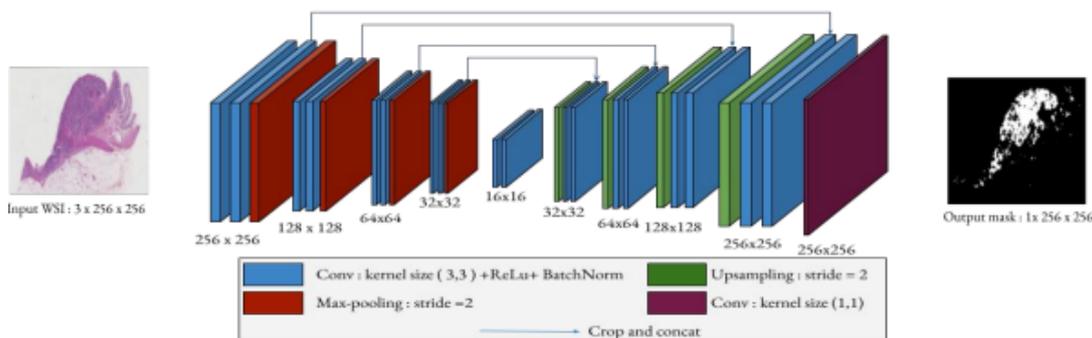


Figure IV.2: Architecture of the used UNET [85]

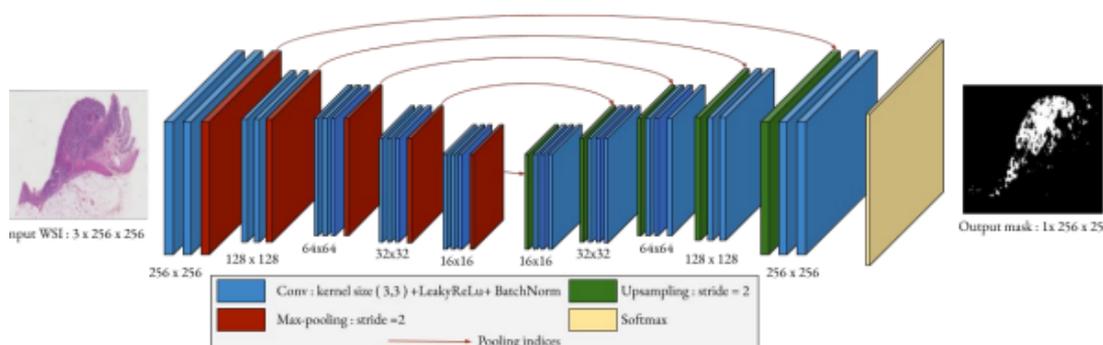


Figure IV.3: Architecture of the used SEGNET [85]

IV.1.4 Eduardo et al. (2021)

“Two Ensemble-CNN Approaches for Colorectal Cancer Tissue Type Classification”

In this study [65], authors proposed Mean-Ensemble-CNN and NN-Ensemble-CNN approaches, which are based on combining four trained CNN architectures. The trained CNN architectures are ResNet101, ResNeXt50, InceptionV3 and DenseNet161. In the Mean-Ensemble-CNN approach, they combined the CNN architectures by averaging their predicted probabilities. In the NN-Ensemble-CNN approach, they combined the deep features from the last fully connected layer of each trained CNN architecture, then feed them into four layers NN. They used two Dataset which are Kather-CRC-2016 [91] and CRC-TP [92], Kather-CRC-2016 contains 5000 images, the size of each image is 150x150 pixels, classified into eight classes such as (Tumor, Stroma, Complex, Lympho, Debris, Mucosa, Adipose, Empty) each tissue type has 625 samples, and CRC-TP [92] contains 280k images, the size of each image is 150x150 pixels, classified into seven classes such as (Tumor 50.000, Complex Stroma 50.000, Stroma 50.000, Smooth Muscle 50.000, Benign 30.000, Inflammatory 30.000, Debris 20.000). The use of NN-Ensemble-CNN achieved on Kather-CRC-2016, CRC-TP 97.50% and 86.99% respectively accuracy rate, The use of Mean-Ensemble-CNN achieved on Kather-CRC-2016, CRC-TP 97.10% and 87.27% respectively accuracy rate.

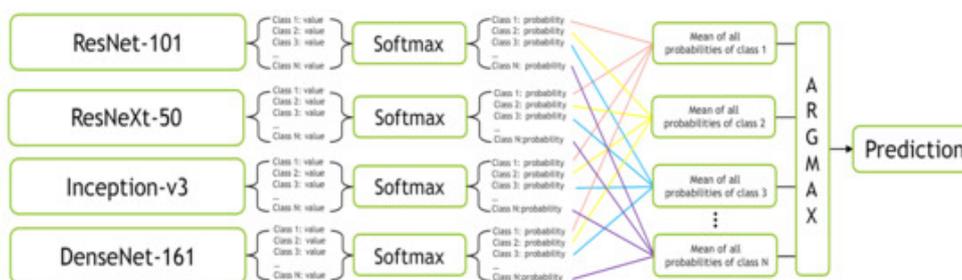


Figure IV.4: The proposed Mean-Ensemble-CNN approach [65]

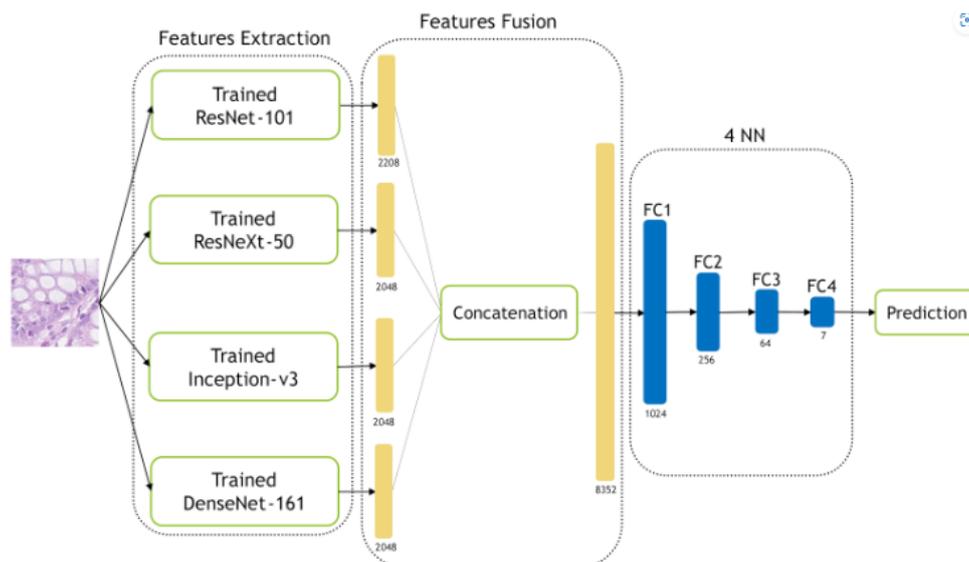


Figure IV.5: The proposed NN-Ensemble-CNN approach [65]

IV.1.5 Min-Jen and Yu-Han (2021)

“Deep Learning Techniques for the Classification of colorectal Cancer Tissue”

In this study [33], authors proposed a classification methodology based on the selected optimizer and modified the parameters of CNN methods, they adopted the transfer learning of deep learning architecture for the classification of colorectal cancer tissue. They used three training network methods optimizer: SGDM (Stochastic gradient descent with momentum), RMSProp (Root mean square propagation) and Adam (Adaptative moment estimation). They took (AlexNet, SqueezeNet, VGG19, GoogleNet, ResNet50) as pretrained models. They utilized Kather-CRC-2016 [91], CRC-VAL-HE-7K [81] and NCT-CRC-HE-100K [94] datasets, NCT-CRC-HE-100K is include 100,000 images, the size of images is 224×224 pixels, in nine different tissue classes which are ADI, BACK, DEB, LYM, MUC, MUS, NORM, STR, TUM. This architecture achieved 97.14% as an accuracy rate after the test of the three optimizer, this accuracy related to RMSProp optimizer.

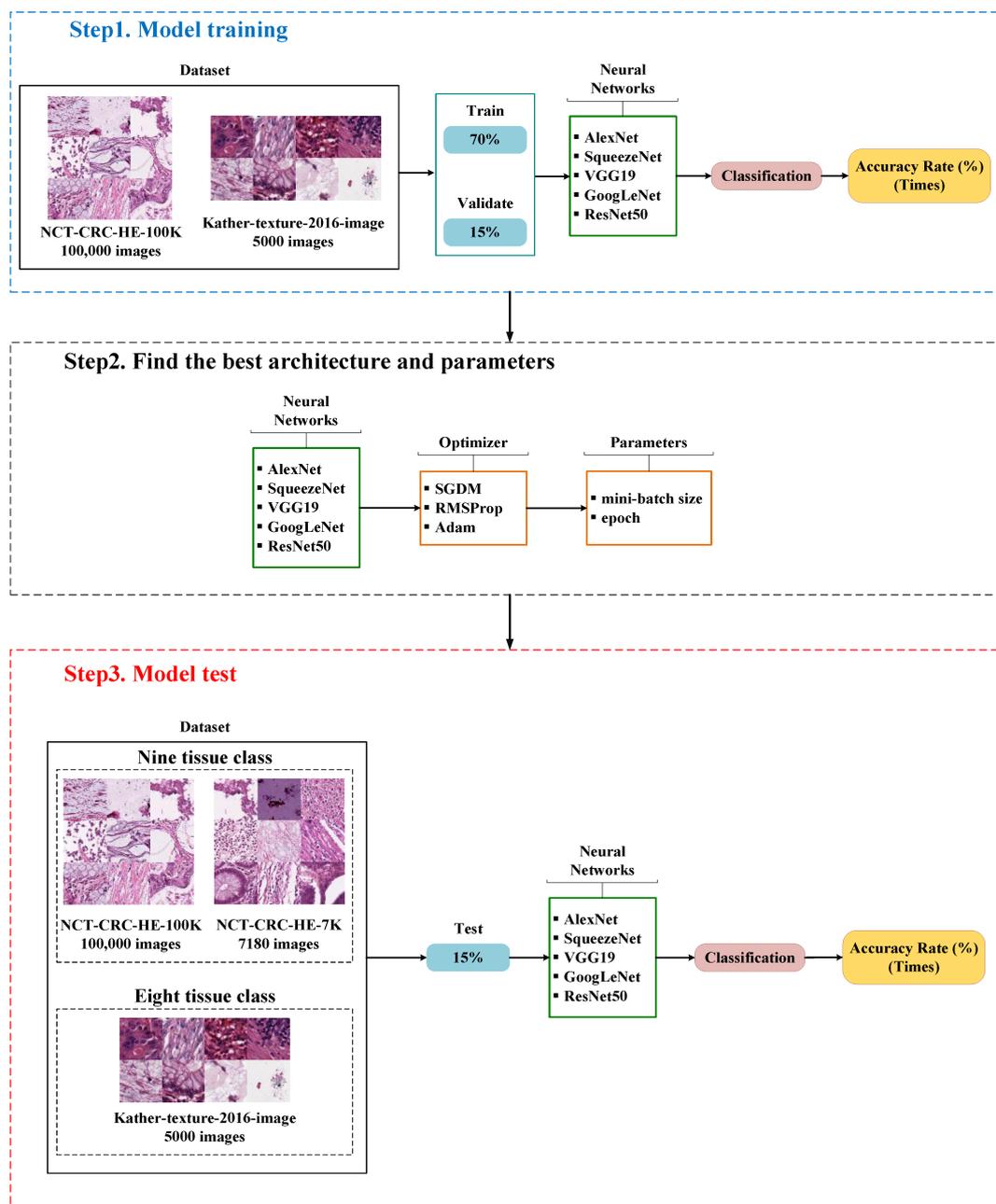


Figure IV.6: Deep learning structures to identify colorectal cancer tissue in this study [33]

IV.1.6 Ahmed et al. (2022)

“An Efficient deep learning approach for Colon Cancer Detection”

In this study [63], authors proposed a new lightWeight approach based on CNN which is a new end-to-end lightWeight deep learning approach based on CNN for efficient colon cancer

detection, it is less complex, The model IV.7 is composed of four convolution blocks, each of which contains a max pool layer. There is a flatten layer on the bottom and a fully connected layer activated by a ReLU activation function. In addition, the dropout layer is added after the flatten layer with a probability of 0.5 and finally SoftMax layer is added for classification. The Adam optimizer and Cross entropy loss function are used for model optimization, they used a collection of histopathological images from LC25000 dataset [90], This dataset contains 10,000 histopathological images of colon tissue classified into two classes such as benign colon (5000 images) and colon adenocarcinomas (5000 images). The size of each image is 768×768 pixels in JPEG format. They divided the data into 6400 for train, 1600 for validation and 2000 for test. The approach achieved a 99.50% accuracy rate.

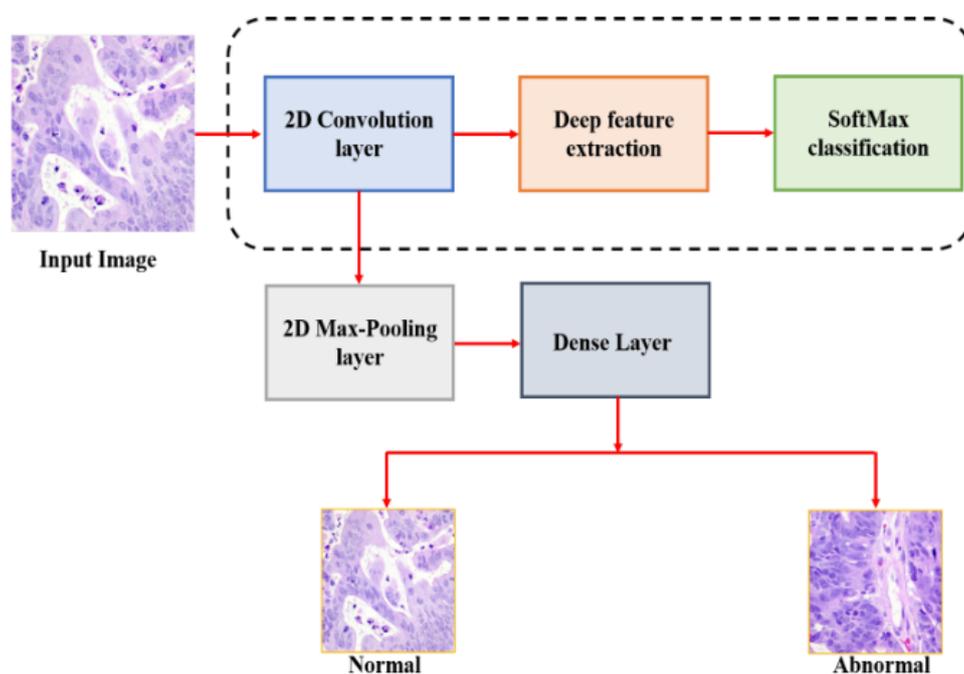


Figure IV.7: General Architecture of the Proposed Approach [63]

IV.1.7 Albashish (2022)

“Ensemble of adapted convolutional neural networks (CNN) methods for classifying colon histopathological images”

In this study [84], the author propose E-CNN (product rule) and E-CNN (majority voting), he adapted pretrained CNN models to classify colon cancer histopathology images into various classes, he constructs an ensemble of the pretrained models with fine-tuning for the colon diagnoses based on histopathological images. Mainly, four pretrained models (DenseNet121, MobileNetV2, InceptionV3 and VGG16) are fine-tuned, and then their predicted probabilities are

fused to produce a final decision for a test/image, the pretrained models utilize transfer learning to mitigate these models weights to handle a similar classification task. Ensemble learning of pretrained models attains superior performance for histopathological image classification. On the one hand, the majority voting is based on the prediction value of the base classifier. On the other hand, the product rule is based on the probabilities of the base classifiers. He use Kather-CRC-2016 [91] and Stoean [93] datasets, stoean is an histology images dateset were collected from the hospital of Craiova.Romania, contains 357 images, classified into four classes such as (normal cancer-Grade0, cancer-grade1, cancer-grade2, and cancer-grade3. The size of each image is 800x600 pixels. The approaches E-CNN(product) and E-CNN(majority voting) achieved 95.20% and 94.52% accuracy rate respectively with the use of Stoean dataset.

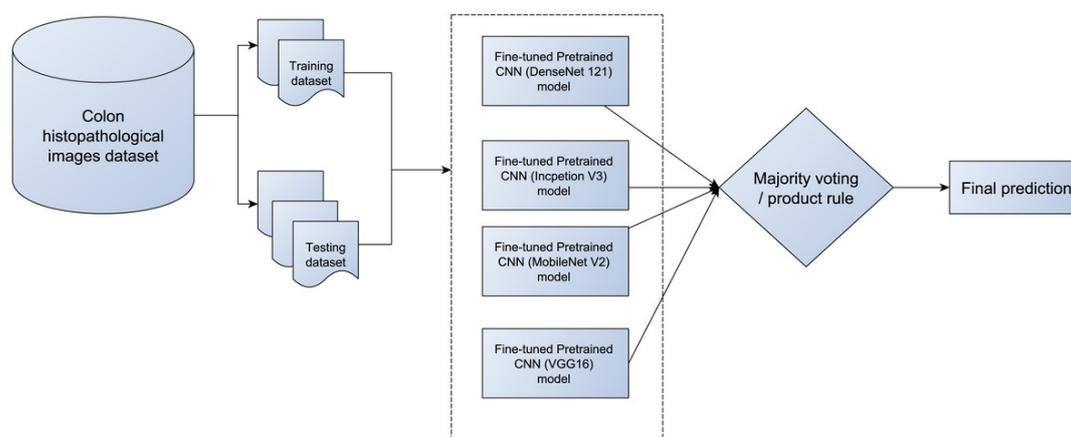


Figure IV.8: The proposed E-CNNs with the four adaptive pretrained models (DenseNet121, MobileNetV2, InceptionV3, and VGG16) [84]

Conclusion

In this chapter, we have established a state-of-the-art on colon cancer prediction which represents a comparative study of all the related works which we have abbreviated, we have presented this in a detailed table describing, outlining the different approaches discussed in the summarized papers, Each approach is accompanied by a succinct paragraph summarizing its key points.

The next chapter will focus on presenting our own approach and delineating its distinct steps.

Chapter V

Experiments and Results

Introduction

In this chapter we will discuss about software tools and the most popular libraries using python as a programming language in Google colab and jupyter notebook that are used to build and train our model, second part contain our CNN Models and a humble discussion about the results.

V.1 Programming languages and frameworks:

V.1.1 Python

Python is a high-level, interpreted programming language that is widely used for web development, scientific computing, data analysis, artificial intelligence, and many other applications. It was created by *Guido van Rossum* and first released in 1991. It has a rich ecosystem of libraries and frameworks for developing and implementing machine learning models. V.1 [66]

V.1.2 Numpy

(Numerical Python extension) is an open-source library that enables numerical computing in Python and is one of the most popular Python libraries for machine learning, useful for fundamental scientific computations. It was created in 2005 as an open-source project on *GitHub*, built on the early work of *Numeric* and *Numarray* libraries.[68]



Figure V.1: Top 10 machine learning libraries in Python[67]

V.1.3 OpenCV

(Open Source Computer Vision Library) is an open-source computer vision and machine learning library developed by *Intel* that has more than 2500 optimized algorithms, which includes a comprehensive set of both classic and state-of-the-art computer vision and machine learning algorithms, including object detection, face recognition, image processing, and robotics. [69]

V.1.4 Matplotlib

Matplotlib is an open-source library that aids in graph plotting. Matplotlib became one of the most extensively used plotting libraries along side the Python programming language for data and computational graph plotting. It is platform independent and can be run on *Windows*, *Mac OS*, and *Linux*. [70]

V.1.5 TensorFlow

TensorFlow is an open-source machine learning framework developed by *Google* in 2015, TensorFlow is at present, the most popular software library. There are several real-world applications of deep learning that make TensorFlow popular. Being an Open-Source library for deep learning and machine learning, TensorFlow plays a role in text based applications, image recognition, voice search, and many more. [71]

V.1.6 Keras

keras is a deep learning framework for Python that provides a convenient way to define and train almost any kind of deep learning model. Keras was initially developed for researchers, with the aim of enabling fast experimentation. Keras is used at *Google*, *Netflix*, *Uber*, *CERN*,

Yelp, *Square*, and hundreds of startups working on a wide range of problems. Keras is also a popular framework on Kaggle, the machine learning competition website, where almost every recent deep learning competition has been won using Keras models.[32]

V.1.7 Tkinter

Tkinter is the standard GUI library for Python. Python when combined with Tkinter provides a fast and easy way to create GUI applications.

Tkinter provides a powerful object-oriented interface to the Tk GUI toolkit, and it a great choice for beginners and experienced programmers alike. [72]

There are several development tools available for building and training CNN models, each with its own unique features and benefits. Some of the commonly used development tools in CNN models include:

V.1.8 Colab

 Google Colab is a free online Jupyter notebook environment that allows you to run and share code in Python, R, and other programming languages. It is a great resource for beginners and professionals alike, as it provides a convenient way to write, run, and debug code in the cloud without having to install any software on your local machine. Free GPUs and TPUs for running computationally intensive tasks are accessible which make it very desirable platform for data analysis and machine learning tasks.[73]

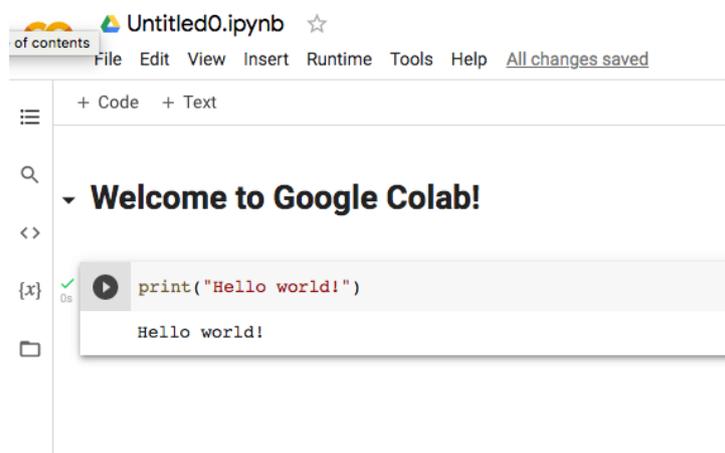


Figure V.2: Google Colab[74]

V.1.9 Anaconda Navigator



Anaconda is a popular open-source distribution of the Python and R programming languages comes with over 1,500 packages preinstalled for scientific computing and data science. It includes a suite of tools and libraries for data science, machine learning, and scientific computing, making it a powerful tool for researchers, developers, and data scientists.[75]

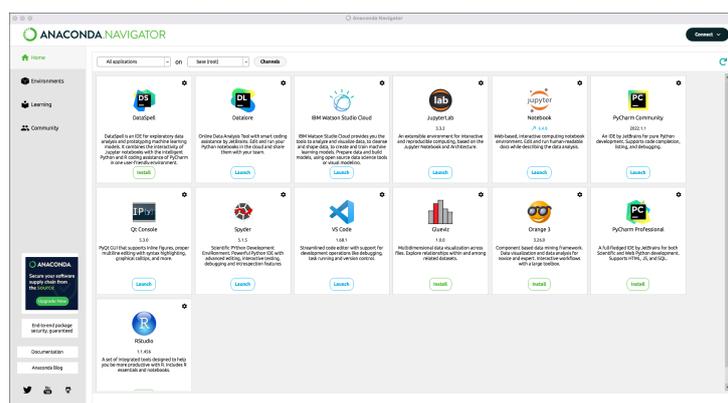


Figure V.3: Anaconda Navigator[76]

V.1.10 Jupyter Notebook



Jupyter Notebook is an open source web application that allows you to create and share documents that contain live code, equations, visualizations, and narrative text. Jupyter Notebook is a popular tool for data scientists and machine learning practitioners because it provides an interactive and flexible environment for working with data and building machine learning models.[77]

V.2 Kaggle

Kaggle is a platform for data scientists and machine learning enthusiasts to explore, share, and compete with data analysis and modeling projects. Kaggle hosts a wide range of datasets that users can use for their data analysis and machine learning projects. The datasets are generally provided in a variety of formats, including *CSV*, *JSON*, *SQL*, and more.[78]

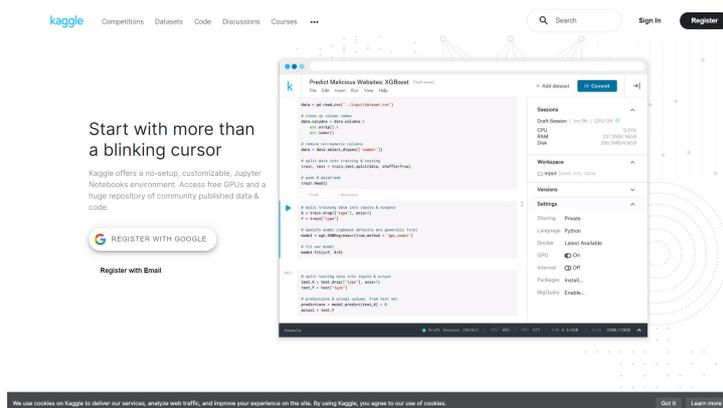


Figure V.4: Kaggle interface[79]

V.3 Methodology

V.3.1 Data description

Data constitute an inevitable part of a DL algorithm, from which the model can learn concealed information or underlying statistics available within them. Data can be in any form such as numbers, audio, images, and videos. [80]

CRC-VAL-HE-7K¹ [81]

In this experiment, we used the open histological dataset of nine tissue classes from “CRC-VAL-HE-7K”, which contained 7180 images. The dimensions of all the images were 224×224 pixels (V.5). The nine classes are categorized as following: [49]

0	MUC	mucus is produced by many tissues in the body, and acts as a protective force.
1	DEB	debris is widely used in histopathology and diagnoses.
2	BACK	histological image background.
3	NORM	Normal tissue refers to healthy and non-pathological tissue.
4	LYM	lymphocytes are the main type of cells found in the lymphatic system.
5	TUM	epithelium tissues of adenocarcinom.
6	ADI	adipose tissue is mainly composed of adipocytes.
7	MUS	smooth muscle, found in the intestines, blood vessels, and uterus.
8	STR	stroma tissues associated with cancer.

Table V.1: The nine classes of database

¹CRC: Colon Cancer, VAL: Validation, HE: Hematoxylin and Eosin, 7K: Represents the number 7000 images

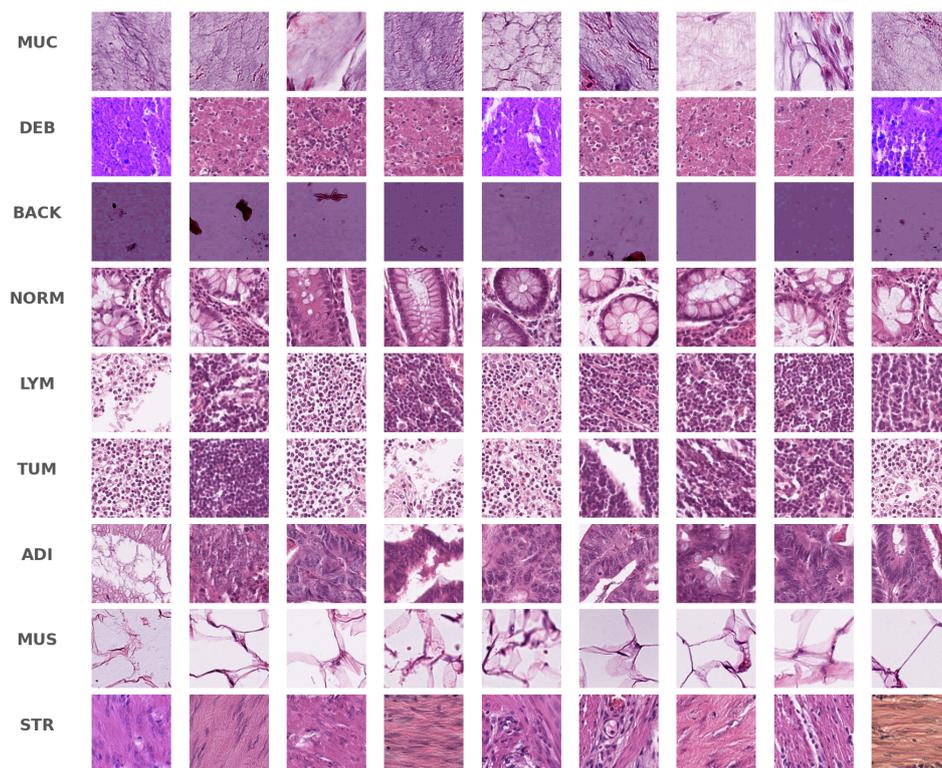


Figure V.5: The first 9 images of every tissue class in our Database

V.3.2 Data Split

We Split Our Database into three data stores: 70% Train set, 15% Validation set and 15% for testing.

This is done with the following code V.6:

```
base_dir = '/content/crc-val-he-7k'
input = os.path.join(base_dir, "CRC-VAL-HE-7K")

# split data into training, vlaidation and testing sets

splitfolders.ratio(input , output="DataSplit", seed = 101, ratio=(0.7, 0.15, 0.15))

data_dir = os.path.join('/content/drive/MyDrive', 'DataSplit')

# Define train, valid and test directories
train_dir = os.path.join(data_dir, 'train')
valid_dir = os.path.join(data_dir, 'val')
test_dir = os.path.join(data_dir, 'test')
```

Figure V.6: Data Split code

V.3.3 Data Augmentation

We used Data augmentation in Our Database for creating new data from the original data by manipulating them in different ways such as resizing, flipping, rotating..etc This is done with the following code V.7:

```
# Define train, valid and test directories
train_dir='/content/DataSplit/train'
valid_dir = '/content/DataSplit/val'
test_dir = '/content/DataSplit/test'

# Train Image DataGenerator
trainGen= train_datagen.flow_from_directory ( train_dir,
                                             batch_size = 128,
                                             target_size = (224,224),
                                             class_mode = 'categorical',
                                             shuffle=True,
                                             seed=42,
                                             color_mode='rgb'
                                             )

validGen = valid_datagen.flow_from_directory(valid_dir,
                                             batch_size=128,
                                             target_size=(224,224),
                                             class_mode='categorical',
                                             shuffle=True,
                                             seed=42,
                                             color_mode='rgb'
                                             )

testGen = test_datagen.flow_from_directory(test_dir,
                                             batch_size=128,
                                             target_size=(224,224),
                                             class_mode='categorical',
                                             shuffle=True,
                                             seed=42,
                                             color_mode='rgb'
                                             )

)

# Data Augmentation
train_datagen = ImageDataGenerator(rescale=1./255.,
                                   horizontal_flip=True,
                                   vertical_flip=True,
                                   shear_range=0.4,
                                   width_shift_range=0.25,
                                   height_shift_range=0.25,
                                   rotation_range=45,
                                   fill_mode='nearest')
valid_datagen = ImageDataGenerator(rescale=1./255)
test_datagen = ImageDataGenerator(rescale=1./255)
```

Figure V.7: Data augmentation code

V.3.4 Hyperparameter

In our CNN models, we used several hyperparameter to control the training process and optimize the performance of the model. Specifically, we used:

Parameter	Description	Value
Image Size	Input	224x224
Filter size	Determines the size of the Convolutional filters that are used to extract features from the input data.	3x3
Batch Size	Specifies the number of training examples that are processed at once during each iteration of the training process.	128,32
Number of Epochs	Is one complete iteration through the entire training dataset.	16,12,5
Dropout	A regularization technique used to prevent over fitting.	0.5
Optimizer	algorithm used to optimize and improve the performance of the model during training .	Adam

Learning rate	Is a hyperparameter that controls how quickly the model learns. It determines the size of the steps taken during optimization to update the model's parameters.	0.0001
Callbacks	Callbacks are functions that are called at specific points during the model training process.	ModelCheckpoint, LambdaCallback, CSVLogger, EarlyStopping
Loss function	The loss function measures the difference between the predicted and actual values of the model.	Categorical Crossentropy

Table V.2: The Parameters used in the models

V.3.5 Evaluation Metrics

To evaluate the performance of the tested methods, we used the following classical metrics: In this work, we adopt accuracy to evaluate the performance of the tested methods, which is the most important performance measure. [82]

$$Accuracy = \frac{TN + TP}{TN + TP + FN + FP}$$

Where:

TN is the number of True Negatives.

FP is the number of False Positive instances.

FN is the number of The False Negative instances.

TP is the number of True Positive instances.

V.4 Implementation

V.4.1 First Model

In the first model we build a model composed of 4 blocs of convolution layers where the activation function that used is *ReLU* following by MaxPooling and we've added the padding² same argument to the Conv2D and we've kept the stride³ at 1. In the last, we add a neural network composed of three layers fully connected, the dropout layer is added with 0.5 probability and finally *SoftMax* layer is added for classification.(See figure V.8)

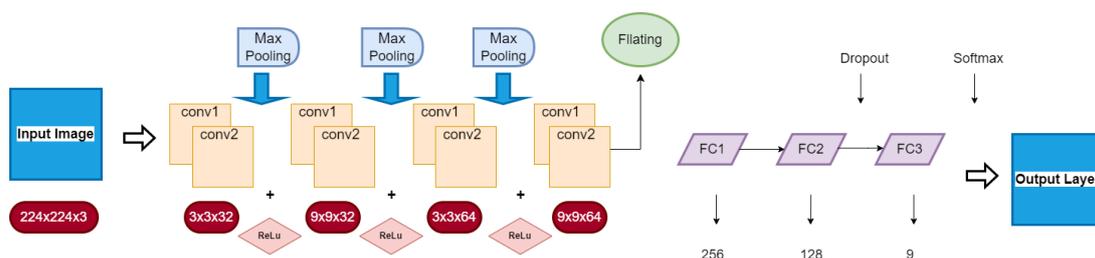


Figure V.8: General Architecture of the Model

V.4.2 Second Model

The second model is a transfer learning model based on VGG19 architecture which present in figure V.9. We used the pretrained VGG19 model as a base model and added several layers on top of it for fine-tuning.

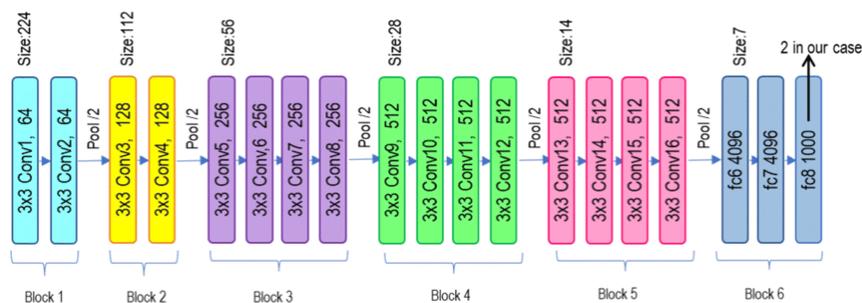


Figure V.9: VGG19 architecture [83]

The added layers include a **Flatten layer**, which flattens the output of the VGG19 model into

²technique used to adjust the size of the input data before applying convolutional operations.

³refers to the number of steps taken by the filter/kernel while moving across the input data during the convolution operation.

a 1D vector. Then, a **BatchNormalization** layer is added to normalize the activation of the previous layer at each batch.

We added several Dense layers with **ReLU** activation function after the BatchNormalization layer. These layers have 256 and 128 neurons, respectively, and are used to perform feature extraction and classification.

To reduce overfitting, we added a **Dropout** layer with a rate of 0.5 after the last Dense layer. The Dropout layer randomly drops out 50% of the neurons in the previous layer during training, preventing the model from overfitting to the training data.

Finally, we added a Dense layer with 9 neurons and *softmax* activation function. This layer outputs the final probabilities for the 9 classes in our classification task. During training, we optimized the model using an **Adam** optimizer, and the loss was calculated using **categorical cross-entropy**. The summary of the model show in figure V.10 :

```

Model: "ModelVGG19"
-----
Layer (type)                Output Shape              Param #
-----
vgg19 (Functional)          (None, 7, 7, 512)        20024384
flatten_2 (Flatten)         (None, 25088)             0
batch_normalization_2 (Batc (None, 25088)             100352
hNormalization)
dense_3 (Dense)              (None, 256)               6422784
batch_normalization_3 (Batc (None, 256)               1024
hNormalization)
dense_4 (Dense)              (None, 128)               32896
dropout_1 (Dropout)         (None, 128)               0
dense_5 (Dense)              (None, 9)                 1161
-----
Total params: 26,582,601
Trainable params: 6,507,529
Non-trainable params: 20,075,072

```

Figure V.10: VGG19 Summary

V.4.3 Third Model

The third model is an ensemble learning approach that combines the predictions of four pretrained models: a model built from *scratch*, a *VGG19* model, a *ResNet50* model, and an *InceptionV3* model.

```

ModelResnet = ResNet50(weights='imagenet', include_top=False, input_shape=(224,224,3), classes=9)

for layers in ModelResnet.layers:
    layers.trainable= False

opt= Adam(epsilon = 0.0001)
ModelResnetoutput =ModelResnet.output

resnet50 = Flatten() (ModelResnetoutput)
resnet50 = Dense(256, activation='relu') (resnet50)
resnet50 = Dense(128, activation='relu') (resnet50)
resnet50 = Dropout(0.3)(resnet50)
resnet50 = Dense(9,activation='softmax')(resnet50)

resnet50model = Model(inputs=ModelResnet.input, outputs=resnet50)

resnet_filepath = 'resnet50.hdf5'
resnet_checkpoint = tf.keras.callbacks.ModelCheckpoint(resnet_filepath, monitor='val_acc', verbose=1, save_best_only=True)
resnet_early_stopping = tf.keras.callbacks.EarlyStopping(monitor='loss', patience=3)
reduce_lr = ReduceLROnPlateau(monitor='val_loss', factor=0.05, patience=5, min_lr=0.000002)
csv_logger = CSVLogger('RESNET50_results.csv')
callbacklist = [resnet_checkpoint,resnet_early_stopping,csv_logger]

```

Figure V.11: ResNet model code

```

InceptionV3_model = InceptionV3(input_shape=(224,224,3),weights='imagenet', include_top=False)
for layers in InceptionV3_model.layers:
    layers.trainable= False

opt= Adam(epsilon = 0.0001)
InceptionV3_last_output = InceptionV3_model.output
InceptionV3_maxpooled_output = Flatten()(InceptionV3_last_output)
InceptionV3_x = Dense(256, activation='relu')(InceptionV3_maxpooled_output)
InceptionV3_x = Dense(128, activation='relu')(InceptionV3_x)
InceptionV3_x = Dropout(0.2)(InceptionV3_x)
InceptionV3_x = Dense(9, activation='softmax')(InceptionV3_x)
InceptionV3_model = Model(inputs=InceptionV3_model.input,outputs=InceptionV3_x)

inception_filepath = 'inceptionv3_'+'-saved-model-{epoch:02d}-loss-{loss:.2f}.hdf5'
inception_checkpoint = tf.keras.callbacks.ModelCheckpoint(inception_filepath, monitor='acc', verbose=1, save_best_only=True)
inception_early_stopping = tf.keras.callbacks.EarlyStopping(monitor='loss', patience=5)
csv_logger = CSVLogger('InceptionV3_results.csv')
callbacklist = [inception_checkpoint,inception_early_stopping,csv_logger]

```

Figure V.12: InceptionV3 model code

We have implemented two different ensemble methods V.13:

- **Average Method:**

In the average method, we take the output predictions of each model and calculate the average of those predictions. This is done by **summing up** the predictions of all models and **dividing** by the total number of models. The average prediction represents the final prediction of the ensemble model.

- **Weighted Averaging Method:**

In the weighted method, we assign **weights** to each model's predictions based on their importance or performance. These weights indicate the relative contribution of each model to the final prediction. we have defined a set of weights for each model, such as [0.1, 0.4, 0.3, 0.2]. The weights are **multiplied** with the corresponding model predictions, and the weighted predictions are then **summed up** to obtain the final prediction.

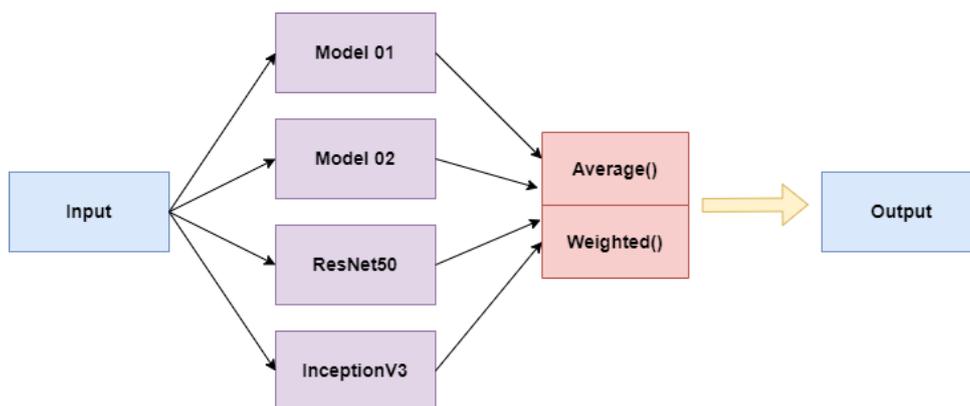


Figure V.13: Ensemble Learning model

V.5 Discussion of the Results

V.5.1 Results of the First Model:

Based on the results provided, it can be observed that the accuracy of the model on both training and validation sets increases with each epoch, indicating that the model is learning more information and improving its performance.

The training set achieved an accuracy rate of 88% with a training error rate of 35%, while the validation set achieved an accuracy rate of 89% with a validation error rate of 31%. (V.14 , V.15)

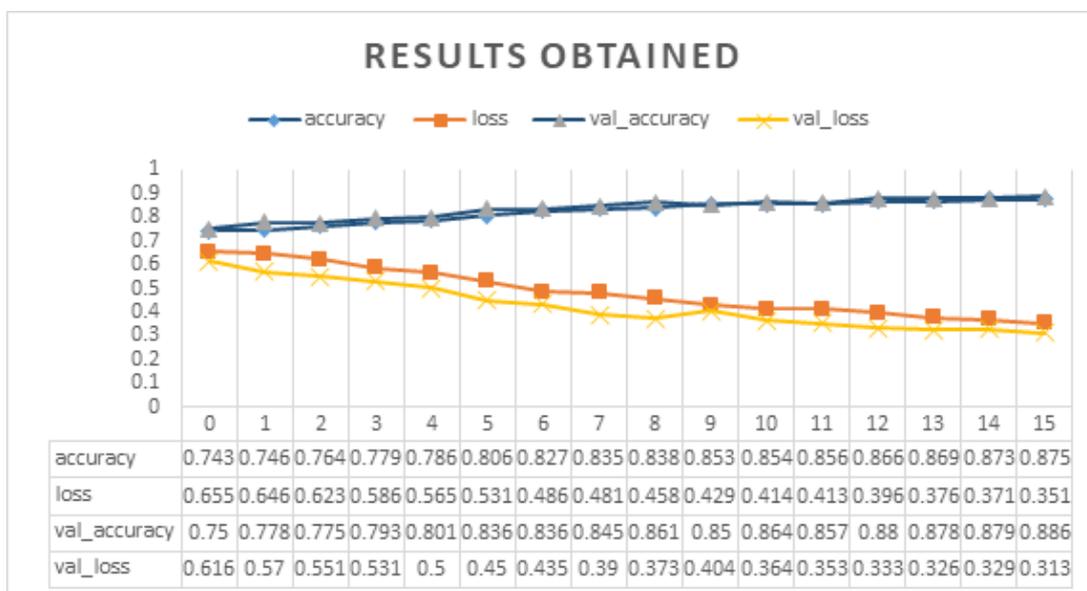


Figure V.14: Model 1 results

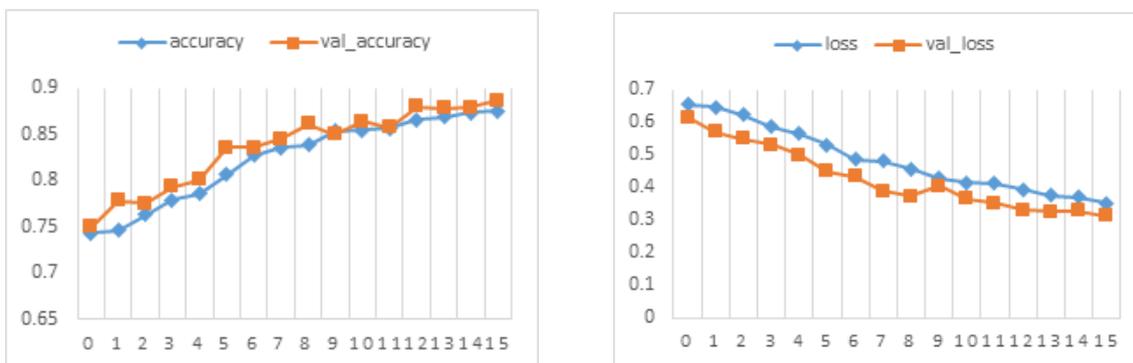


Figure V.15: Accuracy & Loss values for Model 1

V.5.2 Results of the Second Model:

When analyzing the results obtained, it can be noted that the model pretrained achieve a high accuracy than the first model. We got an error rate of 07% in train and validation, and an accuracy rate of 97%in train and 97% in validation. the results shown in V.16:

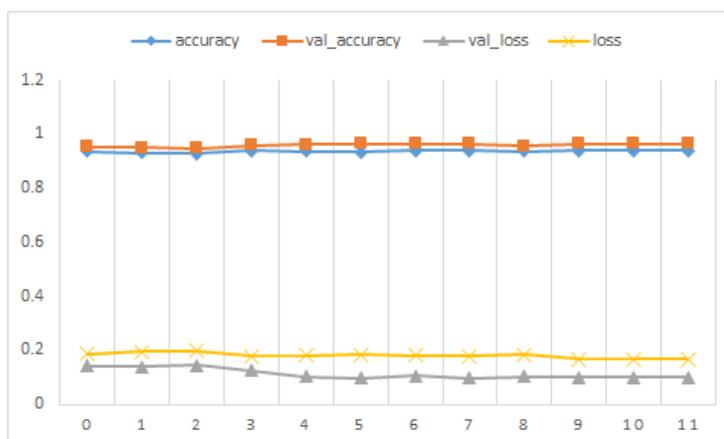


Figure V.16: Model 2 results

V.5.3 Results of the Third Model:

In order to improve the accuracy of the models, we train each model separately on our training dataset and using ensemble methods, the final model was able to achieve better results. The results of ResNet50 and InceptionV3 shown in figures:



Figure V.17: ResNet50 results

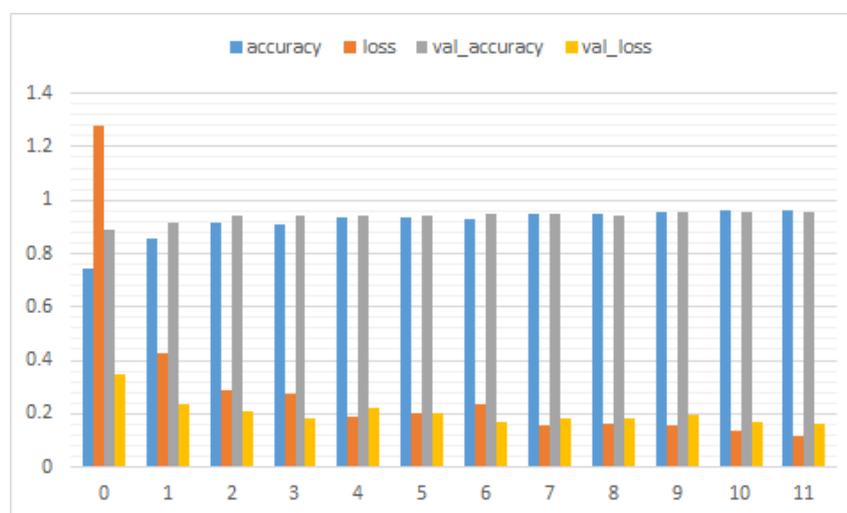


Figure V.18: InceptionV3 results

The outputs of the pretrained models are averaged using the *Average* layer from Keras to produce the final ensemble output, and also we used *weighted Averaging* method.

Using the **Average method**, our ensemble model achieved an accuracy rate of 96.75% on the training set with a loss of 0.29. On the validation set, the model achieved an accuracy rate of 97.20% with a loss of 0.26. For the testing set, the model achieved an accuracy rate of 98.62% with a loss of 0.25. V.19



Figure V.19: Results of the Average method

Using the **Weighted Averaging** method, our ensemble model achieved a training loss of 0.24 and an accuracy rate of 97.11%. On the validation set, the model achieved a loss of 0.20 and an accuracy rate of 98.32%. For the testing set, the model obtained a loss of 0.21 and an accuracy rate of 97.97%.V.20

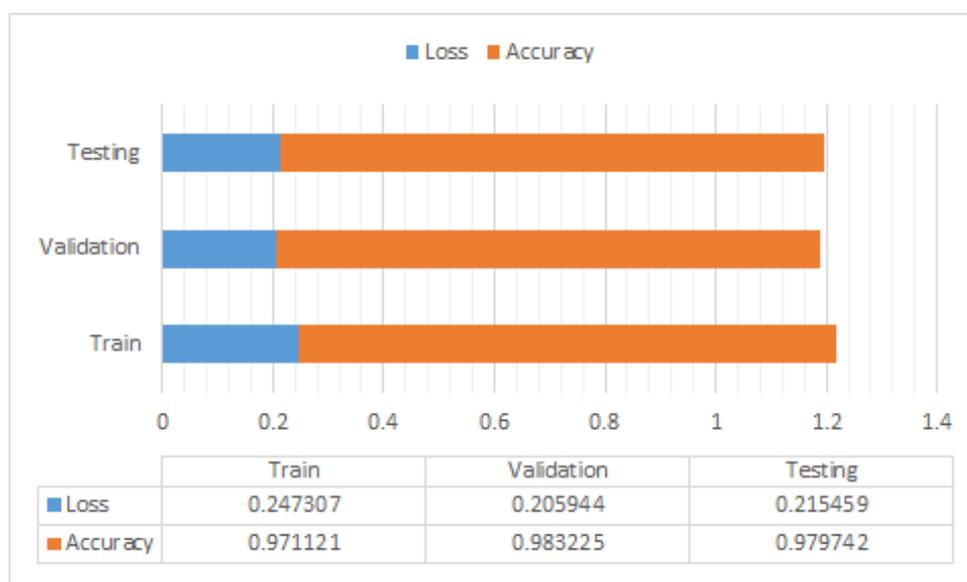


Figure V.20: Results of Weighted Averaging method

V.5.4 Results Comparison

As seen in the Table, the from scratch training has noticeable low accuracy compared to the transfer learning performance rates and the E-CNN model which achieved the highest accuracy compared with other models.

Models	Description	Accuracy	Validation accuracy	Error	Validation Error
Model 1	From Scratch	88%	89%	35%	31%
Model 2	VGG19	97%	97%	07%	07%
Model 3	Average()	96%	94%	29%	26%
	Weighted Averaging ()	97%	98%	24%	20%

Table V.3: The results of our Models

In this section, We will compare our best result with state-of-the-art methods.

Table contains the comparison between our proposed model and the state-of-the-art methods.

The comparison will be based on three key factors:

Pretrained CNN: models approved in ImageNet challenge.

Dataset: indicates the data sources used for the implementation of the approach for the prediction of colon cancer.

Results: the results of the approach (Accuracy).

Literature	Pretrained CNNs	Dataset	Accuracy (%)
[63]	From scratch (14 layers)	LC25000	99.50
[64]	VGG16	Histological H&E images (WSIs)	96.82
[65]	ResNet101, ResNeXt50, InceptionV3, DenseNet161	Kather-CRC-2016, CRC-TP	97.50
[84]	DensNet121, MobileNetV2, InceptionV3, VGG16	Stoean, Kather-CRC-2016	95.20
[85]	AlexNet, VGG16, ResNet, DensNet, InceptionV3	AiCOLO, CRC-5000, CRC-100K	81.22

[86]	From scratch	Histological CRC data (CHU Nancy Brabois Hospital)	99.17
[33]	AlexNet, SqueezeNet, VGG19, GoogleNet, ResNet50	NCT-CRC-HE-100K,kather-CRC, CRC-VAL-HE-7K	97.14
Our approach	From scratch, VGG19, Resnet50, InceptionV3	CRC-VAL-HE-7K	98%

Table V.4: Comparison between our best model and the state-of-the-art methods

V.6 Desktop Application

Python script builds a GUI application for colon cancer detection using a pretrained Convolutional Neural Network (CNN) model. The application uses the Tkinter library.

The window consists of the following elements:

- *"Open Image"* to select an image from the local system.
- *"Predict"* to initiate the prediction process.
- *"Guide"* provides additional information about the application.
- *"Exit"* to close the application.
- *Result Table* showing the predicted classes and their corresponding percentages.

In addition, the *PyInstaller* tool is used to convert the Python script to an **executable file**. The **dist** folder contains the distribution package that can be distributed to other users, while the **build** folder contains intermediate files generated during the build process.

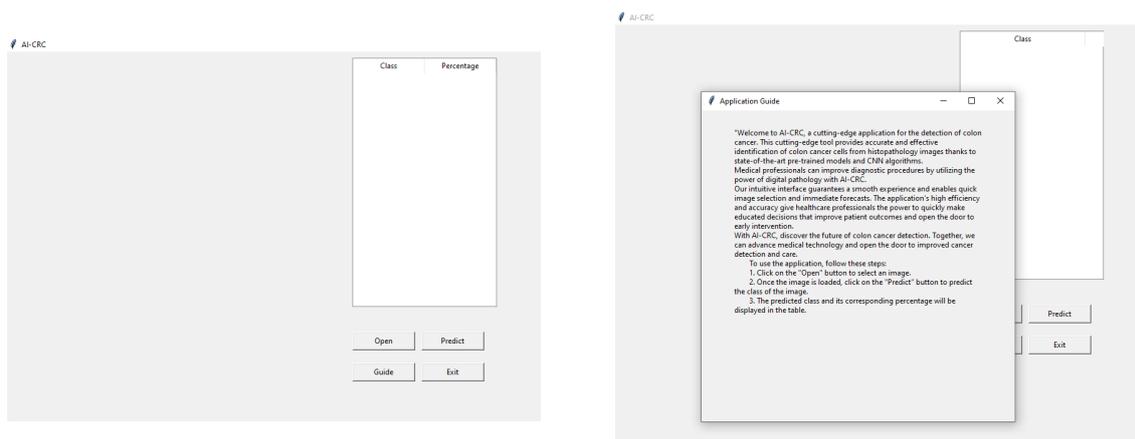


Figure V.21: User interface

Overall, our Application combines deep learning techniques and desktop application development to provide a practical solution for image classification and user-friendly interface that will make it simple for medical professionals to interact and traverse the system.

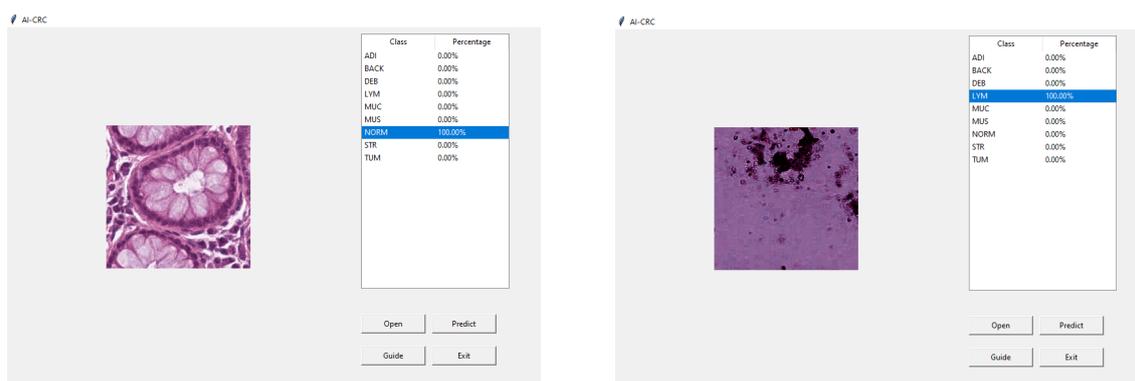


Figure V.22: Test Results

Conclusion

The main contribution of this chapter was to propose a different approaches based on CNN for colon cancer detection and compared the different results obtained, the results obtained using both the average and weighted averaging methods demonstrate the effectiveness of ensemble learning in improving accuracy and robustness in our predictive model. In the end we built a GUI application using Tkinter.

General Conclusion

Convolutional neural networks (CNNs) have emerged as a powerful and effective approach in a variety of fields, including medical image analysis. CNNs have shown remarkable capabilities in tasks such as tissue type classification and disease detection such as colorectal cancer (CRC). Our results showed that these techniques have the potential to improve the accuracy and speed of colon cancer detection, especially when compared to traditional diagnostic methods.

Our study utilized three different models, including a CNN built from scratch, a transfer learning model using VGG19, and an ensemble learning model. We found that the ensemble learning model provided the highest accuracy in our experiments. However, the limited availability of high-quality data posed a significant challenge in developing and testing our models. We had to overcome these challenges by using data augmentation techniques and carefully selecting the best-performing models to achieve the highest possible accuracy. Future studies should focus on addressing this challenge to further improve the accuracy and effectiveness of these techniques.

Overall, our findings highlight the potential of AI and deep learning techniques to revolutionize the field of colon cancer detection using histopathology images. The ability to accurately detect colon cancer at an early stage can have a significant impact on patient outcomes and survival rates. With continued research and development, these techniques have the potential to significantly improve the early detection and treatment of colon cancer, ultimately saving lives and improving patient outcomes.

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مخطط نموذج العمل التجاري

Business Model Canvas

BMC

