DEPARTMENT OF

NAME OF THE DEPARTMENT



NOVA University Lisbon  
Month, year

MASTER IN MSC PROGRAM NAME

A VERY LONG AND IMPRESSIVE

THESIS TITILE WITH A FORCED LINE BREAK

SOME THOUGHTS ON THE LIFE, THE UNIVERSE,

AND EVERYTHING ELSE

JOHN VERY LONGNAME DOE

BSc in name of previous degree

DEPARTMENT OF  
NAME OF THE DEPARTMENT



DOCTORATE / MASTER IN MSC PROGRAM NAME

NOVA University Lisbon  
Month, year

|  |  |
| --- | --- |
| **Examination Committee:** | |
| **Chair:** | Name of the committee chairperson, Full Professor, FCT-NOVA |
| **Rapporteurs:** | Name of a rapporteur, Associate Professor, Another University Name of another rapporteur,  Assistant Professor, Another University |
| **Adviser:** | Name of the adviser present in defense, Associate Professor, University | |
| **Members:** | Yet another member of the committee,  Full Professor, Another University Yet another member of the committee,  Assistant Professor, Another University | |

|  |  |
| --- | --- |
| **Adviser:** | Mary Doe Adviser Name *Full Professor, NOVA University Lisbon* |
| **Co-advisers:** | John Doe Co-Adviser Name Associate Professor, NOVA University Lisbon  John Doe other Co-Adviser Name Full Professor, NOVA University Lisbon |

A VERY LONG AND IMPRESSIVE

THESIS TITLE WITH A FORCED LINE BREAK

SOME THOUGHTS ON THE LIFE, THE UNIVERSE,

AND EVERYTHING ELSE

**JOHN VERY LONGNAME DOE**

BSc in name of previous degree

**A Very Long and Impressive Thesis Title with a Forced Line Break**

Copyright © <Author’s Name>, NOVA School of Science and Technology, NOVA University Lisbon.

The NOVA School of Science and Technology and the NOVA University Lisbon have the right, perpetual and without geographical boundaries, to file and publish this dissertation through printed copies reproduced on paper or on digital form, or by any other means known or that may be invented, and to disseminate through scientific repositories and admit its copying and distribution for non-commercial, educational or research purposes, as long as credit is given to the author and editor.

This document was created with Microsoft Word text processor and the NOVAthesis Word template [1].

# 

Dedicatory lorem ipsum.

Acknowledgments

Acknowledgments are personal text and should be a free expression of the author.

However, without any intention of conditioning the form or content of this text, I would like to add that it usually starts with academic thanks (instructors, etc.); then institutional thanks (Research Center, Department, Faculty, University, FCT / MEC scholarships, etc.) and, finally, the personal ones (friends, family, etc.).

But I insist that there are no fixed rules for this text, and it must, above all, express what the author feels.

“You cannot teach a man anything; you can only help him  
discover it in himself.” (Galileo).

Abstract

The identification of cancer cells is a critical task in biomedical research and clinical practice, with significant implications for disease diagnosis, treatment, and prognosis. However, current methods often rely on manual annotation and interpretation of large datasets, which can be time-consuming, labor-intensive, and prone to human error.

This thesis explores the potential application of **Large Language Models (LLMs)** to identify cancer cells from various data sources, more specifically ultrasound, mammogram and thermogram images, tomosynthesis 3D images and histopathology slides. While LLMs are typically trained on text-based data, their ability to learn patterns and relationships within language can be leveraged in conjunction with other methods to analyze images and signals associated with cancer cells and masses. The challenge lies in finding ways to integrate these different approaches effectively, and to develop novel methods that can take advantage of the unique strengths of each technique. By exploring the potential applications of LLMs in image analysis, we may uncover new insights into the possibilities for combining language-based and visual-based approaches to solve complex problems in biomedical research.

The proposed research is interesting and challenging because it pushes the boundaries of what is possible using LLMs. By investigating the feasibility of applying LLMs to this problem, we aim to contribute to a deeper understanding of the potential applications of language models in biomedical research. This thesis can bring new insights into the strengths and limitations of LLMs for breast cancer identification and has the potential to contribute to the development of novel diagnostic tools and approaches.

**Keywords**: Breast Cancer, Large Language Models, Deep Learning, Artificial Inteligence.

Resumo

A identificação de células cancerígenas é uma tarefa crítica na investigação biomédica e na prática clínica, com implicações significativas no diagnóstico, tratamento e prognóstico da doença. No entanto, os métodos actuais baseiam-se frequentemente na anotação e interpretação manual de grandes conjuntos de dados, o que pode ser moroso, trabalhoso e propenso a erros humanos.

Esta tese explora a potencial aplicação de modelos de linguagem de grande dimensão (LLM) para identificar células cancerígenas a partir de várias fontes de dados, mais especificamente imagens de ultra-sons, mamografias e termogramas, imagens 3D de tomossíntese e lâminas histopatológicas. Embora os LLMs sejam normalmente treinados em dados baseados em texto, a sua capacidade de aprender padrões e relações dentro da linguagem pode ser aproveitada em conjunto com outros métodos para analisar imagens e sinais associados a células e massas cancerígenas. O desafio reside em encontrar formas de integrar eficazmente estas diferentes abordagens e desenvolver novos métodos que possam tirar partido dos pontos fortes únicos de cada técnica. Ao explorar as potenciais aplicações de LLMs na análise de imagens, podemos descobrir novas perspectivas sobre as possibilidades de combinar abordagens baseadas na linguagem e visuais para resolver problemas complexos na investigação biomédica.

A investigação proposta é interessante e desafiadora porque ultrapassa os limites do que é possível fazer com LLMs. Ao investigar a viabilidade da aplicação de LLMs a este problema, pretendemos contribuir para uma compreensão mais profunda das potenciais aplicações de modelos de linguagem na investigação biomédica. Esta tese pode trazer novos conhecimentos sobre os pontos fortes e as limitações dos LLMs para a identificação do cancro da mama e tem o potencial de contribuir para o desenvolvimento de novas ferramentas e abordagens de diagnóstico.

(Traduzido com a versão gratuita do tradutor - DeepL.com)

**Palavras chave**: Cancro da mama, *Large Language Models*, *Deep Learning*, Inteligência Artificial.

Contents

[1 Introduction 1](#_Toc1)

[1.1 The problems 1](#_Toc2)

[1.2 Proposed Solution 2](#_Toc3)

[1.3 Context and Motivation 3](#_Toc4)

[1.4 Document Structure 3](#_Toc5)

[2 State of the art 5](#_Toc6)

[2.1 Conventional exam methods 5](#_Toc7)

[2.1.1 Mammography 5](#_Toc8)

[2.1.2 Ultrasound 7](#_Toc9)

[2.1.3 Thermogram 8](#_Toc10)

[2.1.4 Tomosynthesis 9](#_Toc11)

[2.1.5 Histopathology 10](#_Toc12)

[2.2 Deep Learning 11](#_Toc13)

[2.2.1 Application in Mammography 12](#_Toc14)

[2.2.2 Application in Ultrasound 13](#_Toc15)

[2.2.3 Application in Thermogram 14](#_Toc16)

[2.3 References to Chapters, Sections, Figures, Tables, etc. 15](#_Toc17)

[2.4 The Bibliography 15](#_Toc18)

[3 Let’s Create Another Chapter 17](#_Toc19)

[3.1 And Now some Text to Fill in the Document 17](#_Toc20)

[3.1.1 Some more text in a subsection 17](#_Toc21)

[3.1.2 Yet another subsection 17](#_Toc22)

[4 And Another Chapter with some More Text to Increase the Document Size 21](#_Toc23)

[4.1 This is a Section 21](#_Toc24)

[4.1.1 This is a Subsection 21](#_Toc25)

[4.1.2 This is another Subsection 22](#_Toc26)

[4.2 Another Section 22](#_Toc27)

[A An Appendix 29](#_Toc28)

[A.1 A Subsection in the Appendix 29](#_Toc29)

[A.2 Another Subsection in the Appendix 29](#_Toc30)

[A.3 Yet another Subsection in the Appendix 30](#_Toc31)

[B Another Appendix 31](#_Toc32)

[B.1 Another Appendix with Subsections 31](#_Toc33)

List of Figures

[Figure 2.1: Example of a mamogram image (Adapted from [14]) 5](#_Toc1)

[Figure 2.1: Example of a tomosynthesis 3D image (Adapted from [27]) 8](#_Toc2)

[Figure 3.1 — Looks list the April’s 25 bridge in Lisbon but it is not. It is the Golden Gate, in S. Francisco in California, USA. 13](#_Toc3)

[Figure 3.1 — And another figure with a caption. 14](#_Toc4)

List of Tables

[Table 2.1 — Portuguese population by age range. 11](#_Toc67153562)

[Table 2.2 — This table is identical to the previous one, but it is here so that we have not only one but rather two tables in our docuemnt. And as this caption is very long, it should be justified and not centered. 12](#_Toc67153563)

Glossary

|  |  |
| --- | --- |
| **Virtual Staining** | Virtual staining is a digital simulation of traditional staining techniques, using algorithms to mimic chemical reactions and reveal specific cellular features. This technology enables pathologists to analyze tissues at multiple scales, enhancing diagnostic accuracy and reducing manual labor and costs. |
| **YOLO** | YOLO stands for "You Only Look Once", a real-time object detection algorithm that detects objects in an image or video by applying a single neural network pass, making it fast and efficient. It is commonly used for tasks such as detecting pedestrians, cars, and other objects in images or videos. In the context of mammography, YOLO can be used to detect masses or tumors in breast images. |
| **Generative Adversarial Networks (GANs)** | A type of deep learning model that consists of two neural networks: the Generator creates synthetic data and the Discriminator evaluates its authenticity. Through an adversarial process, they improve each other's performance, producing realistic synthetic images. This can be applied in mammography to generate training data. |
| **Deep Generalized Canonical Correlation Analysis (Dg-CCA)** | A deep learning technique that aims to maximize the correlation between features from multiple sources, such as images and clinical data. By doing so, it enables the extraction of high-dimensional features that are most relevant for diagnosis, thus enhancing diagnostic precision in mammography. |
| **Disentangled Variational Autoencoder (D-VAE)** | A type of deep learning model that enables the disentanglement of complex features in medical images into meaningful, independent factors. This allows for the extraction of relevant information from images and the generation of synthetic data that preserves the underlying structure of the original data, improving the performance of downstream tasks such as classification in mammography. |
| **Area Under the Curve (AUC)** | A measure of the accuracy of a model's predictions. It represents the probability that the model will correctly rank a randomly chosen positive instance (e.g. malignant tumor) higher than a negative instance (e.g. benign tumor). A higher AUC value indicates better performance, with 1 being perfect and 0.5 being no better than chance. |
| **VGG16** | A type of convolutional neural network (CNN) architecture designed for image classification tasks. It was introduced in the ImageNet Large Scale Visual Recognition Challenge 2014 and has since been widely used as a pre-trained model for various applications, including mammography analysis. The "16" in VGG16 refers to its depth, with 16 layers of convolutional and pooling operations followed by fully connected layers. |
| **DarkNet-53** | A deep CNN architecture that has been widely used for object detection tasks in computer vision applications, including those involving ultrasound images. It consists of 53 layers, with a series of convolutional and downsampling operations followed by a global average pooling layer to extract features from the input data. |
| **CBIS-DDSM** | Stands for Curated Breast Imaging Subset of Digital Database for Screening Mammography. It is a large dataset of ultrasound images collected from various sources, specifically designed to support the development and evaluation of computer-aided detection (CAD) systems for breast cancer diagnosis. The CBIS-DDSM dataset contains annotated images with labels indicating the presence or absence of masses, calcifications, and other abnormalities, making it a valuable resource for researchers working on deep learning-based image analysis techniques. |

.

Acronyms

|  |  |
| --- | --- |
| **LLM** | Large Language Model |
| **UI** | User Interface |
| **DBT** | Digital Breast Tomosynthesis |
| **CNNs** | Convolutional Neural Networks |
| **YOLO** | You Only Look Once |
| **GANs** | Generative Adversarial Networks |
| **MAP** | Mean Average Precision |
| **RNNs** | Recurrent Neural Networks |
| **ABUS** | Automated Breast Ultrasound |

Symbols

|  |  |
| --- | --- |
| **π** | The ratio of the circumference of a circle to its diameter, having a value rounded to eight decimal places of 3.14159265 (symbol: π). |
| ***r*** | The radius of a circle. |

# Introduction

The accurate identification of cancer cells is a critical task in biomedical research and clinical practice, with significant implications for disease diagnosis, treatment, and prognosis. The exponential growth of medical imaging technologies has led to an overwhelming volume of image data, which must be analyzed and interpreted by clinicians and researchers. However, current methods for analyzing these images often rely on manual annotation and interpretation, a time-consuming process that is prone to human error [1].

The limitations of traditional image analysis methods have been compounded by the increasing demand for precision medicine and personalized healthcare. The development of targeted therapies and immunotherapies requires a deep understanding of individual patient biology, which can only be achieved through detailed analysis of large-scale imaging data. However, the manual annotation of these images is often a significant bottleneck in research and clinical settings.

Researchers have been exploring various solutions to overcome the challenges of image analysis, including the development of novel algorithms and techniques that leverage advances in machine learning and computer vision. However, more work is needed to develop practical and effective methods for analyzing complex imaging data. This thesis aims to contribute to this effort by investigating the potential application of **Large Language Models (LLMs)** in analyzing images of cancer cells and masses [1] [2].

## The problems

The process of identifying cancer cells from medical images is a complex and time-consuming task, often requiring extensive expertise and specialized knowledge. Clinicians and researchers are faced with the daunting challenge of analyzing vast amounts of imaging data, which can be overwhelming even for experienced professionals. The consequences of inaccurate or delayed diagnoses can be severe, highlighting the need for more effective and efficient image analysis methods [3].

One of the primary limitations of current image analysis approaches is their rigid structure and reliance on standardized protocols. While these methods have been refined over time, they can struggle to adapt to emerging trends and technologies in medical imaging. The increasing availability of high-resolution images and advanced imaging modalities has created a need for more flexible and dynamic analysis techniques that can accommodate the diverse range of data being generated [4].

The potential integration of LLMs into image analysis presents both opportunities and challenges. On one hand, these models have been successfully applied to a wide range of natural language tasks and may offer new insights into visual data representation. However, their adaptation to image analysis requires significant modifications to address the unique characteristics of visual information. For instance, language-based models must be able to interpret complex spatial relationships and patterns within images, which can be difficult to articulate in textual form [5].

Furthermore, the implementation of language-based models in medical imaging raises important questions about bias, accuracy, and transparency. It is essential that these models are designed with careful consideration of the potential pitfalls associated with their use, such as perpetuating existing biases or introducing new ones through their training processes. Additionally, the need for clear and interpretable results cannot be overstated, particularly in high-stakes medical decision-making environments [6].

## Proposed Solution

To address the challenges of image analysis in cancer cell identification, we propose a multi-modal approach that leverages the strengths of various Large Language Models (LLMs) to analyze different types of medical images. Specifically, we will utilize a combination of publicly available LLMs trained on natural language processing tasks to extract relevant features from mammograms, ultrasounds, thermograms, tomosynthesis images, and histopathology slides. To facilitate the integration of these models with visual data, we will convert the image pixels into base64-encoded strings, enabling the LLMs to process and analyze the images in a textual format [7].

We will utilize a combination of pre-trained LLMs and adapt them to our specific task by fine-tuning them on publicly available medical imaging datasets [8] [9]. This approach allows us to leverage the strengths of each LLM architecture while also ensuring that they are optimized for our particular application.

Then, to evaluate the effectiveness of our proposed solution, we will conduct an extensive analysis of the models’ accuracy, precision, recall, and F1-score on various image types. We will also investigate the impact of different hyperparameters, such as learning rates and batch sizes, on model performance and select the most suitable settings for each LLM architecture.

Our proposed multi-modal approach using LLMs offers a promising framework for analyzing medical images and identifying cancer cells. By leveraging the strengths of multiple models, we can develop a more robust and reliable system that improves upon existing methods. While our study focuses on comparing the performance of several different LLM architectures, it also highlights the need for further research into this area. Future work could involve exploring other LLM architectures or developing more sophisticated methods for combining multiple models to improve overall performance [6].

## Context and Motivation

Traditional machine learning and deep learning methods have been widely used for medical image analysis, but they often require extensive technical expertise to implement and interpret. In contrast, LLMs offer a more accessible and user-friendly approach that can be easily integrated into existing clinical workflows. By representing images as text using base64 encoding through a front-end UI, we can leverage the strengths of LLMs in processing sequential data, while also making it easier for clinicians to interact with the system.

The ease of use is particularly important in medical image analysis, where doctors and clinicians may not have extensive technical knowledge or experience with machine learning algorithms. With traditional deep learning methods, clinicians often require significant training and support to accurately interpret results and fine-tune models to their specific needs. In contrast, LLMs can be easily fine-tuned using a user-friendly interface, allowing clinicians to quickly adapt the system to their workflow without requiring extensive technical expertise [10].

Furthermore, LLMs are pre-trained on vast amounts of natural language data, allowing them to learn complex patterns and relationships that may not be apparent through traditional feature engineering. This means that clinicians can focus on interpreting results rather than spending hours fine-tuning models or hand-crafting features [11].

By making medical image analysis more accessible and user-friendly, we can empower clinicians to make more accurate diagnoses and improve patient outcomes.

## Document Structure

The current chapter 1 is an introductory text to contextualize the reader and present the currrent challenges at hand, as well as the brief solution to implement our work.

On chapter 2 we will present the research made by other researchers in this regard, as well as the state-of-the-art technologies that are currently used regarding this subject.

Next, on chapter 3 we will dive a bit deeper in the technical details of the implementation of our system while also presenting a work schedule and the work that is alrready beign developed.

Finally, on chapter 4 we will analyze our results and take our conclusions from it, deciding on the acccurracy (mostly) of the different models in all the situations considered durring the study.

# State of the art

Image analysis has long been an area of active research in the field of medical examination, more specifically breast cancer detection. In recent years, the use of AI techniques has revolutionized the field, enabling the development of highly accurate models for tasks such as tumor segmentation, lesion detection, and image classification.

However, despite these advances, there is still much work to be done in developing robust and reliable medical image analysis systems that can be widely adopted in clinical settings. This chapter provides an overview of the current state of the art in medical image analysis, highlighting recent advances and challenges in areas such as deep learning architectures, data augmentation techniques, and model interpretability.

## Conventional exam methods

The detection of breast cancer relies heavily on a combination of conventional examination techniques, including mammography, ultrasound, digital breast tomosynthesis (DBT), and thermography. While these modalities have revolutionized the field of breast imaging, they all share one common limitation: the reliance on human interpretation [12]. Each modality requires specialized training and expertise to accurately interpret results, which can lead to variability in diagnosis and treatment recommendations between healthcare providers. Furthermore, even with the aid of advanced technology, these methods are inherently limited by their inability to provide a comprehensive view of the breast tissue, leaving some cancers undetected or misdiagnosed.

This chapter explores the conventional examination methods currently used in clinical practice, highlighting both their strengths and limitations.

### Mammography

Mammography has been the primary screening tool for breast cancer since its introduction in the 1960s [13]. It involves the use of low-energy X-rays to produce images of the breast tissue. The technique is based on the principle that dense breast tissue absorbs more X-ray energy than fatty tissue, resulting in a higher contrast between normal and pathological tissues.

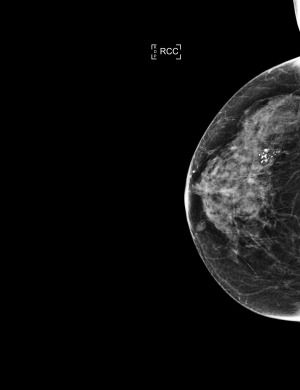


Figure 2.1: Example of a mamogram image (Adapted from [14])

When a radiologist examines a mammogram, they are searching for subtle clues that may indicate the presence of breast cancer. The interpretation process is both nuanced and complex, requiring a deep understanding of the various features that can be present within the image.

One key area of focus is the detection of calcifications - small deposits of calcium that can accumulate within the breast tissue. These tiny formations can often be indicative of cancer, particularly when they appear in a characteristic pattern or are associated with other suspicious findings. In addition to calcifications, radiologists also look for masses - solid or cystic lesions that may indicate the presence of a tumor. Densities - areas of increased breast density - can also be an area of concern, as these can be caused by fibrosis (scarring), inflammation, or even cancer. Finally, radiologists will examine the symmetry and shape of the breasts, searching for any signs of asymmetry that may indicate an underlying issue.

While mammography has been a powerful tool in the detection of breast cancer, it is not without its limitations. One major concern is the issue of false positives - benign lesions are often identified as suspicious, leading to unnecessary biopsies and subsequent anxiety for patients.

Conversely, some cancers may be missed altogether due to their small size or location within the breast. This can be particularly problematic in women with dense breast tissue, who may be at higher risk for false negatives [15]. Furthermore, mammography sensitivity can vary by age and ethnicity, with younger women and those of African descent being at higher risk for false negatives [13]. It is also important to consider the factor of human error in the analysis of these sets of images.

### Ultrasound

Ultrasound imaging has become an increasingly important tool in the assessment of breast lesions, particularly in conjunction with mammography and other diagnostic modalities. Ultrasound uses high-frequency sound waves to create images of structures within the body, allowing for real-time visualization of the breast tissue [16].

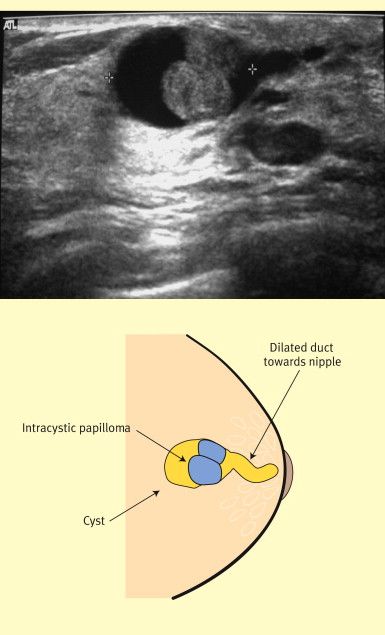


Figure 2.2: Example of a Mammogram (Adapted from [17])

One of the key strengths of ultrasound is its ability to characterize lesions, distinguishing between benign and malignant growths. This enables clinicians to develop targeted treatment plans that maximize patient outcomes. Moreover, ultrasound provides precise measurements of tumor size, which is essential for determining the most effective course of treatment. In addition to these benefits, ultrasound can also guide biopsy procedures, ensuring that tissue samples are obtained with precision and accuracy. By reducing the risk of complications and improving diagnostic yield, ultrasound plays a critical role in the early detection and treatment of breast cancer [18].

Despite its many advantages, ultrasound is not without limitations. The quality of ultrasound images depends heavily on the skill and experience of the operator, which can lead to variations in image interpretation. Furthermore, ultrasound waves have limited penetration depth, making it challenging to image deeper structures within the breast [19].

### Thermogram

As a relatively new technology in breast imaging, thermography is a non-invasive imaging modality that uses heat signatures to detect breast abnormalities. This technique has gained popularity in recent years due to its ability to provide a unique perspective on breast health. It relies on the principle that abnormal tissues, such as tumors, exhibit altered blood flow and metabolism. As a result, these areas produce increased heat signatures compared to normal tissue. The thermographic camera captures these heat patterns, providing a visual representation of thermal activity within the breast [20].

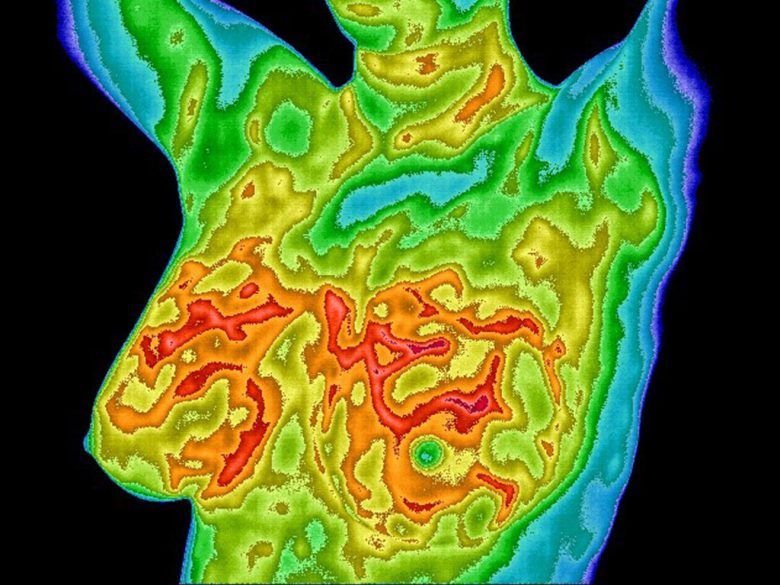


Figure 2.3: Example of a thermogram image. (Adapted from [21])

While thermography has shown promise in detecting breast abnormalities, its use is not without challenges. Several limitations and controversies have been raised regarding its sensitivity and specificity, operator variability, and regulatory status [22].

As with the other methods mentioned before the quality of thermographic images can be influenced by a range of factors, including the skill level of the operator. Beyond human factors, external elements such as ambient temperature, patient positioning, menstrual cycle variations, and the application of creams or lotions can influence thermographic results, potentially affecting both accuracy and reproducibility. This variability may impact diagnostic accuracy, emphasizing the need for more effective image acquisition techniques [23]. Researchers are actively exploring ways to enhance the sensitivity and specificity of thermography, as well as its regulatory recognition, therefore an integration with some kind of computer aided technique would be beneficial to the scientific research community of this topic [24].

### Tomosynthesis

Breast tomosynthesis, also known as **Digital Breast Tomosynthesis (DBT)**, is a cutting-edge imaging modality that has revolutionized the field of breast imaging. This advanced technique offers several benefits over traditional mammography, making it an essential tool in modern breast cancer screening and diagnosis [25]. It works by capturing multiple low-dose X-ray images from different angles around the breast. These images are then reconstructed into a 3D dataset, allowing for detailed visualization of breast tissue. This technique enables clinicians to evaluate the breast in thin slices, reducing the overlap and artifacts that can occur with traditional mammography [26].

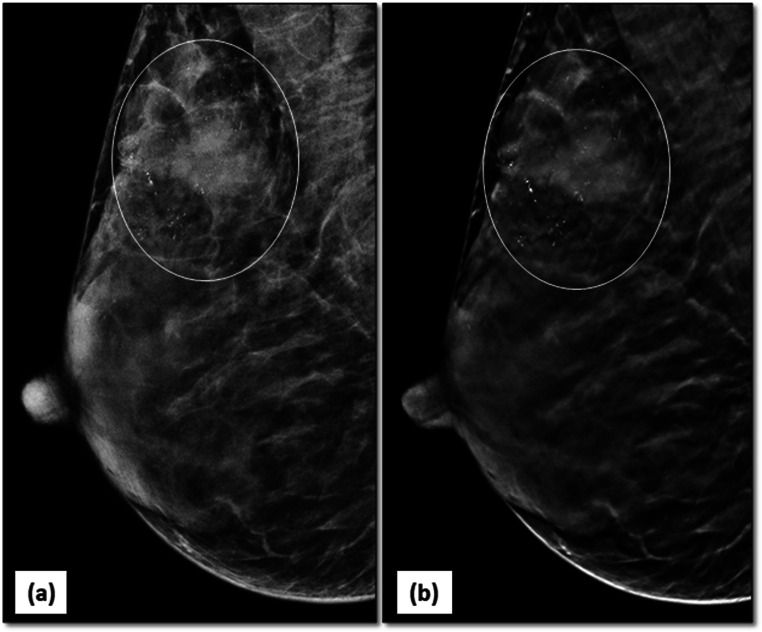


Figure 2.1: Example of a tomosynthesis 3D image (Adapted from [27])

Tomosynthesis has certainly revolutionized the field of breast imaging, but it's not without its challenges. One of the main concerns is the high upfront cost of purchasing a tomosynthesis system, which can be a significant barrier for some medical facilities. Additionally, while tomosynthesis uses lower doses of radiation than traditional mammography, the cumulative exposure over time can still be a concern for patients [26].

Interpreting tomosynthesis images requires a high level of expertise, and clinicians need to undergo specialized training to get the most out of this technology. The sheer volume of data generated by tomosynthesis can also be overwhelming, making it difficult for some clinicians to accurately interpret results. Because of this, this method is also influenced by human factors [6].

### Histopathology

Histopathology has been a cornerstone of cancer diagnosis for decades, but recent advancements in technology have transformed this field into a dynamic and rapidly evolving discipline [28].

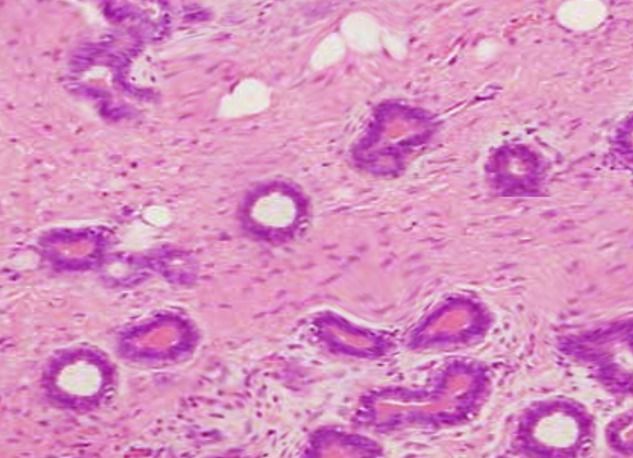


Figure 2.1: Example of a histopathology image (Adapted from [29])

Unlike all the other methods referenced before in this chapter, histopathology provides a detailed examination of individual cells instead of focusing on mass detection, allowing pathologists to identify subtle abnormalities and diagnose cancer with unprecedented accuracy. The advent of digital slides has streamlined diagnostic workflows, enabling pathologists to access high-quality images from anywhere in the world. This shift towards digital pathology has also facilitated collaboration among experts, enabling them to share knowledge and best practices more efficiently [30]. The development of *virtual staining* technology has eliminated the need for physical samples, reducing costs and increasing efficiency. Moreover, AI-powered algorithms can automatically detect tumor boundaries, differentiate between cancerous and benign tissue, and even predict disease progression and treatment response at the cellular level [31].

High-quality images and meticulous annotation are essential for accurate diagnoses, but even with these in place, human factors can still impact results. Pathologists, like any other professionals, are susceptible to fatigue, stress, and variability in judgment, which can lead to errors in interpretation [30].

The integration of multiple systems and platforms is also a significant concern, as the lack of standardization in hardware and software can create obstacles to seamless collaboration. This lack of standardization is particularly evident when considering the various digital pathology platforms currently available on the market, each with their own proprietary formats and interfaces [32]. As such, this thesis aims to contribute to the development of standardized protocols for data collection, annotation, and analysis, which will enable more efficient and effective communication between different systems and stakeholders.

## Deep Learning

As mentioned before, the analysis of medical images is a complex task that requires a high degree of accuracy and attention to detail. In recent years, researchers have explored various approaches to improving image analysis, including the use of deep learning techniques. This chapter will examine the application of deep learning methods to conventional examination modalities used in breast cancer screening, such as mammography, ultrasound, DBT, thermography and histopathology.

Deep learning models have been found to possess several key characteristics that make them particularly well-suited for medical imaging applications. For example, they are able to extract complex patterns from data through a process of automatic feature extraction. This allows them to identify subtle abnormalities in images that may not be visible to the naked eye. Additionally, deep learning models can rapidly and accurately process large datasets without requiring explicit programming [31] [32].

This ability to automatically extract features from data has led to significant advancements in the field of medical imaging. Researchers have been able to develop models that outperform traditional machine learning approaches in tasks such as image recognition and classification. However, the integration of new technologies into clinical practice is a gradual process, requiring careful evaluation and validation before widespread adoption.

In the case of deep learning methods applied to medical images, researchers must consider several factors, including model interpretability, data quality, and regulatory frameworks, to ensure safe and effective implementation [3]. This chapter will provide an overview of the current state of research in this area, highlighting both the potential benefits and challenges associated with the use of deep learning techniques.

### Application in Mammography

The application of deep learning techniques in mammography analysis has garnered significant attention in recent years, driven by the need for more accurate and efficient detection of breast cancer cells. One of the primary approaches employed is the use of **Convolutional Neural Networks (CNNs)**, which have proven effective in tasks such as lesion localization, detection, and classification. The success of CNNs can be attributed to their ability to automatically learn features from large image datasets, eliminating the need for manual feature extraction [1].

Researchers have leveraged pre-trained models, such as *AlexNet*, *ResNet*, *MobileNet*, and *EfficientNet*, as a starting point for fine-tuning in mammography analysis. This transfer learning approach has shown improved accuracy compared to training models from scratch. Additionally, data augmentation techniques are often employed to increase the size of training datasets, which is essential due to the scarcity of large, high-quality medical image datasets. Furthermore, advanced techniques like ***YOLO (You Only Look Once)***, Attention mechanisms, and ***Generative Adversarial Networks (GANs)*** have been utilized for simultaneous detection and classification of masses [12], while feature fusion methods, such as ***Deep Generalized Canonical Correlation Analysis (Dg-CCA)*** combined with ***Disentangled Variational Autoencoder (D-VAE)***, aim to maximize feature correlation across modalities [2].

When looking at raw result values, various studies have reported high accuracy rates, with one notable example being a fine-tuned residual network achieving improved accuracy and sensitivity rates of 93.15% and 93.83%, respectively. Additionally, a deep learning system for breast cancer screening demonstrated impressive results, registering high accuracy, recall, and ***AUC (Area Under the Curve)*** values of 0.960, 0.929, and 0.928, respectively [1].

The same researchers have also explored the use of attention mechanisms to enhance performance in mammography analysis. The same study incorporated an attention mechanism into *VGG16* with feature selection, resulting in a notable improvement in accuracy, achieving a rate of 96.07%. Furthermore, transfer learning techniques have been employed successfully in mammography, with one study demonstrating an enhanced DCNN yielding an accuracy rate of 82.5% [1].

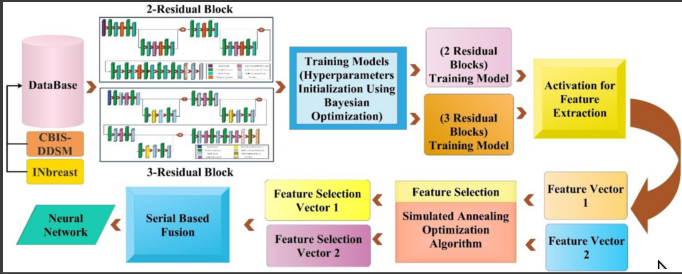


Figure 2.1: Suggestion of an implementation of a system to classify images. (Adapted from [1])

Other researchers made use of EfficientNet models has also shown exceptional performance, achieving an overall accuracy rate of 98.29% in classifying mammogram images into benign and malignant categories [33].

The development of two-stage deep learning methods has also led to significant increases in detection accuracy. For example, one separate study improved **mean average precision (MAP)** from 0.85 to 0.94, underscoring the potential of these approaches for improving breast cancer diagnosis and screening outcomes [34].

### Application in Ultrasound

Recent advances in deep learning have revolutionized the field of ultrasound diagnostics. Specifically, Convolutional Neural Networks (CNNs) have emerged as a powerful tool for analyzing ultrasound images. As mentioned before, these networks excel at extracting high-level features from large-scale image datasets, making them an ideal choice for various tasks such as classification, recognition, object detection, and segmentation.

In this context, several CNN-based models have been explored and adapted for specific applications. Notable examples include *AlexNet*, *ResNet*, *MobileNetV2*, InceptionV3, Xception, NasNetMobile, VGG19, DarkNet-53, ShuffleNet, and SqueezeNet. Among these, *DarkNet-53* has garnered significant attention due to its exceptional performance in object detection tasks. Researchers have successfully modified this model using transfer learning, leveraging pre-trained weights to improve accuracy on ultrasound image classification tasks [1] [18].

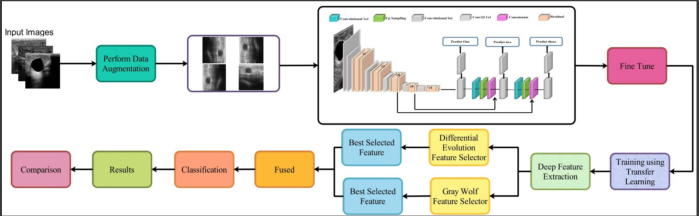


Figure 2.1: Proposed implementation off the framework employed in [18]. (Adapted from [18])

Segmentation is a critical step in ultrasound image analysis, allowing for precise location and extraction of areas with specific information. Hybrid approaches combining CNNs with **Recurrent Neural Networks (RNNs)** have also been explored to analyze temporal components in dynamic ultrasound image sequences. These models extract both spatial and temporal features, enabling researchers to better understand the dynamics of biological systems [1].

Some studies have demonstrated that DL-based computerized techniques can assist clinicians in detecting and classifying breast cancer correctly, while also enhancing image quality. For instance, one set of researchers were able to achieve impressive results by fine-tuning residual networks on large datasets, such as *CBIS-DDSM*, resulting in high accuracy and sensitivity rates of up to 93.83% and 96%, respectively [1].

Another notable achievement is the development of optimized 3D CNN models for automatic detection in **Automated Breast Ultrasound (ABUS)** images. These models have achieved remarkable sensitivities of up to 100% with an average of only 1.9 false positives per volume. Furthermore, a proposed framework combining DarkNet-53, feature selection, and probability-based fusion has achieved a best accuracy of 99.1% on an augmented BUSI dataset, while also significantly reducing computational time [3].

In the same study, researchers analyzed 20 other studies comprising 14,955 cases, reporting a combined sensitivity of 0.93 and specificity of 0.90 across all studies. Interestingly, multimodal ultrasound demonstrated superior performance compared to B-mode ultrasound alone. Additionally, researchers have also explored the potential of pre-training models on minimal datasets, which has been shown to improve accuracy by up to 14% [3].

Finally, some DL models have achieved remarkable results in breast cancer classification from ultrasound images. For example, the DeepbreastcancerNet model reached an impressive accuracy of 99.35% on a standard dataset and 99.63% on a binary dataset. These findings underscore the potential of deep learning-based computerized techniques to revolutionize breast cancer diagnosis using ultrasound imaging [36].

### Application in Thermogram

To overcome these challenges, researchers must focus on refining deep learning algorithms to improve model interpretability and accuracy. Future directions include developing real-time clinical deployment frameworks that can incorporate real-time image analysis for faster diagnoses [35].

The integration of AI-based breast density assessments with other features, such as patient demographics and medical history, holds promise for developing more accurate risk prediction models. Moreover, DL models that can accurately identify cancer-free patients on mammograms can reduce radiologists' workload and potentially improve access to care in underserved areas.

There is also interest in exploring the potential of machine learning algorithms for automating clinical tasks and improving patient outcomes. However, their effective deployment requires addressing limitations such as data quality issues, bias in training datasets, and domain-specific knowledge gaps.

To ensure the safe and responsible use of AI in mammography analysis, researchers must prioritize developing robust validation frameworks and governance mechanisms that address concerns around data privacy, accountability, and transparency.

Despite the advancements made in applying deep learning techniques to mammography analysis, several challenges remain. One of the most significant hurdles is the computational burden and processing time associated with high-resolution images, which can hinder the adoption of these technologies in clinical settings. Furthermore, there is a persistent need for large, diverse datasets that are collected using standardized protocols. This is crucial not only for training robust models but also for ensuring their generalizability across various datasets, vendors, and imaging acquisition techniques [34].

## References to Chapters, Sections, Figures, Tables, etc.

Whenever you refer to a numbered object present in the text, you should not insert the number as text, but insert a cross-reference using the appropriate menu. In this way, if the objects are renumbered (for example, because inserting a new figure in the middle of two existing figures), the curated references will also be updated automatically.

## The Bibliography

The bibliography appears after the main body of the text and before the Appendices and Annexes.

There are many bibliographic standards and styles. Each scientific area has its own way of presenting both citations and bibliographic references. The most common styles are the APA (American Psychological Association - author/date), now in its 7th edition, and the IEEE (Institute of Electrical and Electronics Engineers - numerical).

There is more than one way to cite/quote other authors in a text, however these can be divided in 2 big classes:

• **Indirect or conceptual citations**, in which we reproduce someone else's ideas in our own words through paraphrases;

• **Direct or formal quotations**, in which we transcribe exactly the words of an author using quotation marks.

The citation models follow 3 systems:

• **Author-date system**, in which the citation appears like this: (Santos, 2003), if there are two authors (Santos and Correia, 2003) and if there are more than 5 authors (Santos, et al., 2003), of which the best known and most used is the [APA style](https://apastyle.apa.org/);

• **Numerical system**, in which each citation is identified with a number [1] and the list of bibliographic references is compiled at the end of the work (bibliography), of which the best known and used style is the [IEEE](https://ieeeauthorcenter.ieee.org/wp-content/uploads/IEEE-Reference-Guide.pdf).

There are also **mixed systems**, in which the citation/quotation in the text is numeric, but the bibliography is sorted alphabetically by the author's surname. Examples of mixed styles are: Springer Lecture notes in Computer Science (alphabetically sorted) and the Council of Science Editors, Citation-Name (numeric alphabetically sorted), amongst others.

The most used styles, in general, are APA and IEEE, FCT is no exception, however you should always define with your advisor the standard or style to use.

The Library of FCT-NOVA provides training on these subjects, as well as support in the use of bibliographic management tools such as Mendeley and Zotero.

# Let’s Create Another Chapter

## And Now some Text to Fill in the Document

Integer sapien est, lobortis ac iaculis et, blandit a quam. Nulla efficitur mauris quis ultricies scelerisque. Morbi nunc massa, tempor sit amet lacus a, dignissim ullamcorper velit. Pellentesque dictum dignissim massa, ac lacinia tortor ornare eget. Proin tincidunt tristique nunc non pharetra. Morbi imperdiet, enim in consectetur euismod, nisl nulla volutpat tellus, in faucibus dolor erat a sem. Quisque sit amet arcu nunc. Nam lacinia magna nec lorem rutrum fermentum. Quisque ante xenim, elementum ac lorem sit amet, dapibus egestas urna. Proin in dolor quis nisl pulvinar sodales sit amet eget justo. Vestibulum ante ipsum primis in faucibus orci luctus et ultrices posuere cubilia curae; Sed venenatis dapibus mauris, quis hendrerit tortor ultricies eu. Cras felis mauris, ultricies et vestibulum in, ultricies sit amet arcu. Donec quis ex mauris.

### Some more text in a subsection

Quisque ut mi vitae lorem interdum dictum id ut urna. Sed accumsan mi nec est dapibus laoreet. Integer est ante, hendrerit a egestas vitae, tincidunt eget leo. Phasellus velit leo, auctor et euismod a, dapibus at justo. Mauris sagittis sagittis libe-ro, eu gravida orci convallis eu. Nunc interdum diam in ex pretium, vel aliquet sapi-en ornare. Class aptent taciti sociosqu ad litora torquent per conubia nostra, per in-ceptos himenaeos. Phasellus aliquet erat nec consectetur faucibus.

### Yet another subsection

Morbi vehicula tellus gravida placerat egestas. Etiam blandit facilisis conse-quat. In ac pretium ipsum, sit amet pretium nulla. Donec vitae ex turpis. Phasellus magna nulla, molestie eu dolor quis, eleifend tempus metus. Maecenas lacinia vesti-bulum ex eu dapibus. Pellentesque feugiat suscipit sapien sit amet congue. Sed euismod libero sed turpis interdum, eu mattis dolor porta. Cras pulvinar mauris est, non iaculis risus pretium sed.

#### One Level Deeper

Etiam eget aliquam ligula. Nunc venenatis metus et arcu fermentum, a consec-tetur tortor vestibulum. Integer euismod ipsum lacus, eu dictum neque cursus sit amet. Quisque pellentesque nulla eget elit pellentesque, sit amet lacinia lorem fringil-la. Nam commodo mollis neque non consectetur. Phasellus eget sodales augue, in rutrum nibh. Donec lobortis erat quis velit molestie tempus. Proin odio erat, malesu-ada et est at, volutpat efficitur urna. Suspendisse et sem lacinia, blandit quam in, euismod ligula. Phasellus a dictum sem. Donec luctus, felis et finibus vulputate, lec-tus diam varius neque, nec ultricies eros tellus eget quam.



Figure 3.1 — Looks list the April’s 25 bridge in Lisbon but it is not. It is the Golden Gate, in S. Francisco in California, USA.

#### Yet another sob-subsection

Phasellus id varius nisi, quis auctor mauris. Aenean id luctus lorem, in viverra lectus. Curabitur ullamcorper consectetur neque, vitae facilisis velit vulputate sed. Maecenas tincidunt scelerisque dolor eu sodales. Nam tempor elit lorem, congue pharetra elit blandit vel. Praesent eu elementum orci, eget egestas leo. Duis ac diam lorem. Morbi vestibulum tincidunt lacus.

Praesent sit amet convallis leo. Vivamus a ultricies urna, nec dictum enim. Ae-nean egestas blandit sagittis. Fusce sed libero fringilla, cursus nisl vitae, hendrerit dolor. Sed ornare augue sit amet tortor semper consectetur. Fusce varius est vitae ali-quam bibendum. Nunc sagittis dolor vel eros dapibus, et vehicula magna maximus. Ut vitae ultrices metus. Nam pellentesque interdum gravida. Duis dui orci, consecte-tur vitae ipsum sed, tempor auctor turpis.

Quisque viverra ultricies mattis. Class aptent taciti sociosqu ad litora torquent per conubia nostra, per inceptos himenaeos. Fusce ut placerat ante. Pellentesque nec elementum quam. Ut gravida egestas justo vel mollis. Aenean hendrerit maximus mauris, non molestie felis porttitor vel. Maecenas vehicula lectus orci. Nam eget lec-tus at neque fermentum consectetur. Maecenas massa dui, vestibulum eu finibus ut, aliquet sed velit. Proin lacinia tincidunt ligula, non mattis justo euismod vitae.

Table 3.1 — Portuguese population by age range.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | 1971 | 1980 | 1990 | 2000 |
| 0–24 | 3 861 916 | 4 131 825 | 3 660 978 | 3 176 450 |
| 25–49 | 2 658 361 | 3 015 450 | 3 312 011 | 3 705 865 |
| 50–74 | 1 851 909 | 2 245 875 | 2 482 266 | 2 718 007 |
| +75 | 271 575 | 373 125 | 527 967 | 689 581 |
| Total | 8 643 756 | 9 766 275 | 9 983 218 | 10 289 898 |

Curabitur laoreet scelerisque nisl, quis elementum justo feugiat at. Aenean quis rutrum ligula. In et libero leo. Nullam nec lectus sodales, lacinia leo facilisis, tempus lacus. Duis fermentum nec est eget sodales. Mauris at arcu sit amet metus ultricies tincidunt. Morbi viverra elementum felis, aliquet egestas dolor. Morbi efficitur nulla arcu, non imperdiet urna lobortis sed. Nulla lectus lorem, euismod sit amet egestas a, posuere a est. Ut ac luctus diam.

Proin nisi orci, condimentum ut vestibulum sed, finibus at libero. Proin vehicu-la nibh nec quam sagittis, vel lobortis nisi ullamcorper. Maecenas dapibus dictum elementum. Nullam porttitor tempor libero eu dapibus. Donec non sapien et elit tin-cidunt tincidunt. Vivamus feugiat tortor ut congue placerat. Ut rutrum auctor lectus sed efficitur. Quisque in blandit sapien. Fusce dictum viverra ex, nec commodo libero porttitor a. Quisque vel turpis nec ex consectetur fringilla quis quis purus. Aenean imperdiet est risus. Vivamus erat tellus, mollis ut risus in, accumsan iaculis risus. Ut quis mauris sem. Morbi enim mauris, egestas eu mauris a, finibus vestibulum mi.

Praesent id turpis a tortor faucibus consectetur. Maecenas efficitur ipsum vel libero dignissim, ac luctus mauris ornare. In lobortis et tortor eu faucibus. Integer libero odio, fringilla vitae ornare sit amet, porta ac justo. Praesent ut quam gravida velit rhoncus tempus ut vitae magna. Pellentesque ut porta leo. Morbi viverra soda-les orci in laoreet. Duis iaculis velit eu nisi luctus ullamcorper. Aliquam porta nisi non mattis vulputate. Integer a mollis neque, sed vulputate lectus. Sed tincidunt ali-quam elit ac fringilla. Aenean sed tempus erat. Maecenas ultrices sed leo in commodo. Phasellus eget lorem finibus, tincidunt massa vel, interdum urna. Nulla facilisi. Integer commodo erat arcu, blandit faucibus metus mattis non. Donec efficitur ornare magna eget cur-sus. Pellentesque feugiat odio at justo sodales imperdiet. Pellentesque sed tincidunt tellus, at laoreet dolor. Duis mi felis, semper sed nulla eget, dictum bibendum nunc. Interdum et malesuada fames ac ante ipsum primis in faucibus. Phasellus porttitor neque et enim vestibulum faucibus. Donec quis lobortis quam. Cras vestibulum eros ac risus dapibus consectetur.



Figure 3.1 — And another figure with a caption.

Table 3.2 — This table is identical to the previous one, but it is here so that we have not only one but rather two tables in our docuemnt. And as this caption is very long, it should be justified and not centered.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | 1971 | 1980 | 1990 | 2000 |
| 0–24 | 3 861 916 | 4 131 825 | 3 660 978 | 3 176 450 |
| 25–49 | 2 658 361 | 3 015 450 | 3 312 011 | 3 705 865 |
| 50–74 | 1 851 909 | 2 245 875 | 2 482 266 | 2 718 007 |
| +75 | 271 575 | 373 125 | 527 967 | 689 581 |
| Total | 8 643 756 | 9 766 275 | 9 983 218 | 10 289 898 |

Integer hendrerit ante in dui viverra, et lacinia orci consectetur. Nullam ut arcu augue. Praesent ultrices enim ac pulvinar malesuada. Donec sed magna ut sapien dictum tincidunt sit amet sit amet felis. Nulla dapibus auctor ante, sit amet tempor sapien tempor sed. Sed auctor nisl suscipit lobortis convallis. Mauris faucibus iaculis cursus. Vivamus turpis dui, tempor nec enim in, aliquet hendrerit mauris. Duis ut tempor velit.

# And Another Chapter with some More Text to Increase the Document Size

Lorem ipsum dolor sit amet, consectetur adipisicing elit, sed do eiusmod tempor incididunt ut labore et dolore magna aliqua. Ut enim ad minim veniam, quis nostrud exercitation ullamco laboris nisi ut aliquip ex ea commodo consequat. Duis aute irure dolor in reprehenderit in voluptate velit esse cillum dolore eu fugiat nulla pariatur. Excepteur sint occaecat cupidatat non proident, sunt in culpa qui officia deserunt mollit anim id est laborum.

## This is a Section

Lorem ipsum dolor sit amet, consectetur adipisicing elit, sed do eiusmod tempor incididunt ut labore et dolore magna aliqua. Ut enim ad minim veniam, quis nostrud exercitation ullamco laboris nisi ut aliquip ex ea commodo consequat. Duis aute irure dolor in reprehenderit in voluptate velit esse cillum dolore eu fugiat nulla pariatur. Excepteur sint occaecat cupidatat non proident, sunt in culpa qui officia deserunt mollit anim id est laborum.

Lorem ipsum dolor sit amet, consectetur adipisicing elit, sed do eiusmod tempor incididunt ut labore et dolore magna aliqua. Ut enim ad minim veniam, quis nostrud exercitation ullamco laboris nisi ut aliquip ex ea commodo consequat. Duis aute irure dolor in reprehenderit in voluptate velit esse cillum dolore eu fugiat nulla pariatur. Excepteur sint occaecat cupidatat non proident, sunt in culpa qui officia deserunt mollit anim id est laborum.

### This is a Subsection

Lorem ipsum dolor sit amet, consectetur adipisicing elit, sed do eiusmod tempor incididunt ut labore et dolore magna aliqua. Ut enim ad minim veniam, quis nostrud exercitation ullamco laboris nisi ut aliquip ex ea commodo consequat. Duis aute irure dolor in reprehenderit in voluptate velit esse cillum dolore eu fugiat nulla pariatur. Excepteur sint occaecat cupidatat non proident, sunt in culpa qui officia deserunt mollit anim id est laborum.

Lorem ipsum dolor sit amet, consectetur adipisicing elit, sed do eiusmod tempor incididunt ut labore et dolore magna aliqua. Ut enim ad minim veniam, quis nostrud exercitation ullamco laboris nisi ut aliquip ex ea commodo consequat. Duis aute irure dolor in reprehenderit in voluptate velit esse cillum dolore eu fugiat nulla pariatur. Excepteur sint occaecat cupidatat non proident, sunt in culpa qui officia deserunt mollit anim id est laborum.

#### This is a sub-subsection

Lorem ipsum dolor sit amet, consectetur adipisicing elit, sed do eiusmod tempor incididunt ut labore et dolore magna aliqua. Ut enim ad minim veniam, quis nostrud exercitation ullamco laboris nisi ut aliquip ex ea commodo consequat. Duis aute irure dolor in reprehenderit in voluptate velit esse cillum dolore eu fugiat nulla pariatur. Excepteur sint occaecat cupidatat non proident, sunt in culpa qui officia deserunt mollit anim id est laborum.

### This is another Subsection

Lorem ipsum dolor sit amet, consectetur adipisicing elit, sed do eiusmod tempor incididunt ut labore et dolore magna aliqua. Ut enim ad minim veniam, quis nostrud exercitation ullamco laboris nisi ut aliquip ex ea commodo consequat. Duis aute irure dolor in reprehenderit in voluptate velit esse cillum dolore eu fugiat nulla pariatur. Excepteur sint occaecat cupidatat non proident, sunt in culpa qui officia deserunt mollit anim id est laborum.

#### This is another sub-subsection

Lorem ipsum dolor sit amet, consectetur adipisicing elit, sed do eiusmod tempor incididunt ut labore et dolore magna aliqua. Ut enim ad minim veniam, quis nostrud exercitation ullamco laboris nisi ut aliquip ex ea commodo consequat. Duis aute irure dolor in reprehenderit in voluptate velit esse cillum dolore eu fugiat nulla pariatur. Excepteur sint occaecat cupidatat non proident, sunt in culpa qui officia deserunt mollit anim id est laborum.

#### Yet another sub-subsection

Lorem ipsum dolor sit amet, consectetur adipisicing elit, sed do eiusmod tempor incididunt ut labore et dolore magna aliqua. Ut enim ad minim veniam, quis nostrud exercitation ullamco laboris nisi ut aliquip ex ea commodo consequat. Duis aute irure dolor in reprehenderit in voluptate velit esse cillum dolore eu fugiat nulla pariatur. Excepteur sint occaecat cupidatat non proident, sunt in culpa qui officia deserunt mollit anim id est laborum.

## Another Section

Lorem ipsum dolor sit amet, consectetur adipisicing elit, sed do eiusmod tempor incididunt ut labore et dolore magna aliqua. Ut enim ad minim veniam, quis nostrud exercitation ullamco laboris nisi ut aliquip ex ea commodo consequat. Duis aute irure dolor in reprehenderit in voluptate velit esse cillum dolore eu fugiat nulla pariatur. Excepteur sint occaecat cupidatat non proident, sunt in culpa qui officia deserunt mollit anim id est laborum.

Bibliografia

[1] Jabeen, K., Khan, M. A., Damaševičius, R., Alsenan, S., Baili, J., Zhang, Y. D., & Verma, A. (2024). An intelligent healthcare framework for breast cancer diagnosis based on the information fusion of novel deep learning architectures and improved optimization algorithm. Engineering Applications of Artificial Intelligence, 137, 109152.

[2] Gupta, N., Kubicek, J., Penhaker, M., & Derawi, M. (2025). A novel diagnostic framework for breast cancer: Combining deep learning with mammogram-DBT feature fusion. Results in Engineering, 25, 103836.

[3] Li, H., Zhao, J., & Jiang, Z. (2024). Deep learning-based computer-aided detection of ultrasound in breast cancer diagnosis: A systematic review and meta-analysis. Clinical Radiology, 79(11), e1403-e1413.

[4] Resch, D., Lo Gullo, R., Teuwen, J., Semturs, F., Hummel, J., Resch, A., & Pinker, K. (2024). Ai-enhanced mammography with digital breast tomosynthesis for breast cancer detection: Clinical value and comparison with human performance. Radiology: Imaging Cancer, 6(4), e230149.

[5] Schiaffino, S., Zhang, T., Mann, R. M., & Pinker, K. (2025). The Role of Large Language Models (LLMs) in Breast Imaging Today and in the Near Future. Journal of Magnetic Resonance Imaging.

[6] Wang, R., Chen, F., Chen, H., Lin, C., Shuai, J., Wu, Y., ... & Pan, J. (2025). Deep Learning in Digital Breast Tomosynthesis: Current Status, Challenges, and Future Trends. MedComm, 6(6), e70247.

[7] Chen, Y., Yang, H., Pan, H., Siddiqui, F., Verdone, A., Zhang, Q., ... & Shen, Y. (2024, October). Burextract-llama: An llm for clinical concept extraction in breast ultrasound reports. In Proceedings of the 1st International Workshop on Multimedia Computing for Health and Medicine (pp. 53-58).

[8] Ollama. (n.d.). Search Results. Retrieved July 13, 2025, from <https://ollama.com/search>

[9] Piao, Y., Chen, H., Wu, S., Li, X., Li, Z., & Yang, D. (2024). Assessing the performance of large language models (LLMs) in answering medical questions regarding breast cancer in the Chinese context. Digital Health, 10, 20552076241284771.

[10] Harini, K. K., Nandhini, R., Rajeswari, A. M., & Deepalakshmi, R. (2024, March). Breast Cancer Image Classification: Leveraging Deep Learning and Large Language Models for Semantic Integration. In 2024 IEEE International Conference on Contemporary Computing and Communications (InC4) (Vol. 1, pp. 1-6). IEEE.

[11] Haider, S. A., Pressman, S. M., Borna, S., Gomez-Cabello, C. A., Sehgal, A., Leibovich, B. C., & Forte, A. J. (2024). Evaluating large language model (LLM) performance on established breast classification systems. Diagnostics, 14(14), 1491.

[12] Qureshi, S. A., Hussain, L., Sadiq, T., Shah, S. T. H., Mir, A. A., Nadim, M. A., ... & Shah, S. A. H. (2024). Breast Cancer Detection using Mammography: Image Processing to Deep Learning. IEEE Access.

[13] Kopans, D. B., Swann, C. A., White, G., McCarthy, K. A., Hall, D. A., Belmonte, S. J., & Gallagher, W. (1989). Asymmetric breast tissue. Radiology, 171(3), 639-643.

[14] Nielsen, S., & Narayan, A. K. (2023). Breast cancer screening modalities, recommendations, and novel imaging techniques. Surgical Clinics, 103(1), 63-82.

[15] Pisano, E. D., Gatsonis, C., Hendrick, E., Yaffe, M., Baum, J. K., Acharyya, S., ... & Rebner, M. (2005). Diagnostic performance of digital versus film mammography for breast-cancer screening. New England Journal of Medicine, 353(17), 1773-1783.

[16] Newman, P. G., & Rozycki, G. S. (1998). The history of ultrasound. Surgical clinics of north America, 78(2), 179-195.

[17] Dunne, R. M., O'Neill, A. C., & Tempany, C. M. (2017). Imaging tools in clinical research: Focus on imaging technologies. In Clinical and Translational Science (pp. 157-179). Academic Press.

[18] Jabeen, K., Khan, M. A., Alhaisoni, M., Tariq, U., Zhang, Y. D., Hamza, A., ... & Damaševičius, R. (2022). Breast cancer classification from ultrasound images using probability-based optimal deep learning feature fusion. Sensors, 22(3), 807.

[19] Ellis, J., Appiah, K., Amankwaa-Frempong, E., & Kwok, S. C. (2024). Classification of 2d ultrasound breast cancer images with deep learning. In Proceedings of the IEEE/CVF conference on computer vision and pattern recognition (pp. 5167-5173).

[20] Khomsi, Z., Elfezazi, M., & Bellarbi, L. (2024). Deep learning-based approach in surface thermography for inverse estimation of breast tumor size. Scientific African, 23, e01987.

[21] Advanced Thermal Imaging LLC. (n.d.). Thermography Services: Breast Thermography. Retrieved January 15, 2024, from https://www.advancedthermalimagingllc.com/thermography-services/breast-thermography/

[22] Munguía-Siu, A., Vergara, I., & Espinoza-Rodríguez, J. H. (2024). The use of hybrid CNN-RNN deep learning models to discriminate tumor tissue in dynamic breast thermography. Journal of Imaging, 10(12), 329.

[23] Bani Ahmad, A. Y., Alzubi, J. A., Vasanthan, M., Kondaveeti, S. B., Shreyas, J., & Priyanka, T. P. (2025). Efficient hybrid heuristic adopted deep learning framework for diagnosing breast cancer using thermography images. Scientific Reports, 15(1), 13605.

[24] Timadius, E. D., Wongso, R., Baihaqi, T., Gunawan, A. A. S., & Setiawan, K. E. (2024, July). Breast Cancer Image Classification Obtained Through Dynamic Thermography using Deep Learning. In 2024 4th International Conference of Science and Information Technology in Smart Administration (ICSINTESA) (pp. 207-212). IEEE.

[25] Oba, K., Adachi, M., Kobayashi, T., Takaya, E., Shimokawa, D., Fukuda, T., ... & Tsunoda, H. (2024). Deep learning model to predict Ki-67 expression of breast cancer using digital breast tomosynthesis. Breast Cancer, 1-7.

[26] Wang, R., Chen, F., Chen, H., Lin, C., Shuai, J., Wu, Y., ... & Pan, J. (2025). Deep Learning in Digital Breast Tomosynthesis: Current Status, Challenges, and Future Trends. MedComm, 6(6), e70247.

[27] Dhamija, E., Gulati, M., Deo, S. V. S., Gogia, A., & Hari, S. (2021). Digital Breast Tomosynthesis: An Overview. Indian Journal of Surgical Oncology, 12(2), 315-329. doi: 10.1007/s13193-021-01310-y

[28] Sajiv, G., Ramkumar, G., Shanthi, S., Chinnathambi, A., & Alharbi, S. A. (2024). Predicting breast cancer risk from histopathology images using hybrid deep learning classifier. Medical Engineering & Physics, 104149.

[29] National Center for Biotechnology Information. (n.d.). Figure 2. Retrieved July 13, 2025, from https://www.ncbi.nlm.nih.gov/books/NBK547732/

[30] Balasubramanian, A. A., Al-Heejawi, S. M. A., Singh, A., Breggia, A., Ahmad, B., Christman, R., ... & Amal, S. (2024). Ensemble deep learning-based image classification for breast cancer subtype and invasiveness diagnosis from whole slide image histopathology. Cancers, 16(12), 2222.

[31] Aldakhil, L. A., Alhasson, H. F., & Alharbi, S. S. (2024). Attention-based deep learning approach for breast cancer histopathological image multi-classification. Diagnostics, 14(13), 1402.

[32] Jiang, B., Bao, L., He, S., Chen, X., Jin, Z., & Ye, Y. (2024). Deep learning applications in breast cancer histopathological imaging: diagnosis, treatment, and prognosis. Breast Cancer Research, 26(1), 137.

[33] Dada, E. G., Oyewola, D. O., & Misra, S. (2024). Computer-aided diagnosis of breast cancer from mammogram images using deep learning algorithms. Journal of Electrical Systems and Information Technology, 11(1), 38.

[34] Ibrokhimov, B., & Kang, J. Y. (2022). Two-stage deep learning method for breast cancer detection using high-resolution mammogram images. Applied Sciences, 12(9), 4616.

[35] Wang, L. (2024). Mammography with deep learning for breast cancer detection. Frontiers in oncology, 14, 1281922.

[36] Raza, A., Ullah, N., Khan, J. A., Assam, M., Guzzo, A., & Aljuaid, H. (2023). DeepBreastCancerNet: A novel deep learning model for breast cancer detection using ultrasound images. Applied Sciences, 13(4), 2082.

1. An Appendix

Lorem ipsum dolor sit amet, consectetur adipisicing elit, sed do eiusmod tempor incididunt ut labore et dolore magna aliqua. Ut enim ad minim veniam, quis nostrud exercitation ullamco laboris nisi ut aliquip ex ea commodo consequat. Duis aute irure dolor in reprehenderit in voluptate velit esse cillum dolore eu fugiat nulla pariatur. Excepteur sint occaecat cupidatat non proident, sunt in culpa qui officia deserunt mollit anim id est laborum.

Lorem ipsum dolor sit amet, consectetur adipisicing elit, sed do eiusmod tempor incididunt ut labore et dolore magna aliqua. Ut enim ad minim veniam, quis nostrud exercitation ullamco laboris nisi ut aliquip ex ea commodo consequat. Duis aute irure dolor in reprehenderit in voluptate velit esse cillum dolore eu fugiat nulla pariatur. Excepteur sint occaecat cupidatat non proident, sunt in culpa qui officia deserunt mollit anim id est laborum.

* 1. A Subsection in the Appendix

Lorem ipsum dolor sit amet, consectetur adipisicing elit, sed do eiusmod tempor incididunt ut labore et dolore magna aliqua. Ut enim ad minim veniam, quis nostrud exercitation ullamco laboris nisi ut aliquip ex ea commodo consequat. Duis aute irure dolor in reprehenderit in voluptate velit esse cillum dolore eu fugiat nulla pariatur. Excepteur sint occaecat cupidatat non proident, sunt in culpa qui officia deserunt mollit anim id est laborum.

* 1. Another Subsection in the Appendix

Lorem ipsum dolor sit amet, consectetur adipisicing elit, sed do eiusmod tempor incididunt ut labore et dolore magna aliqua. Ut enim ad minim veniam, quis nostrud exercitation ullamco laboris nisi ut aliquip ex ea commodo consequat. Duis aute irure dolor in reprehenderit in voluptate velit esse cillum dolore eu fugiat nulla pariatur. Excepteur sint occaecat cupidatat non proident, sunt in culpa qui officia deserunt mollit anim id est laborum. Lorem ipsum dolor sit amet, consectetur adipisicing elit, sed do eiusmod tempor incididunt ut labore et dolore magna aliqua. Ut enim ad minim veniam, quis nostrud exercitation ullamco laboris nisi ut aliquip ex ea commodo consequat. Duis aute irure dolor in reprehenderit in voluptate velit esse cillum dolore eu fugiat nulla pariatur. Excepteur sint occaecat cupidatat non proident, sunt in culpa qui officia deserunt mollit anim id est laborum.

* 1. Yet another Subsection in the Appendix

Lorem ipsum dolor sit amet, consectetur adipisicing elit, sed do eiusmod tempor incididunt ut labore et dolore magna aliqua. Ut enim ad minim veniam, quis nostrud exercitation ullamco laboris nisi ut aliquip ex ea commodo consequat. Duis aute irure dolor in reprehenderit in voluptate velit esse cillum dolore eu fugiat nulla pariatur. Excepteur sint occaecat cupidatat non proident, sunt in culpa qui officia deserunt mollit anim id est laborum.

Lorem ipsum dolor sit amet, consectetur adipisicing elit, sed do eiusmod tempor incididunt ut labore et dolore magna aliqua. Ut enim ad minim veniam, quis nostrud exercitation ullamco laboris nisi ut aliquip ex ea commodo consequat. Duis aute irure dolor in reprehenderit in voluptate velit esse cillum dolore eu fugiat nulla pariatur. Excepteur sint occaecat cupidatat non proident, sunt in culpa qui officia deserunt mollit anim id est laborum.

1. Another Appendix

Lorem ipsum dolor sit amet, consectetur adipisicing elit, sed do eiusmod tempor incididunt ut labore et dolore magna aliqua. Ut enim ad minim veniam, quis nostrud exercitation ullamco laboris nisi ut aliquip ex ea commodo consequat. Duis aute irure dolor in reprehenderit in voluptate velit esse cillum dolore eu fugiat nulla pariatur. Excepteur sint occaecat cupidatat non proident, sunt in culpa qui officia deserunt mollit anim id est laborum.

* 1. Another Appendix with Subsections

Lorem ipsum dolor sit amet, consectetur adipisicing elit, sed do eiusmod tempor incididunt ut labore et dolore magna aliqua. Ut enim ad minim veniam, quis nostrud exercitation ullamco laboris nisi ut aliquip ex ea commodo consequat. Duis aute irure dolor in reprehenderit in voluptate velit esse cillum dolore eu fugiat nulla pariatur. Excepteur sint occaecat cupidatat non proident, sunt in culpa qui officia deserunt mollit anim id est laborum.



A VERY LONG AND IMPRESSIVE THESIS TITILE WITH A FORCED LINE BREAK

JOHN DOE

year

