SEGMENTATION OF BREAST CANCER MASS USING TWO APPROACHES: CONNECTED U-NETS AND MULTISCALE ADVERSARIAL NETWORK

Presented by :

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- Tutors: Prof & Consultant Naoual EL ABOUDI
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PLAN

01 Host Organization

National Institute of Oncology

- Founded: 1976
- Sector: Oncology and Cancer Treatment
- Services Offered: Diagnostic services, cancer treatment, patient monitoring, epidemiological studies, multidisciplinary research, medical and paramedical education
- Objective: To diagnose, treat, and monitor cancer patients, conduct cancer epidemiological studies, research diagnostic and treatment methods, and contribute to medical, paramedical, and scientific education.

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- Leaders with extensive experience in designing and implementing IT solutions
- Expertise and training services promoting leadership based on technological innovation
- Guarantees the security of IT solutions and facilitates knowledge transfer

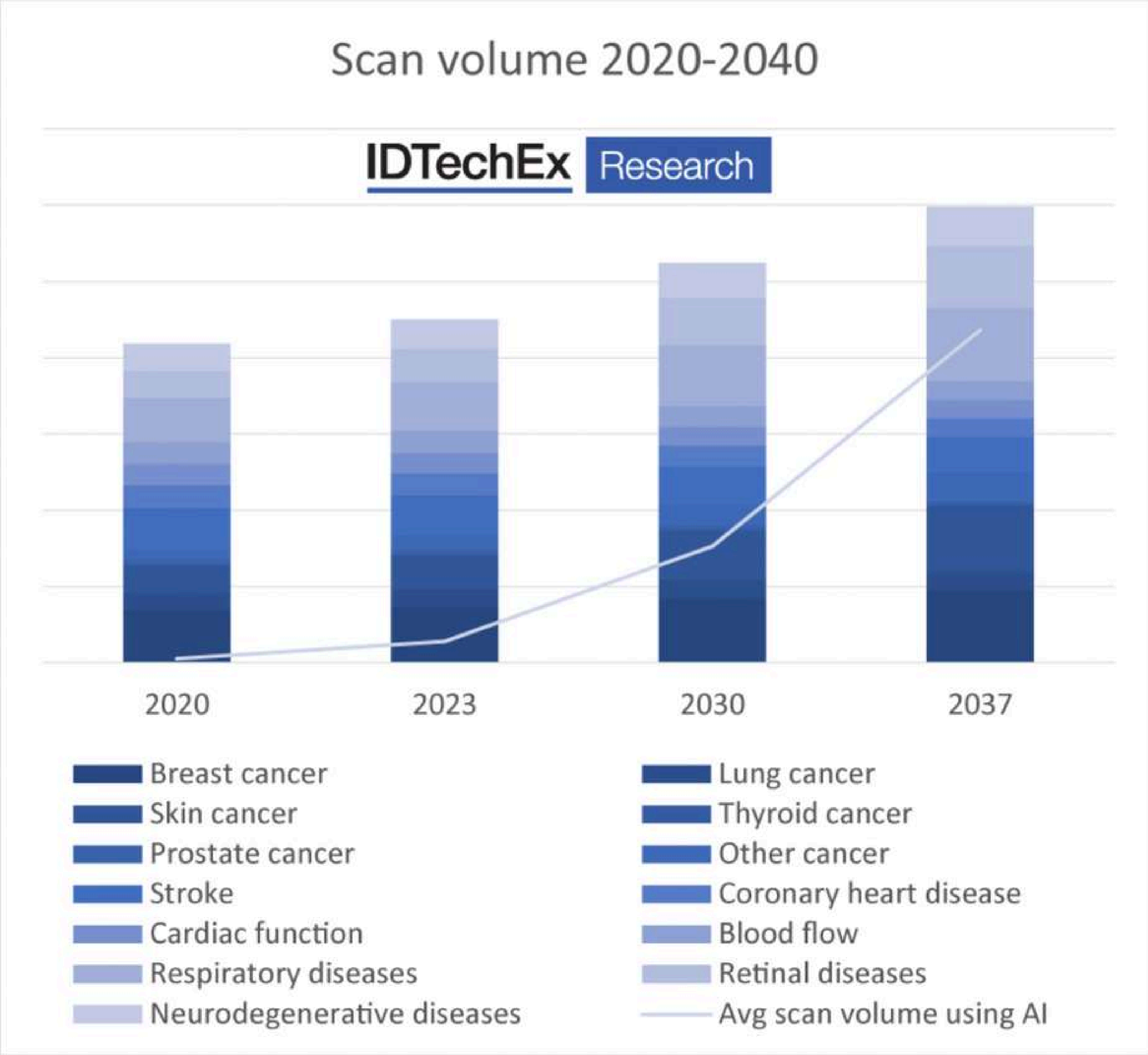
01 Host Organization

Presentation of the Organizational Chart

Context and Objectives of the Research

02 Context of the Study

AI in Medical Imaging | mammography screening | Problem Statement | Objectives of the Research

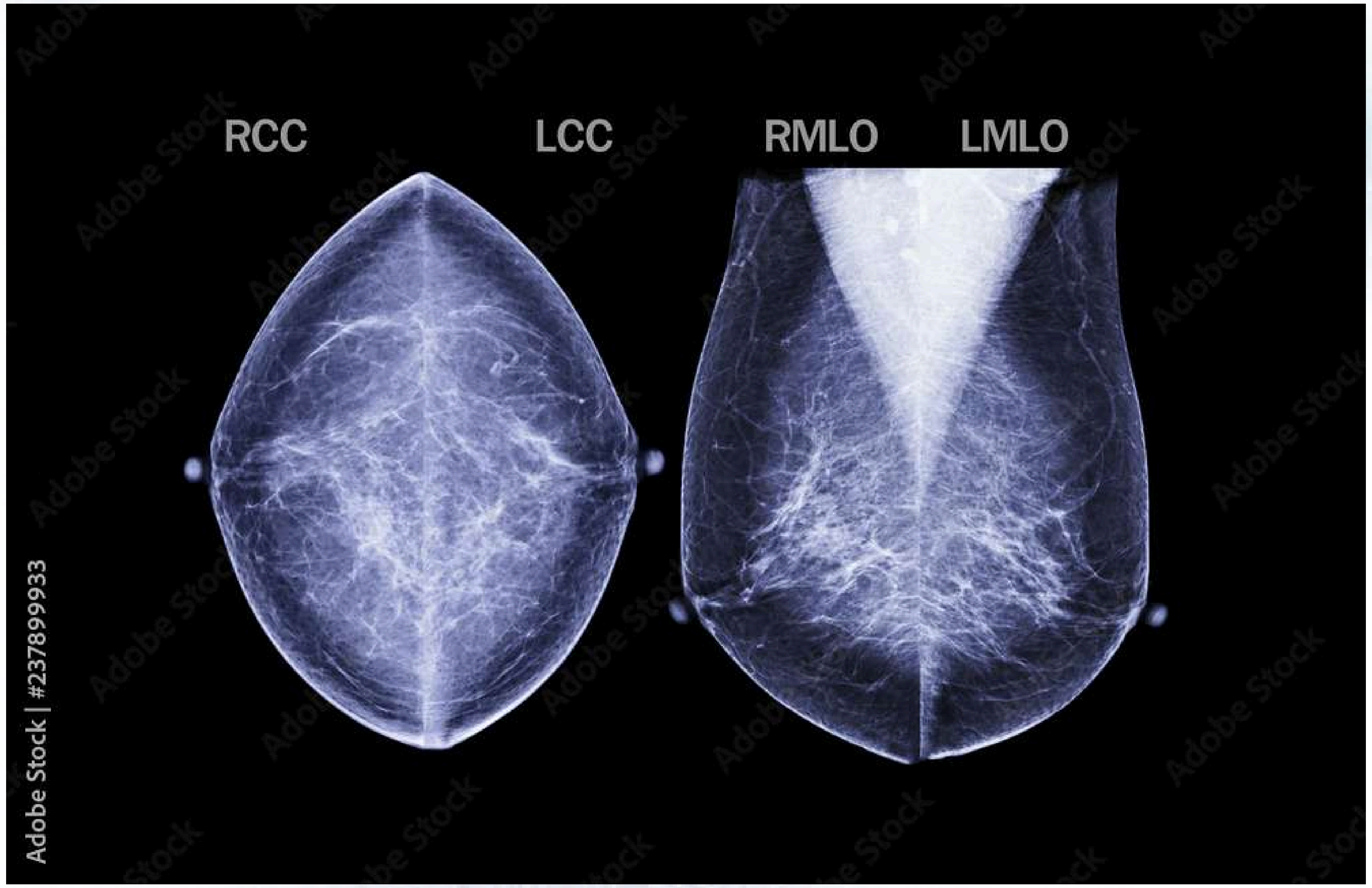


- Significant increase in scan volume using AI from 2020 to 2040.
- Breast cancer scans show substantial growth, indicating rising reliance on AI for early detection and diagnosis.
- AI technology is improving diagnostic accuracy, leading to better outcomes in breast cancer treatment.
- The adoption of AI in medical imaging is also expanding across other diseases such as skin cancer, prostate cancer, and lung cancer.

02 Context of the Study

AI in Medical Imaging | **Mammography Screening** | Problem Statement | Objectives of the Research

- Mammography is widely used in the Moroccan context because it is accessible and cost-effective.
- Provides early detection of breast cancer, improving treatment outcomes.
- Non-invasive procedure with minimal discomfort for patients.
- High accuracy in identifying breast abnormalities.
- Can be performed on both right and left breasts.
- Different imaging views (MLO, CC) provide comprehensive assessment.



02 Context of the Study

AI in Medical Imaging | Mammography Screening | **Problem Statement** | Objectives of the Research

Preprocessing Issues

Manual Evaluation

Data Proliferation

Timely Identification

Noise and artifacts of images

Data Confidentiality

Diagnostic Accuracy

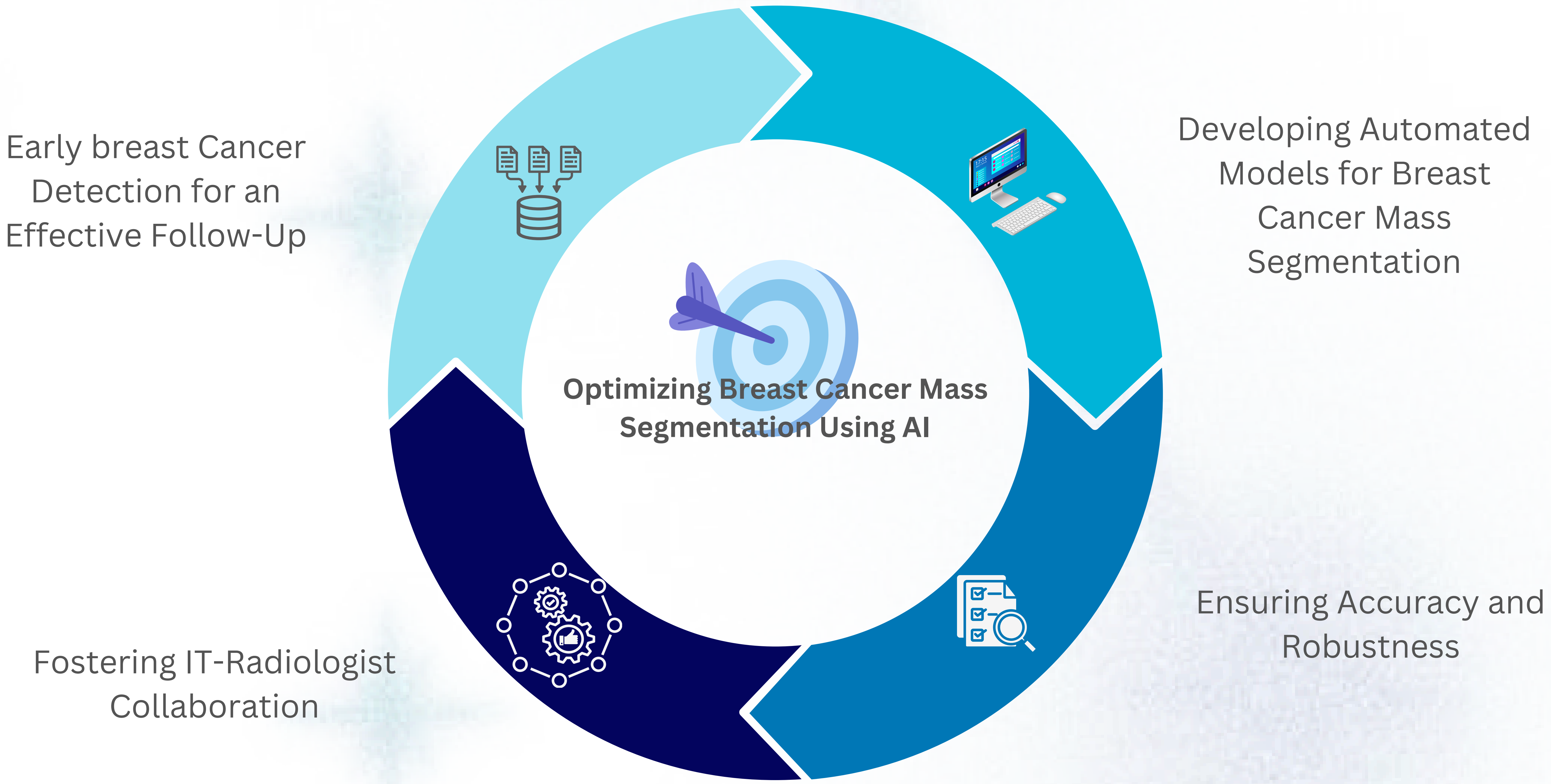
Irregular shapes of mass

How can we develop accurate and robust breast cancer mass segmentation models, fostering collaboration between IT specialists and radiologists to improve diagnosis and treatment?

02

Context of the Study

AI in Medical Imaging | Mammography Screening | Problem Statement | **Objectives of the Research**



Literature Review

03 Literature Review

Principal Works

Comparative Table

Connected U-Nets

Multiscale Approach

2019

CU-Net: Cascaded U-Net with Loss Weighted Sampling for Brain Tumor Segmentation

2021

Connected-UNets: a deep learning architecture for breast mass segmentation

2023

Connected-SegNets: A Deep Learning Model for Breast Tumor Segmentation from X-ray Images

03 Literature Review

Principal Works

Comparative Table

Connected U-Nets

Multiscale approach

2020(Dec)

MA-Unet: An improved version of Unet based on multi-scale and attention mechanism for medical image segmentation

2020(JULY)

Cascade Residual Multiscale Convolution and Mamba-Structured UNet for Advanced Brain Tumor Image Segmentation

2024

A deep learning based multiscale approach to segment cancer area in liver whole slide image

Principal Works

Comparative Tables

Connected U-Nets

Multiscale Approach

Article Title	Authors	Approach	Methods Used	Datasets	Key Metrics	Performance
CU-Net: Cascaded U-Net with Loss Weighted Sampling for Brain Tumor Segmentation (2019)	Hongying Liu, Xiongjie Shen, Fanhua Shang, Fei Wang	Cascaded U-Net, Loss Weighted Sampling	Residual blocks, auxiliary supervision, between-net connections	BraTS 2017	Dice score, Sensitivity, Specificity	Dice score 0.888, Sensitivity 0.903 for whole tumor, etc.
Connected-UNets: a deep learning architecture for breast mass segmentation (2021)	Asma Baccouche, Begonya Garcia-Zapirain, Cristian Castillo Olea, Adel S. Elmaghraby	Connected-UNets	Modified skip connections, ASPP, CycleGAN	CBIS-DDSM, INbreast, private dataset	Dice score, IoU score	Dice score 89.52%, 95.28%, and 95.88% for CBIS-DDSM, INbreast, and private dataset, respectively
Connected-SegNets: A Deep Learning Model for Breast Tumor Segmentation from X-ray Images (2022)	Mohammad Alkhaleefah, Tan-Hsu Tan, Chuan-Hsun Chang, Tzu-Chuan Wang, Shang-Chih Ma, Lena Chang, Yang-Lang Chang	Connected-SegNets	Skip connections, IoU loss function, CLAHE, image augmentation	INbreast, CBIS-DDSM, private dataset	Dice score, IoU score	Dice score 96.34%, 92.86%, and 92.25% on INbreast, CBIS-DDSM, and private dataset, respectively; IoU score 91.21%, 87.34%, and 83.71%

03 Literature Review

Principal Works

Comparative Tables

Connected U-nets

Multiscale Approach

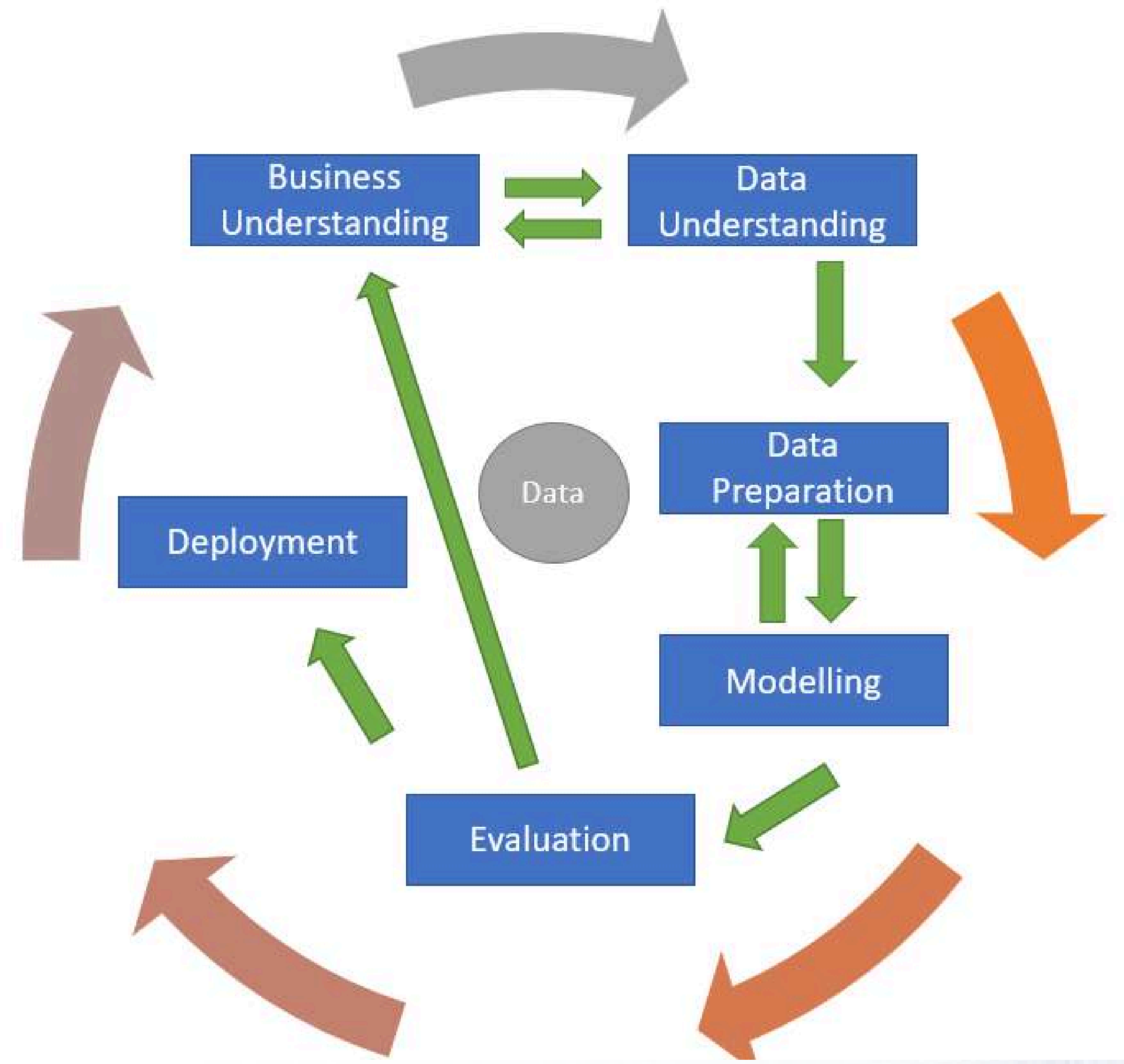
Article Title	Approach	Methods Used	Datasets	Key Metrics	Performance
"A Deep Learning Based Multiscale Approach to Segment Cancer Area in Liver Whole Slide Image"	Multi-scale image processing	Gaussian pyramid, U-Net, Attention U-Net, etc.	MICCAI PAIP Challenge	Jaccard Score, F1 Score, Directed Hausdorff Distance	Best Jaccard Score: 0.7964
"Cascade Residual Multiscale Convolution and Mamba-Structured UNet for Advanced Brain Tumour Image Segmentation"	Cascade residual multi-scale convolution	MambaBTS, CBAM, hybrid loss function	MICCAI BraTS 2019	Dice Coefficients, PPV, Sensitivity	WT: 0.8450, TC: 0.8606, ET: 0.7796
"MA-Unet: An Improved Version of Unet Based on Multi-scale and Attention Mechanism for Medical Image Segmentation"	Multi-scale and attention mechanism	MA-Unet, Attention Gates, Multi-scale predictive fusion	LUNA, Sun Yat-sen University	MIOU, MDC	Lung: MIOU: 95.76%, MDC: 97.52%; Esophageal: MIOU: 65.3%, MDC: 75.49%

Methodology and Conceptual phase

04 Methodology and Conceptual phase

Methodology | Functional Requirements | Conceptual Phase | Techniques and tools used

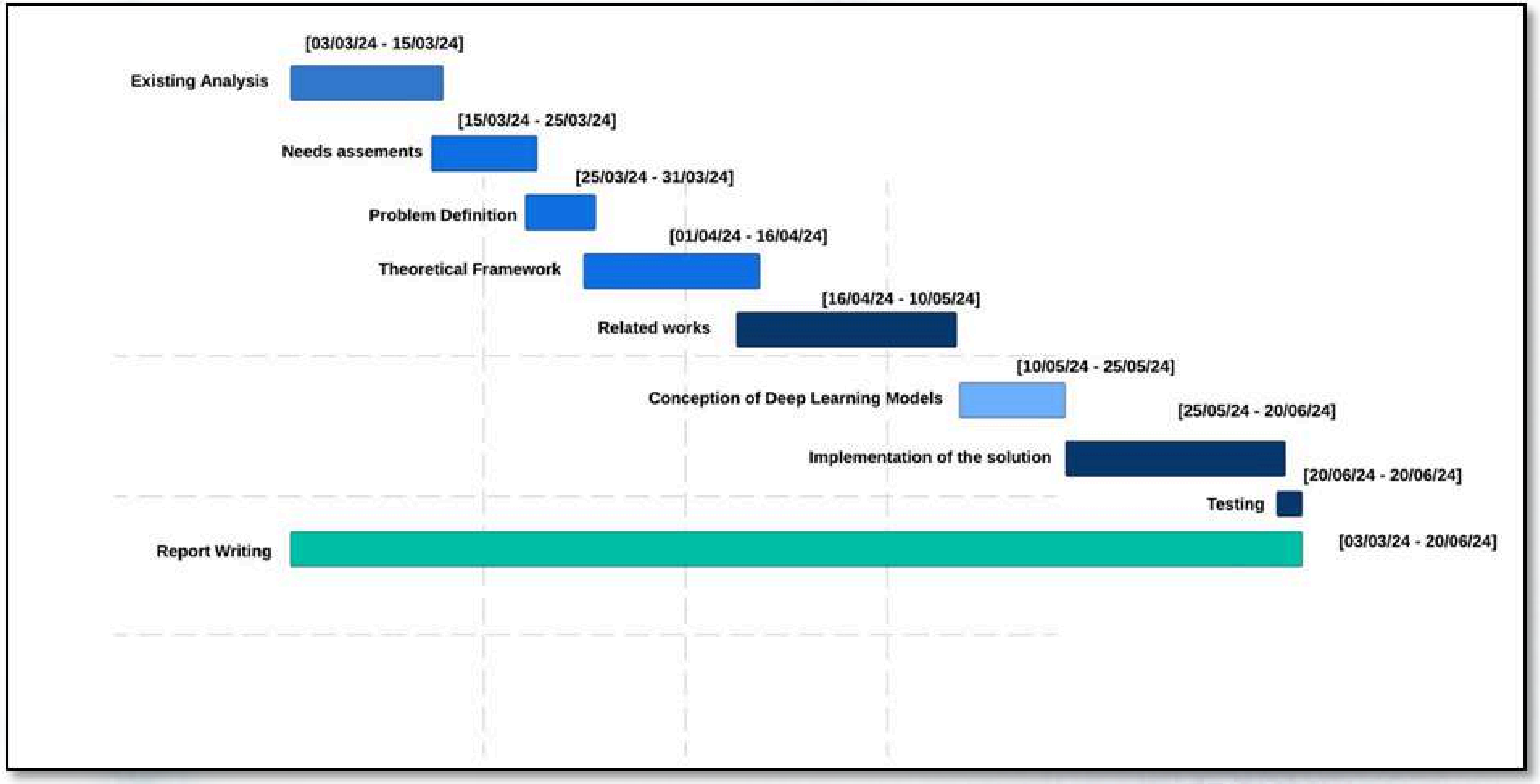
Using CRISP-DM to maximize accuracy and minimize cycle times in Breast Cancer Mass Segmentation



04 Methodology and Conceptual phase

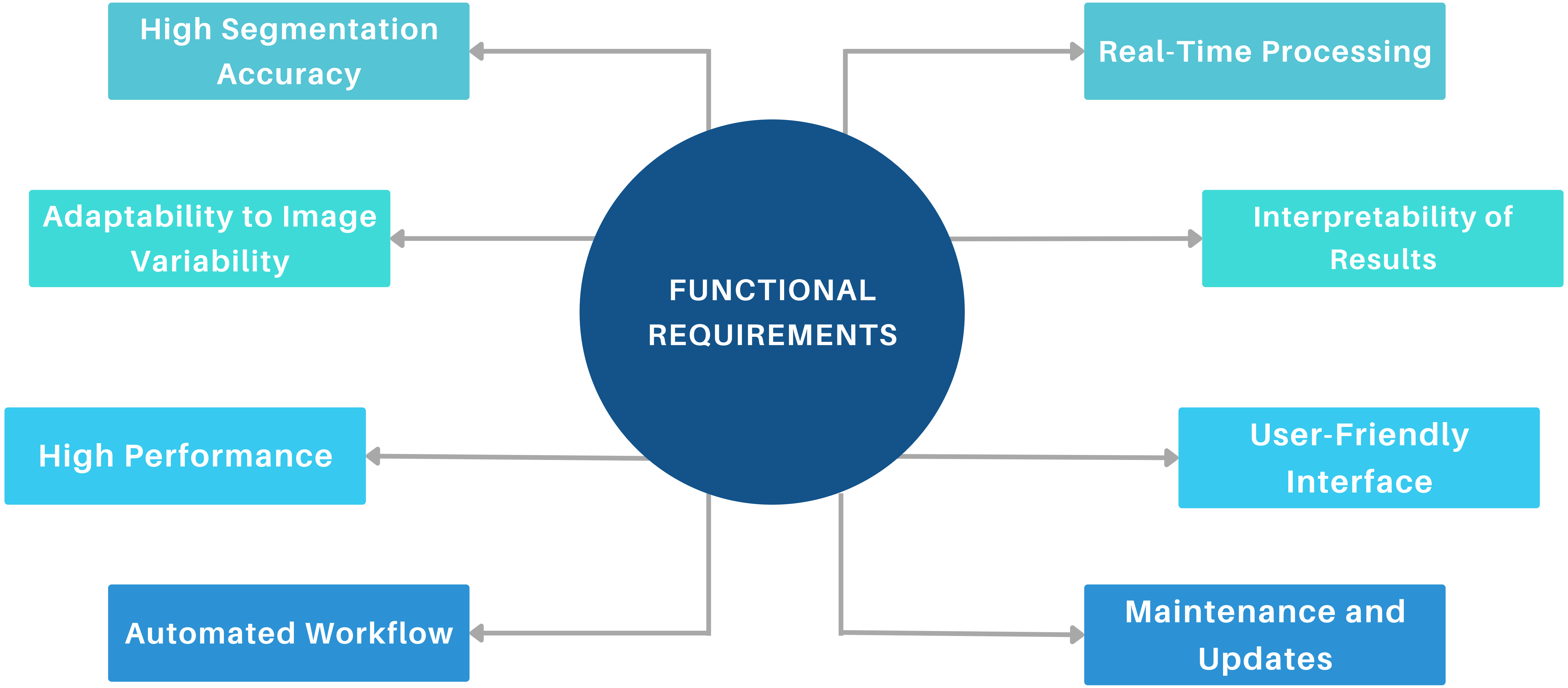
Methodology | Functional Requirements | Conceptual Phase | Techniques and tools used

We used Gantt chart to outline the timeline for our various project tasks



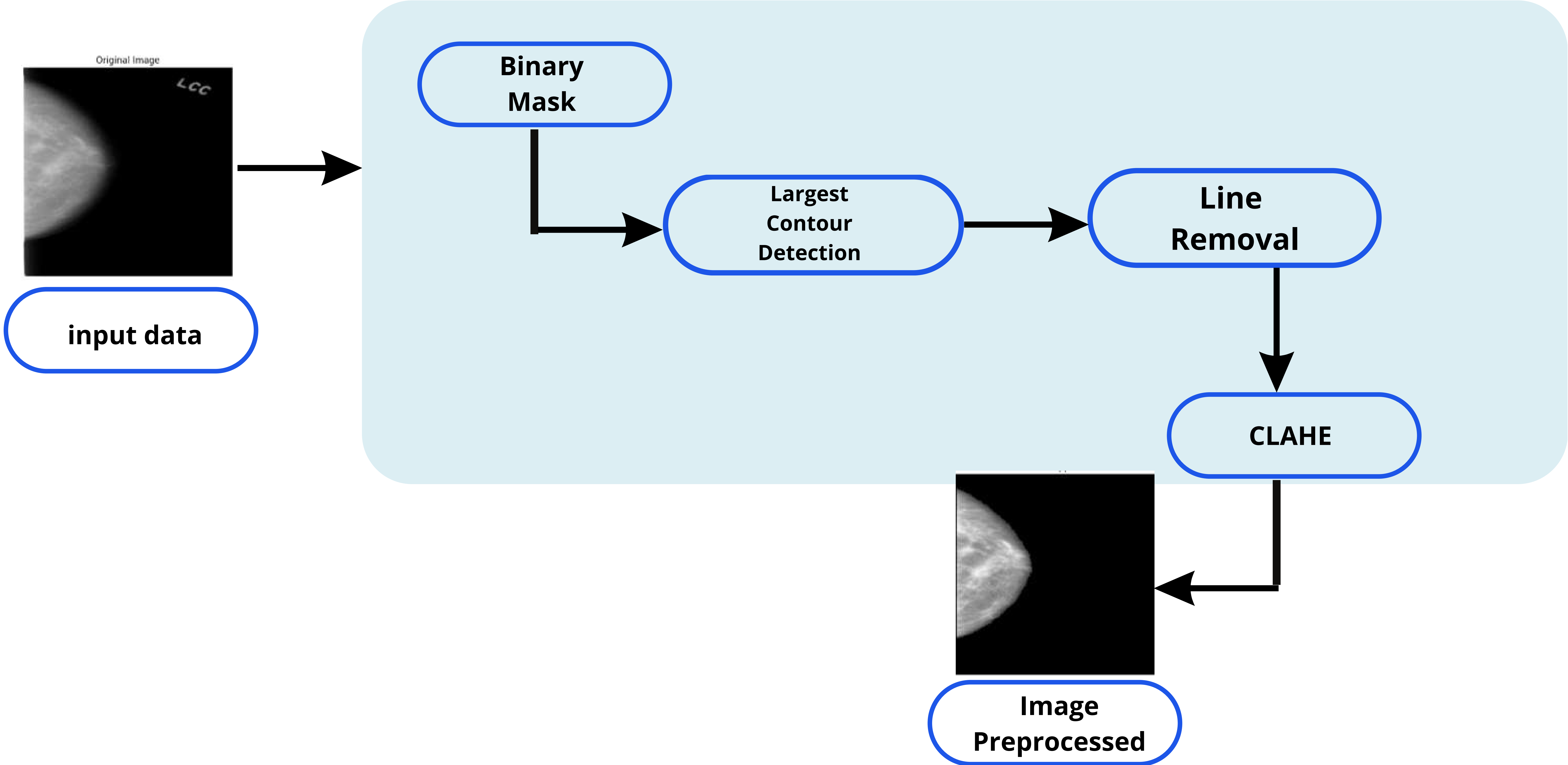
04 Methodology and Conceptual phase

Methodology | **Functional Requirements** | Conceptual Phase | Techniques and tools used



04 Methodology and Conceptual phase

Methodology | Functional Requirements | **Conceptual Phase** | Techniques and tools used



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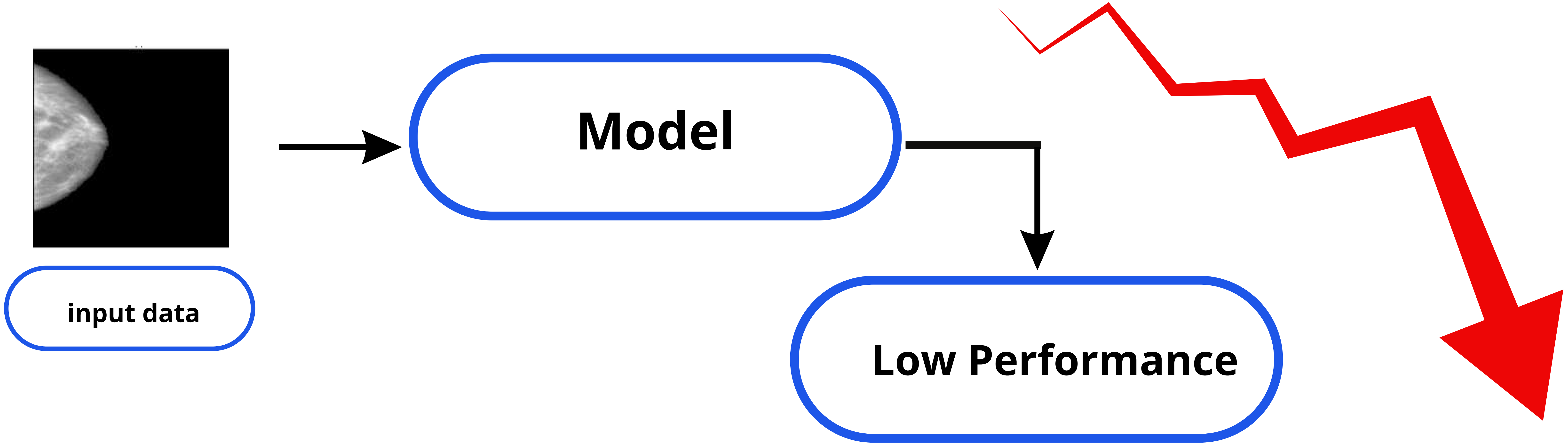

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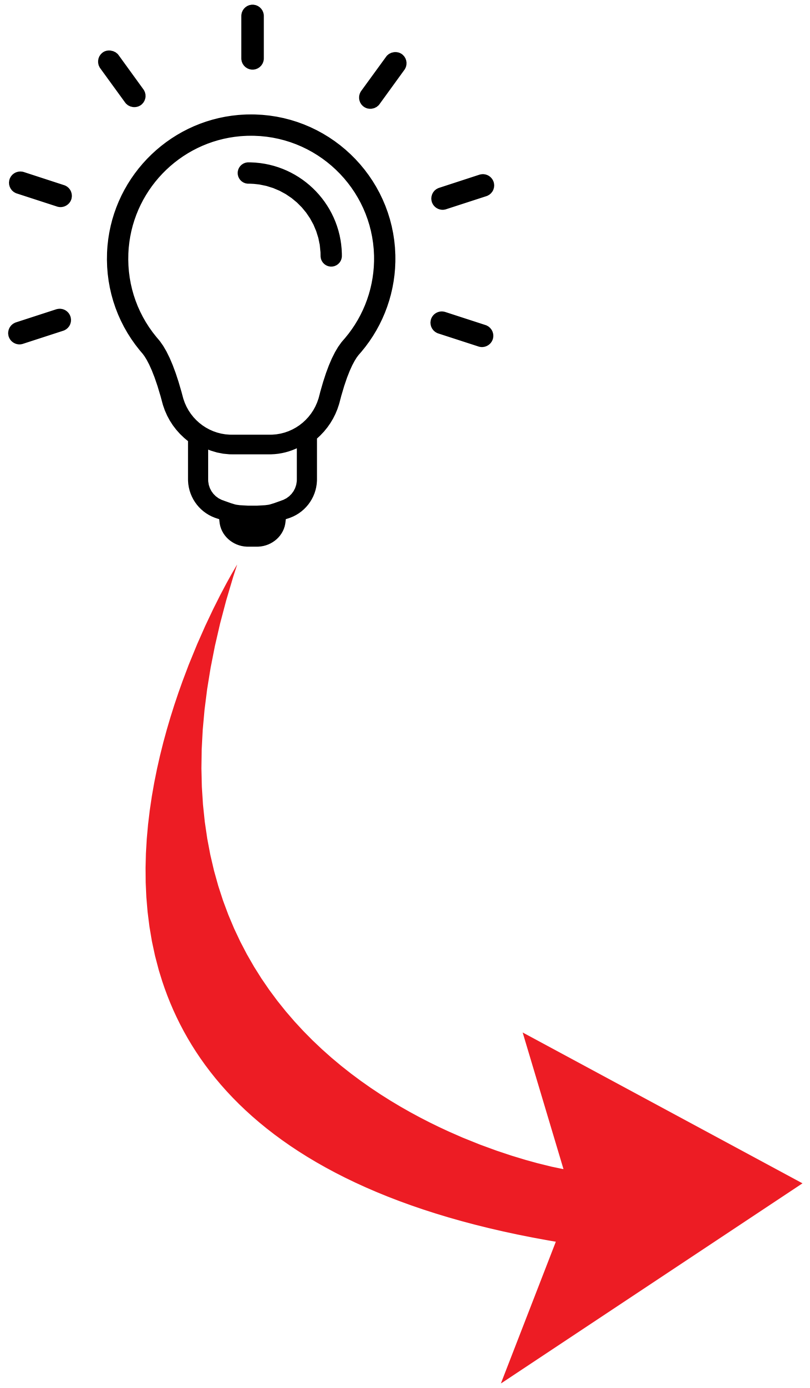
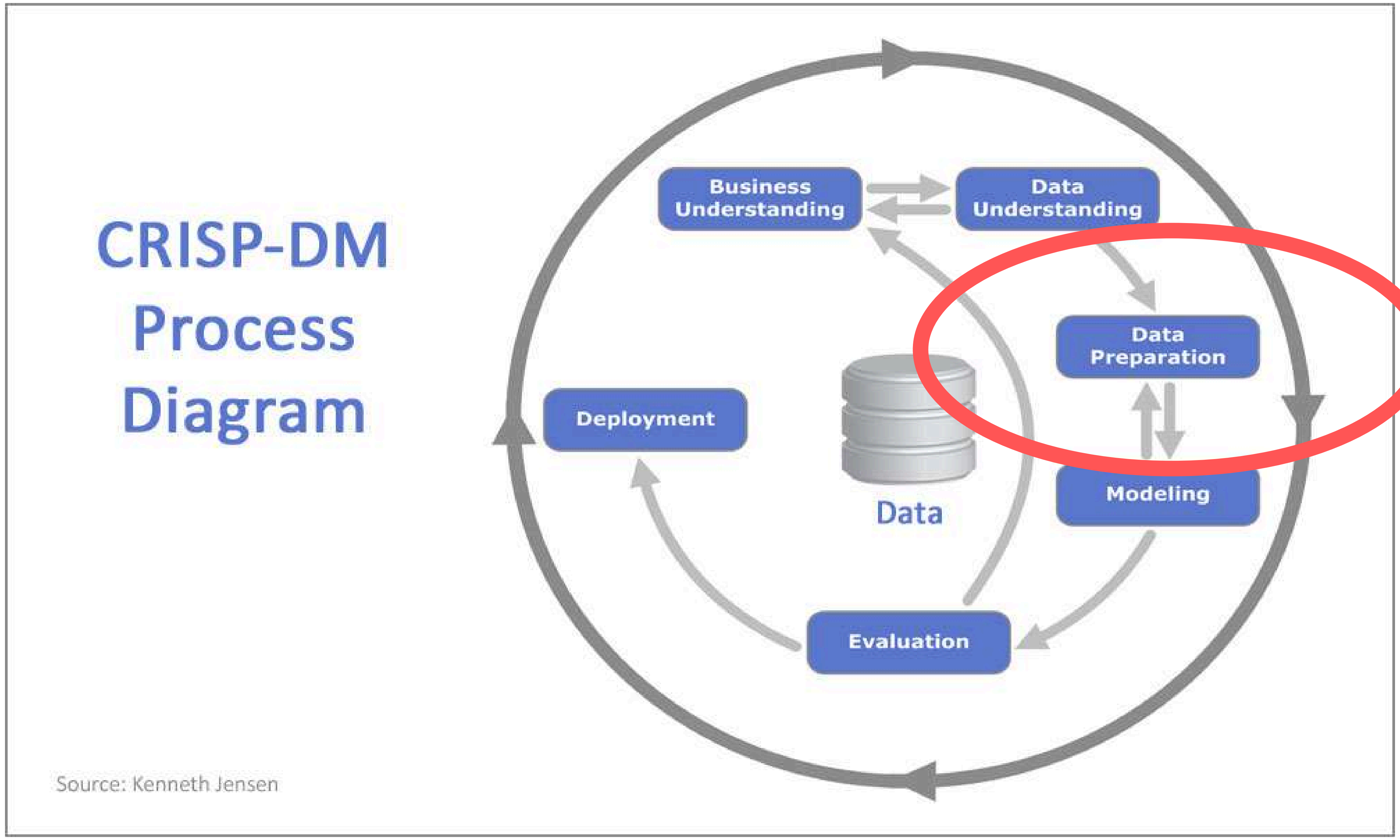
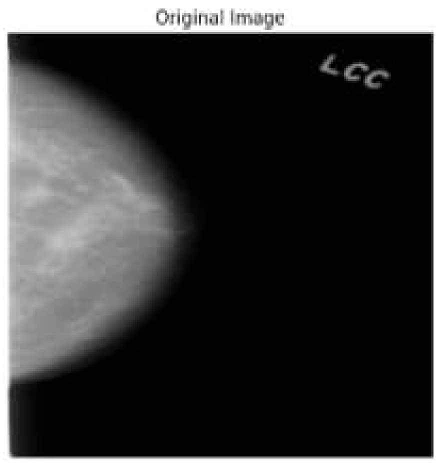


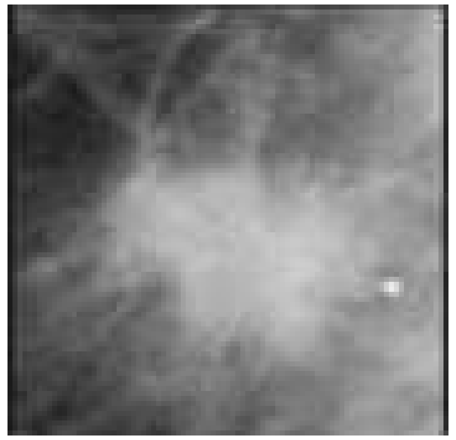


04 Methodology and Conceptual phase

Methodology | Functional Requirements | **Conceptual Phase** | Techniques and tools used



input data



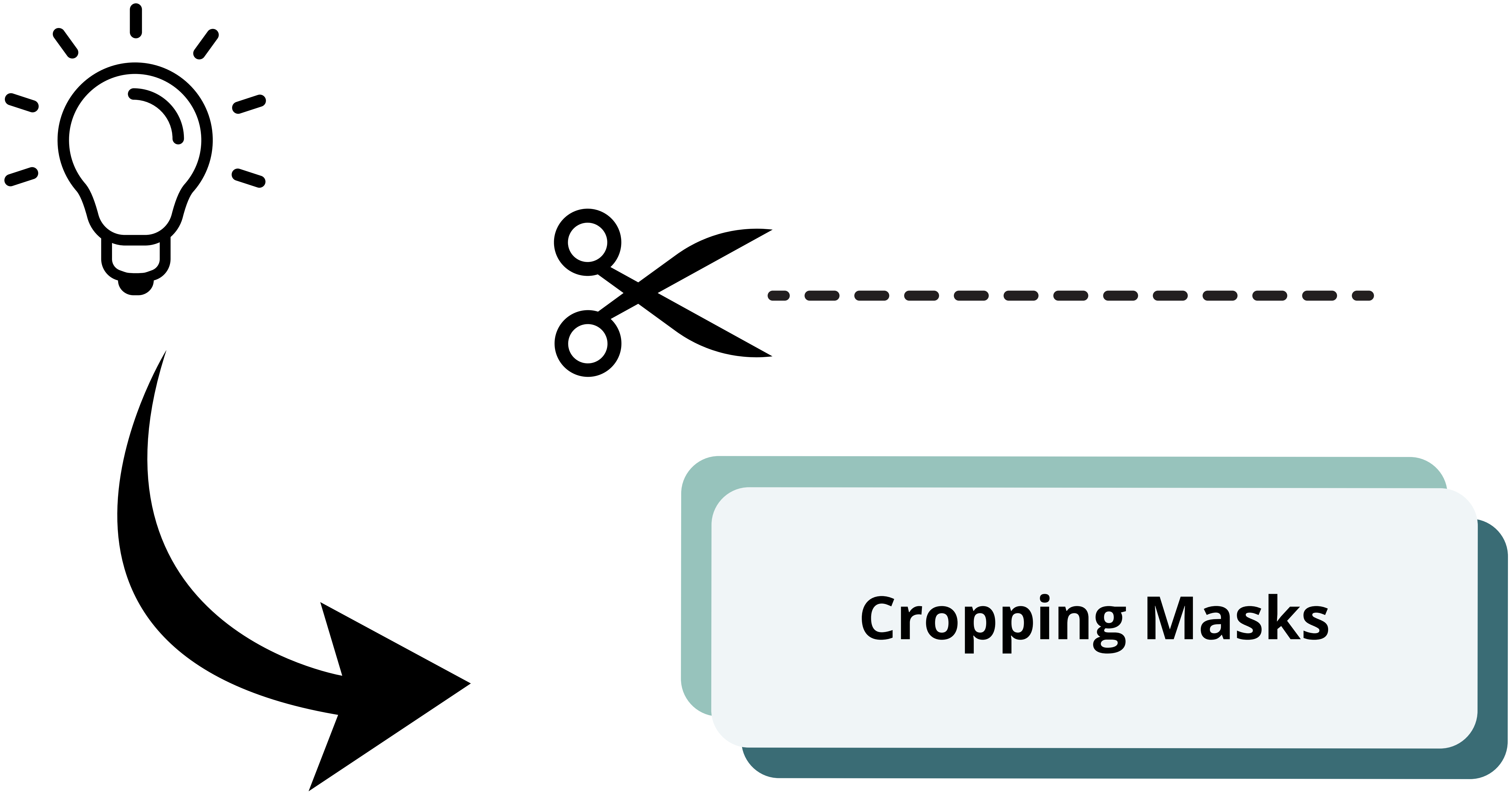
Cropped data

Non cropped Mask corresponding

Mismatching masks and images

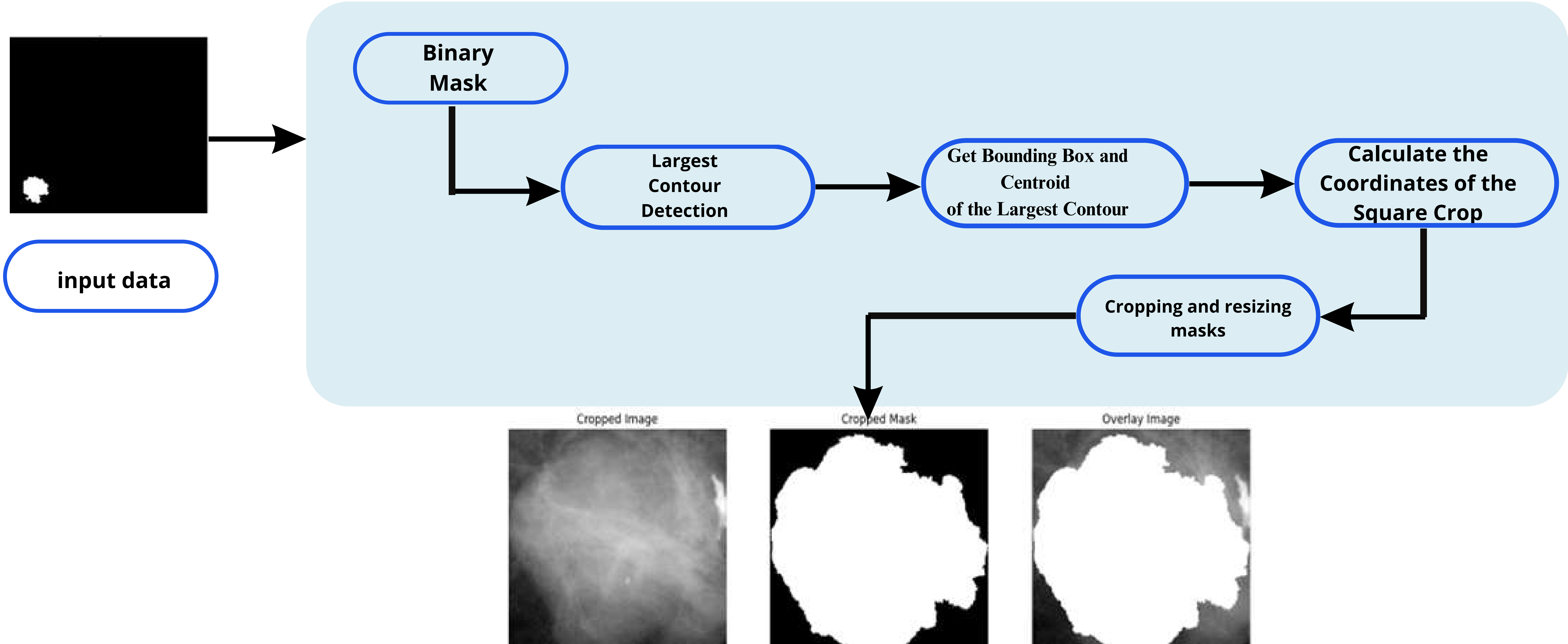
04 Methodology and Conceptual phase

Methodology | Functional Requirements | **Conceptual Phase** | Techniques and tools used



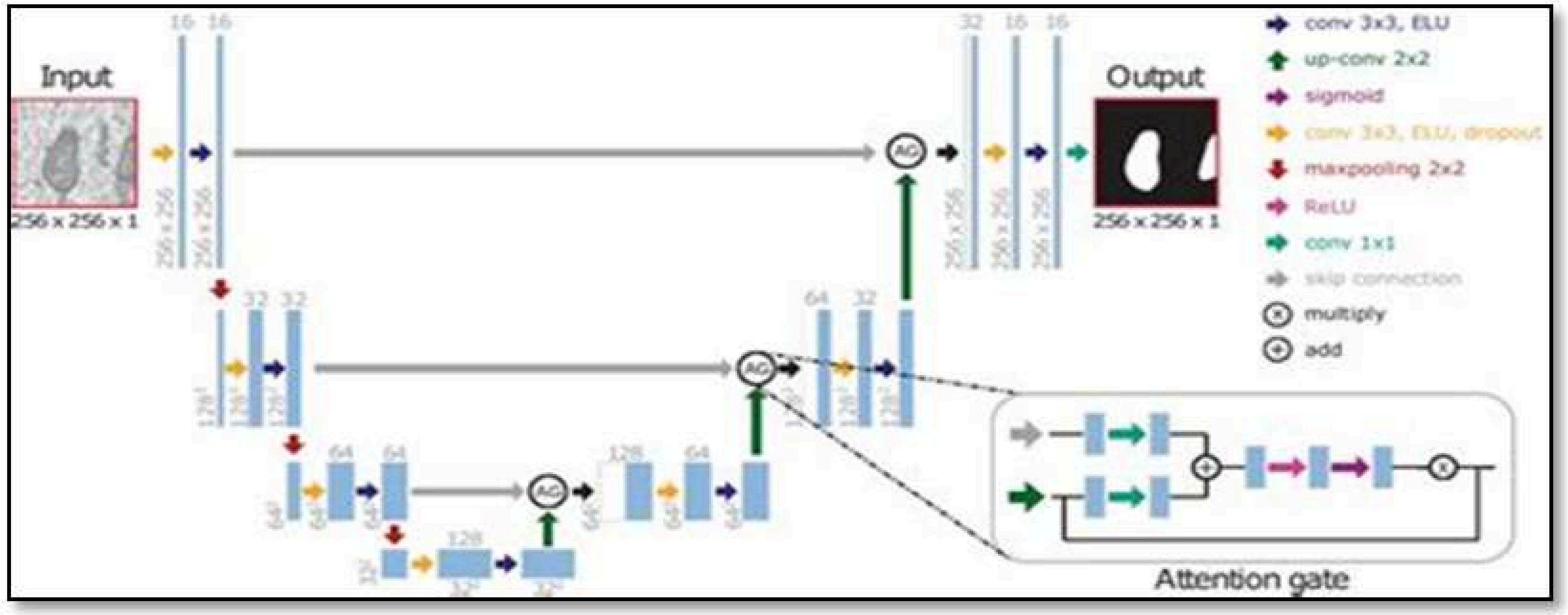
04 Methodology and Conceptual phase

Methodology | Functional Requirements | **Conceptual Phase** | Techniques and tools used

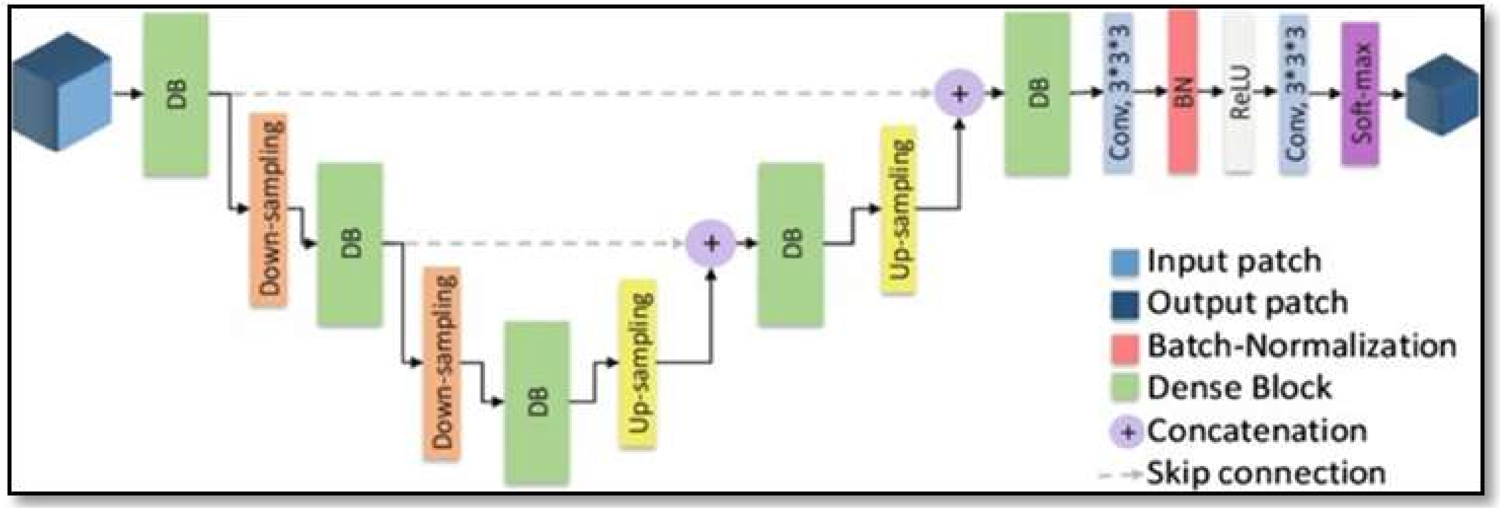


04 Methodology and Conceptual phase

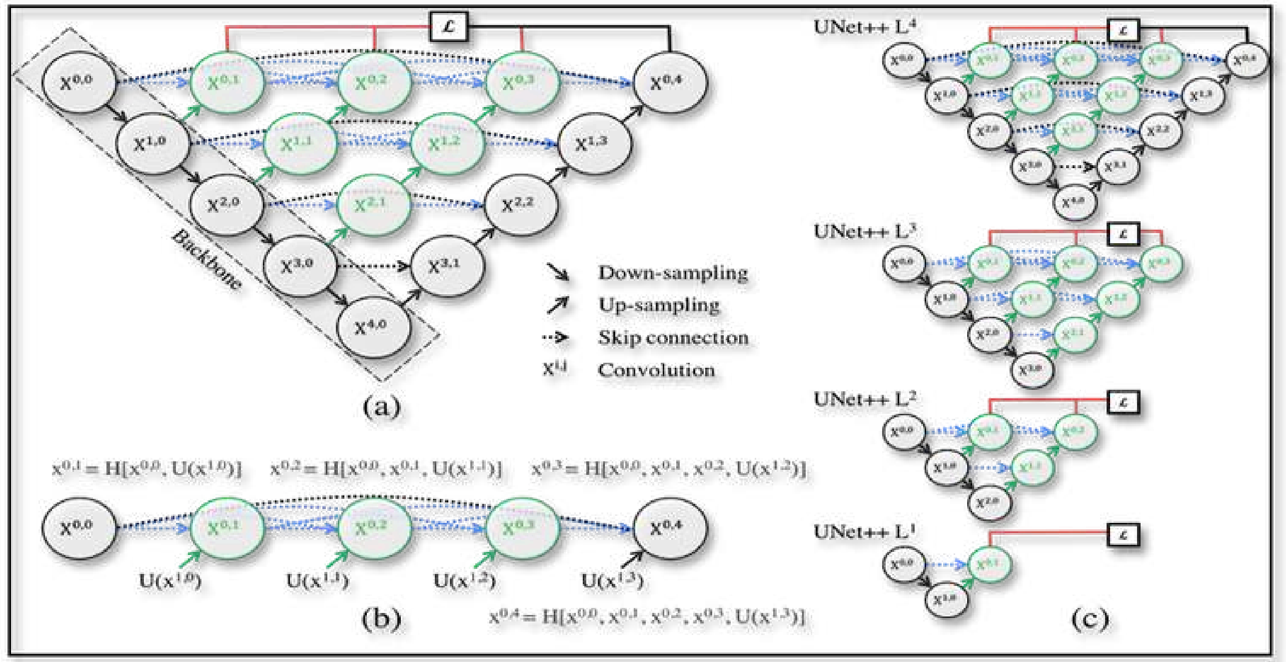
Methodology | Functional Requirements | **Conceptual Phase** | Techniques and tools used



Attention U-Net



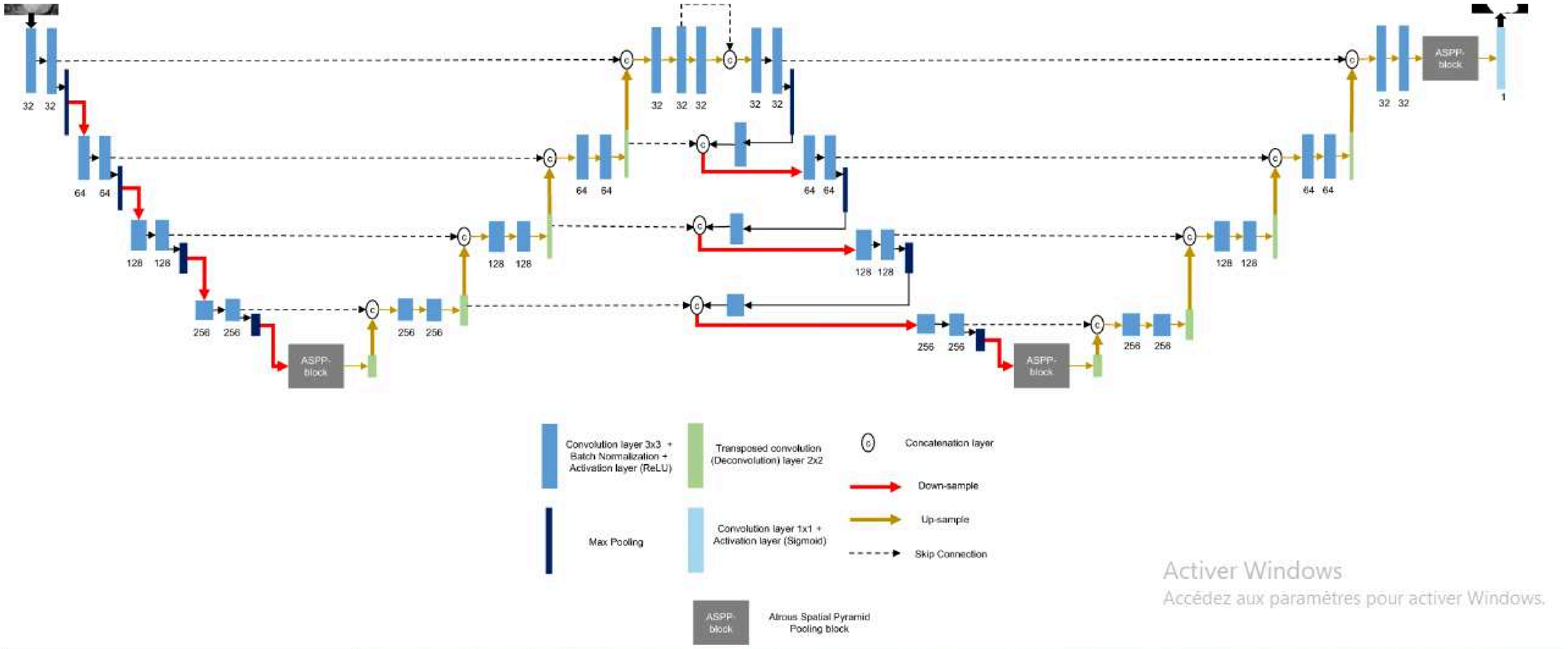
Dense U-Net



U-Net plus plus

04 Methodology and Conceptual phase

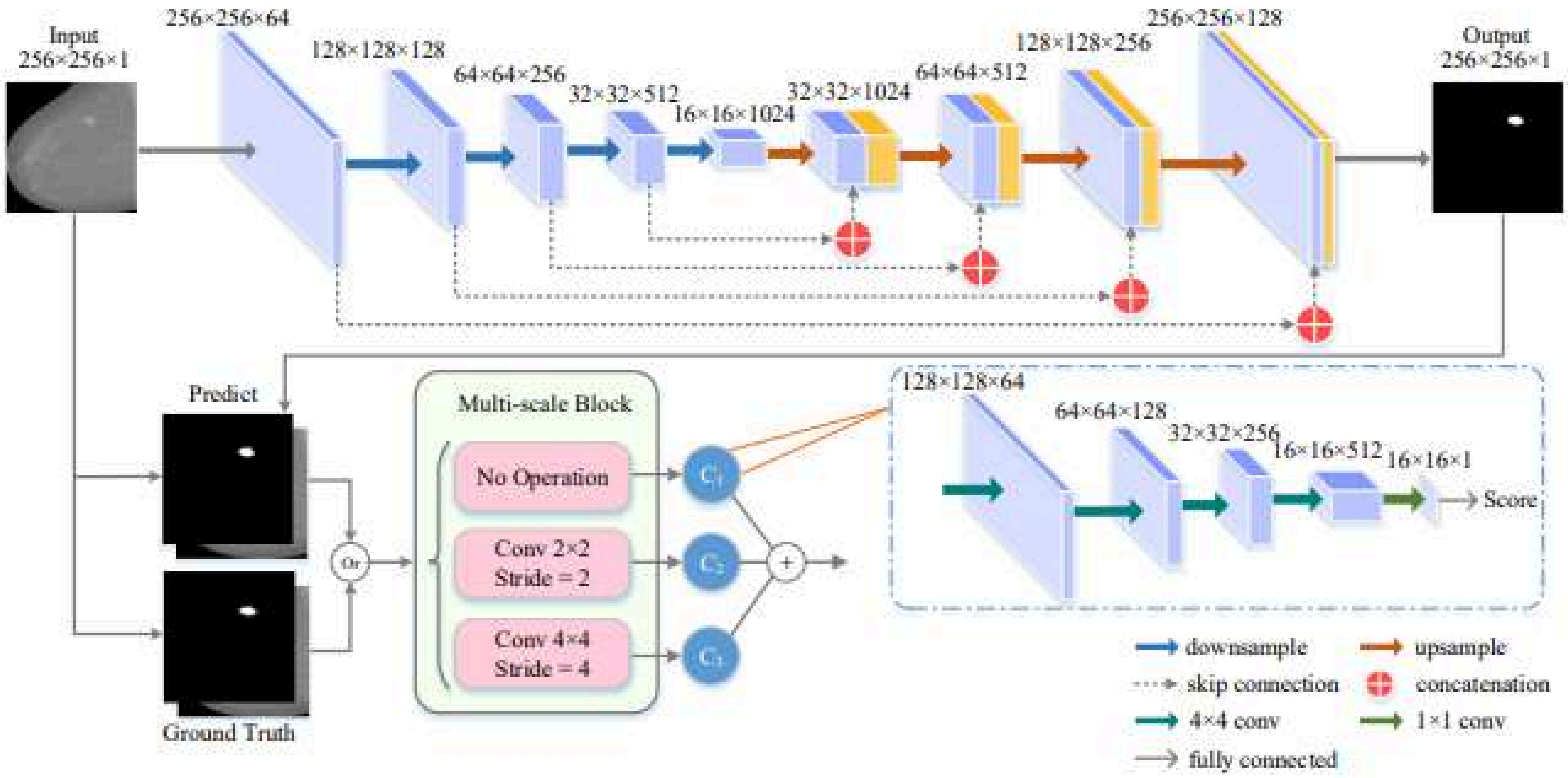
Methodology | Functional Requirements | **Conceptual Phase** | Techniques and tools used



Connected U-Nets

04 Methodology and Conceptual phase

Methodology | Functional Requirements | **Conceptual Phase** | Techniques and tools used



Multiscale Adversarial Network Architecture

04 Methodology and Conceptual phase

Methodology | Functional Requirements | Conceptual Phase | **Techniques and tools used**

TensorFlow + Keras

OpenCV

pandas

Implmentation

Buisness Understanding

Objective

Constraints

Requirements

Develop a deep learning model for accurate segmentation of breast cancer masses in mammography images

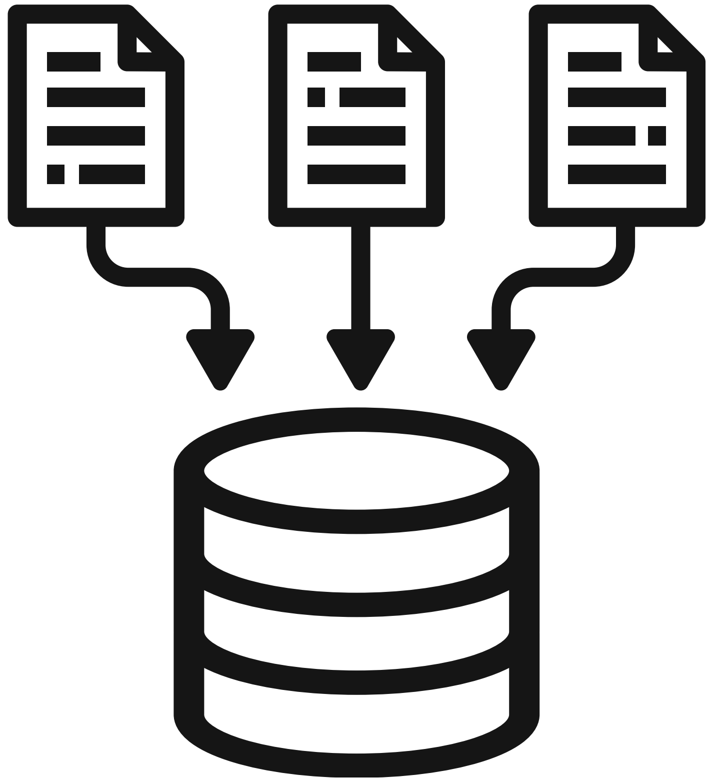
05 Implementation

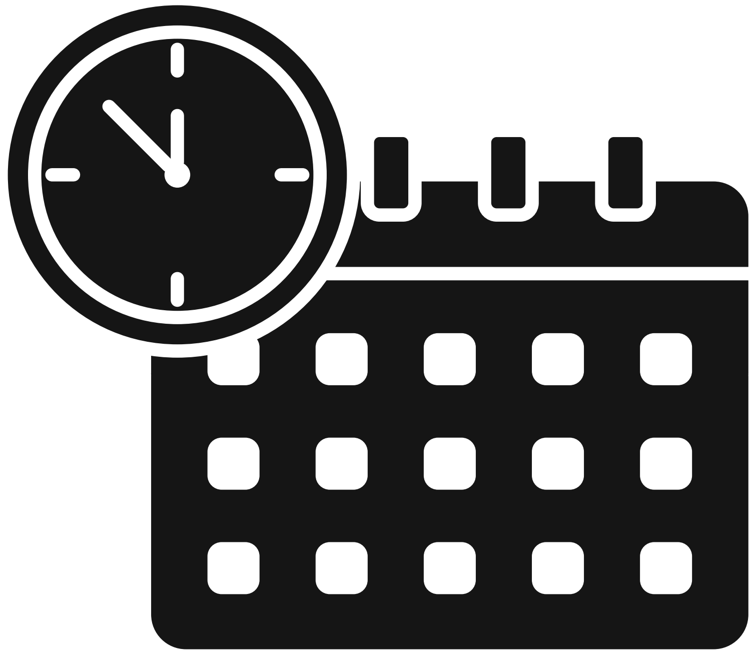
Buisness Understanding

Objective | **Constraints** | Requirements

We found the main constraints in deep learning project:

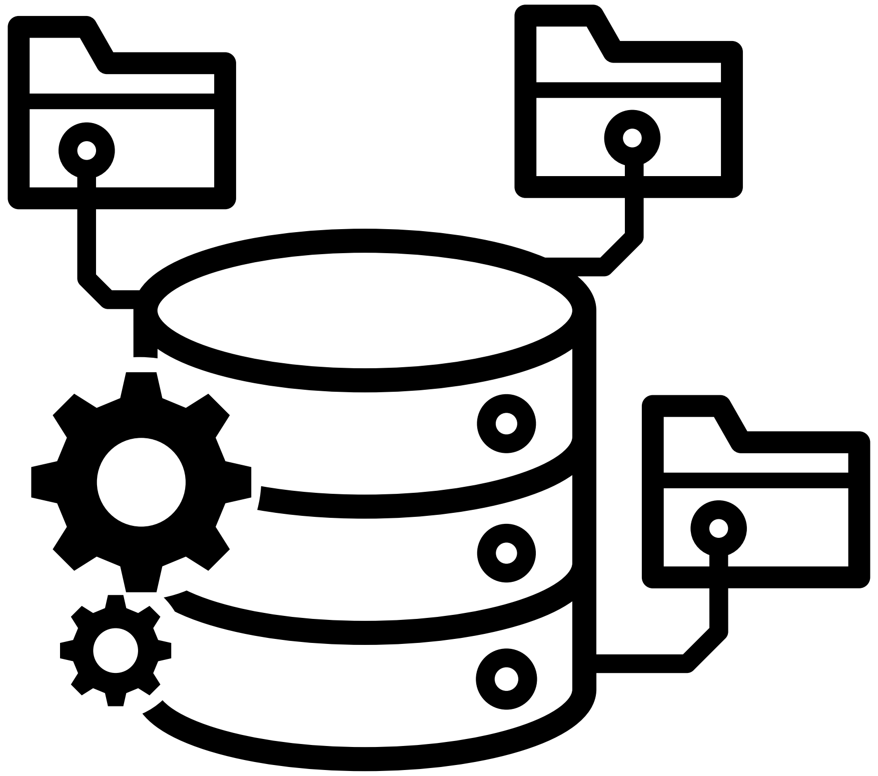
- **Budget**
- **Annoted data**
- **Time**



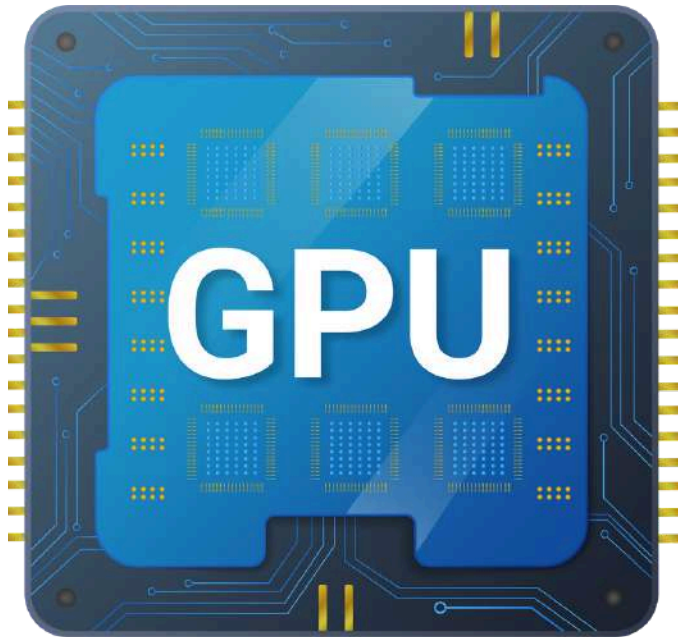


Buisness Understanding

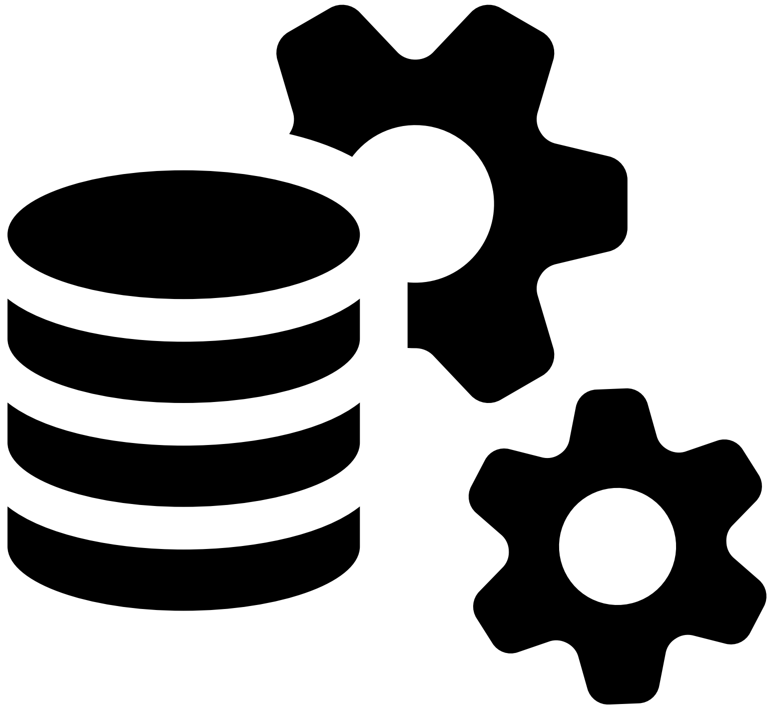
Objective | Constraints | **Requirements**



Data storage



Computional ressources



Annotated data

05 Implementation

Data Understanding

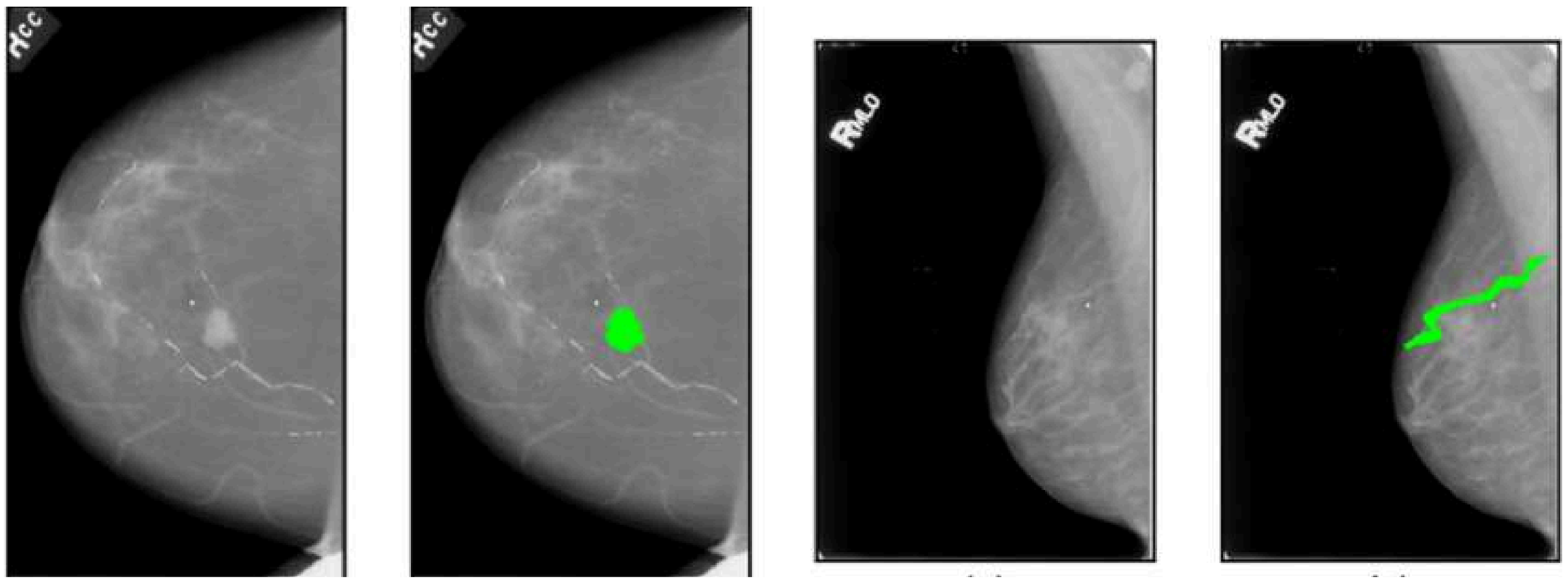
Data Collection

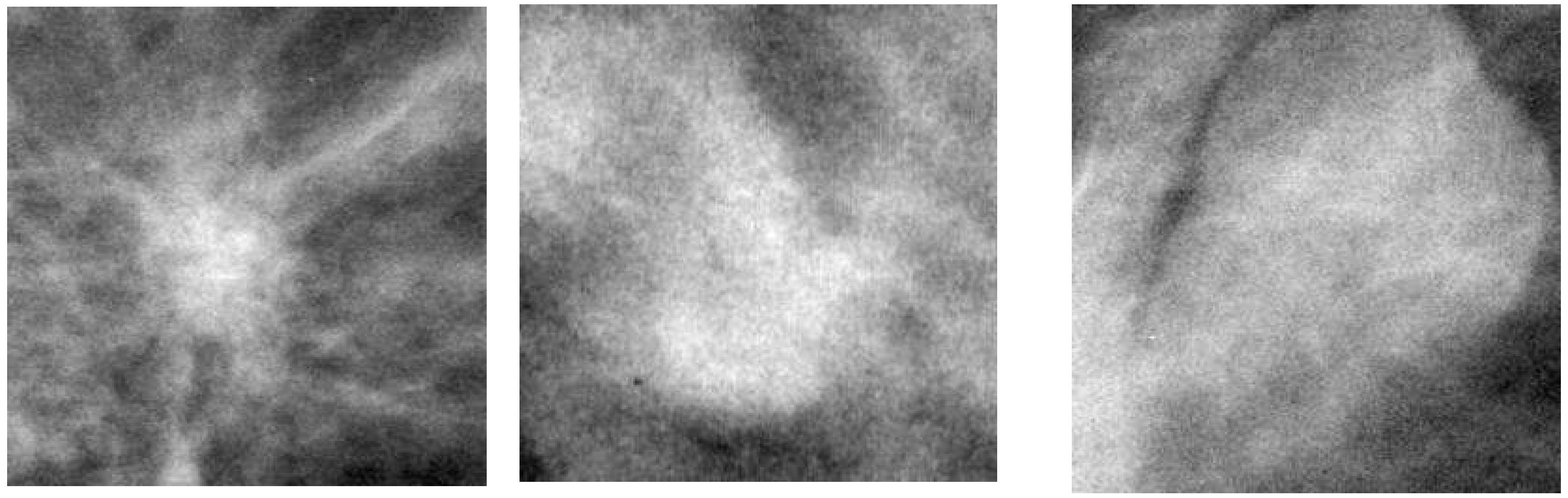
Data Exploration

Data source Verification

We utilized the CBIS-DDSM dataset formed by a total of 1,318 mammograms. This dataset is an updated and standardized version of the Digital Database for Screening Mammography (DDSM).

Attribute	Description
Samples in dataset (total)	1318 mammograms
Dimension	256 × 256 pixels
Color Grading images Color Grading Masks	RGB Gray scale





Data Collection | **Data Exploration** | data Source Verification

Advantages

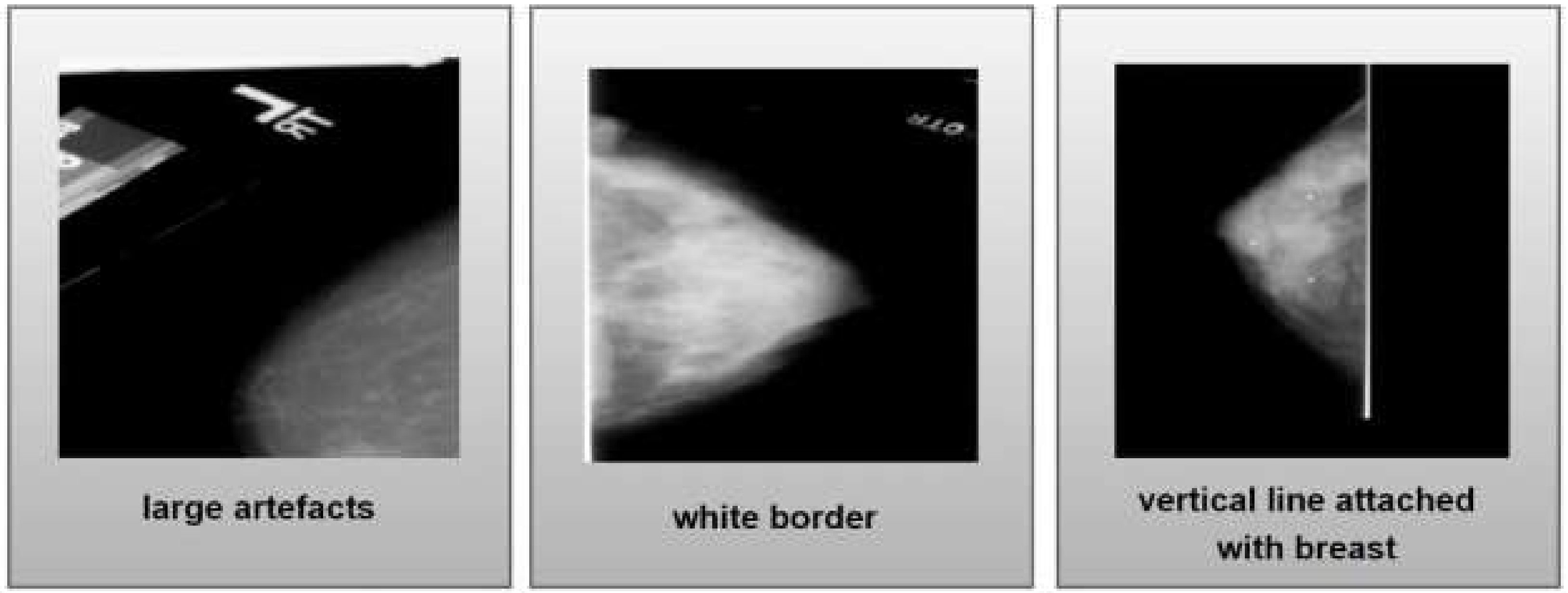
- **Detailed Annotations: Provides precise pixel-wise segmentation masks.**
- **Diverse Image Types: Includes both cropped masses and full mammograms.**
- **Open Source Accessibility: Publicly available and easy to access for research.**
- **Mammograms modality matching Moroccan context**

Data Understanding

Data Collection | **Data Exploration** | data Source Verification

Challenges of the dataset

- **Presence of Artifacts: Contains large texts and marks that interfere with analysis.**
- **Irregular Tumor Shapes: Malignant tumors have ambiguous and blurred edges.**
- **Surrounding Area Challenges: Difficulties in preserving surrounding tissue during segmentation.**
- **Poor Image Quality: Some images have low brightness and contrast.**
- **Structural Complexity: Complex structures and artifacts in breast ima**



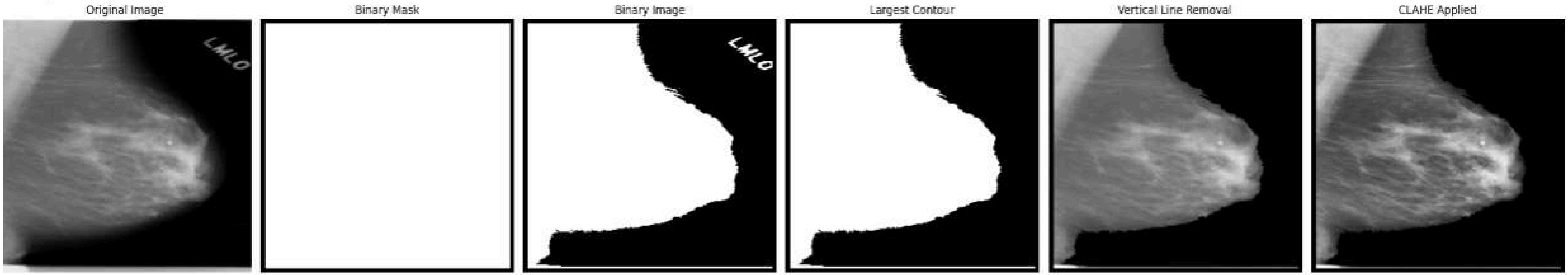
Data Understanding

Data Collection | Data Exploration | Data source verification

https://www.cancerimagingarchive.net/collection/cbis-ddsm/

Data Preparation

Data Cleaning | Data Transformation | Data splitting | Data management



Data Preparation

Data Cleaning | Data Transformation | Data splitting | Data management

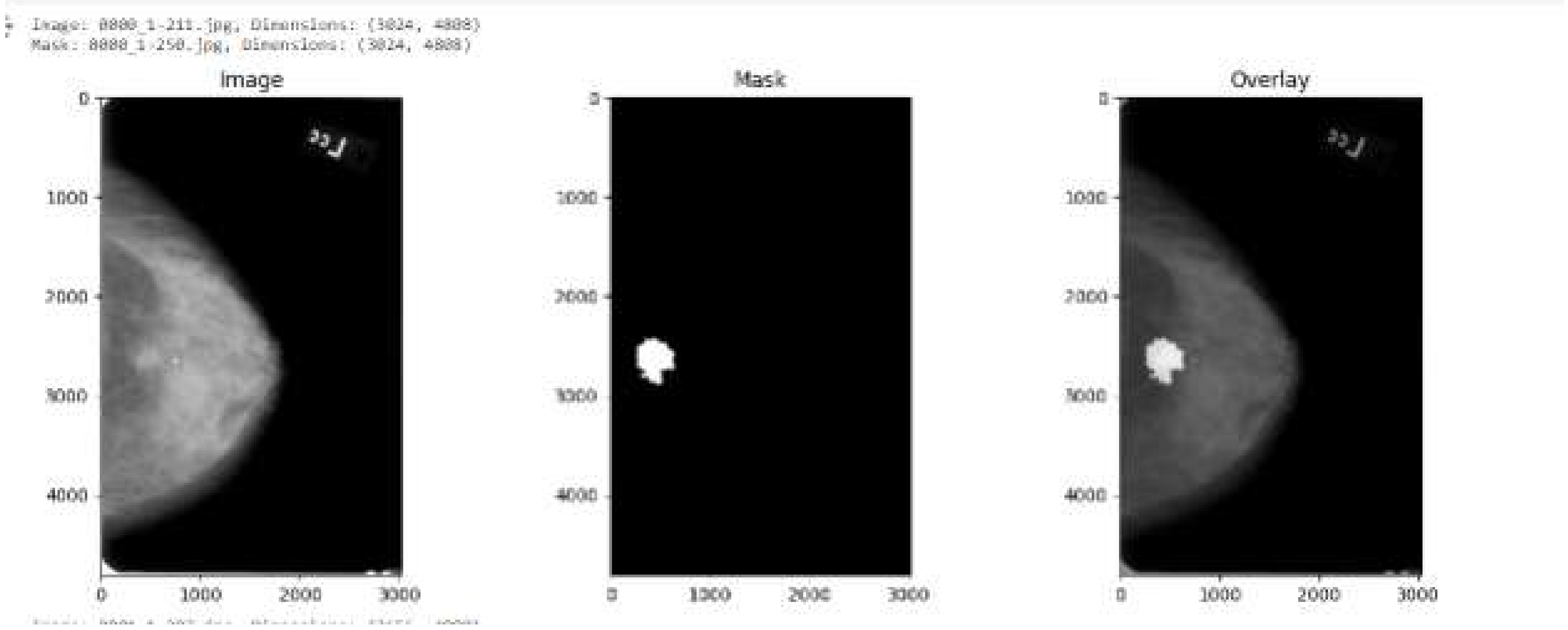
Algorithms	Functions	Values of Parameter
Binary masking	OpenCV rectangle()	Width = 5
Largest contour detection	OpenCV findContours()	Mode for contour approximation = CHAIN_APPROX_SIMPLE Retrieval mode of contour = RETR_EXTERNAL
	max()	Meassure key = contourArea
	OpenCV drawContours()	Index = largest contour, color of contour boarder = (255, 255, 255), width = 1
Vertical line removal	OpenCV Canny()	Minimum Value = 50, maximum Value = 150 and Size of aparture = 3
	OpenCV HoughLines()	edges = Canny(), rho = 1, theta = numpy. pi/50, threshold = 50
	Line	Color value = (0,0,0), Width = 5
Gamma correction	Numpy array()	Value of gamma = 2.0
CLAHE	OspenCV createCLAHE()	Clip Limit = 1.0, tile Grid Size = (8, 8)

05 Implementation

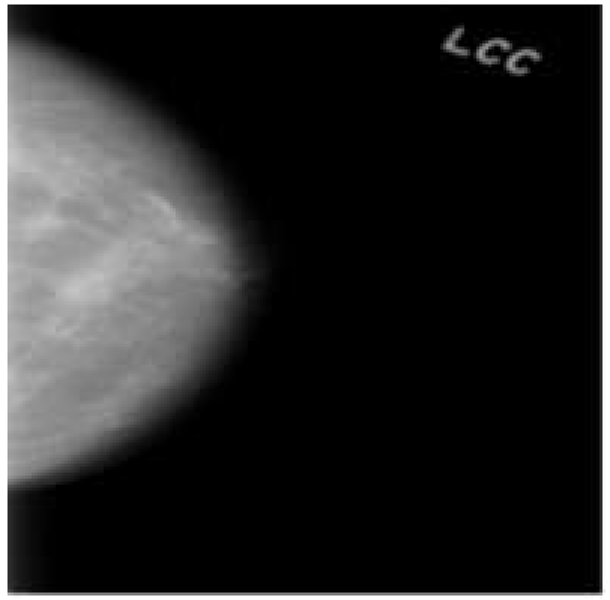
Data Preparation

Data Cleaning | **Data Transformation** | Data splitting | Data management

Data Transformation for Full Mammography



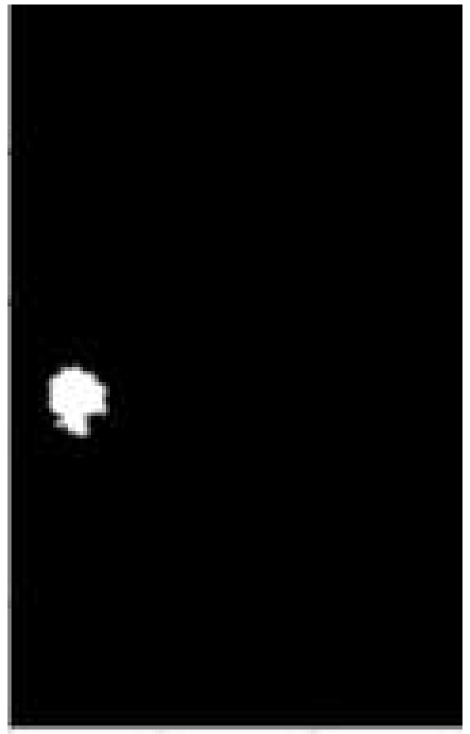
Resizing to 256*256



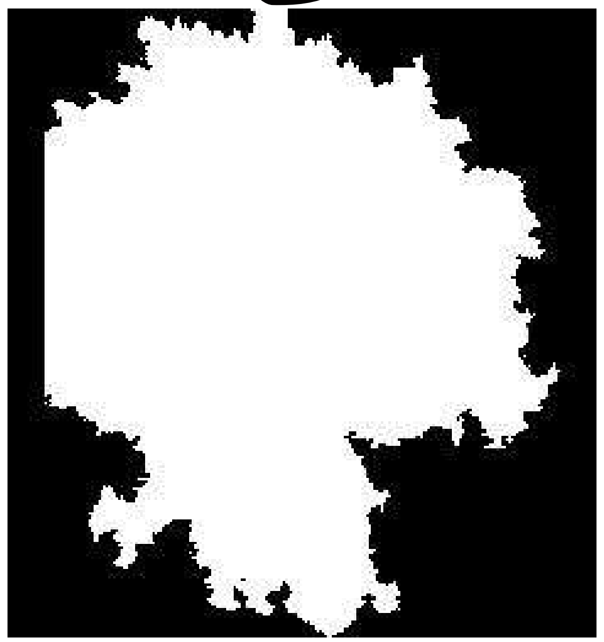
Data Preparation

Data Cleaning | **Data Transformation** | Data splitting | Data management

Data Transformation for Cropped images



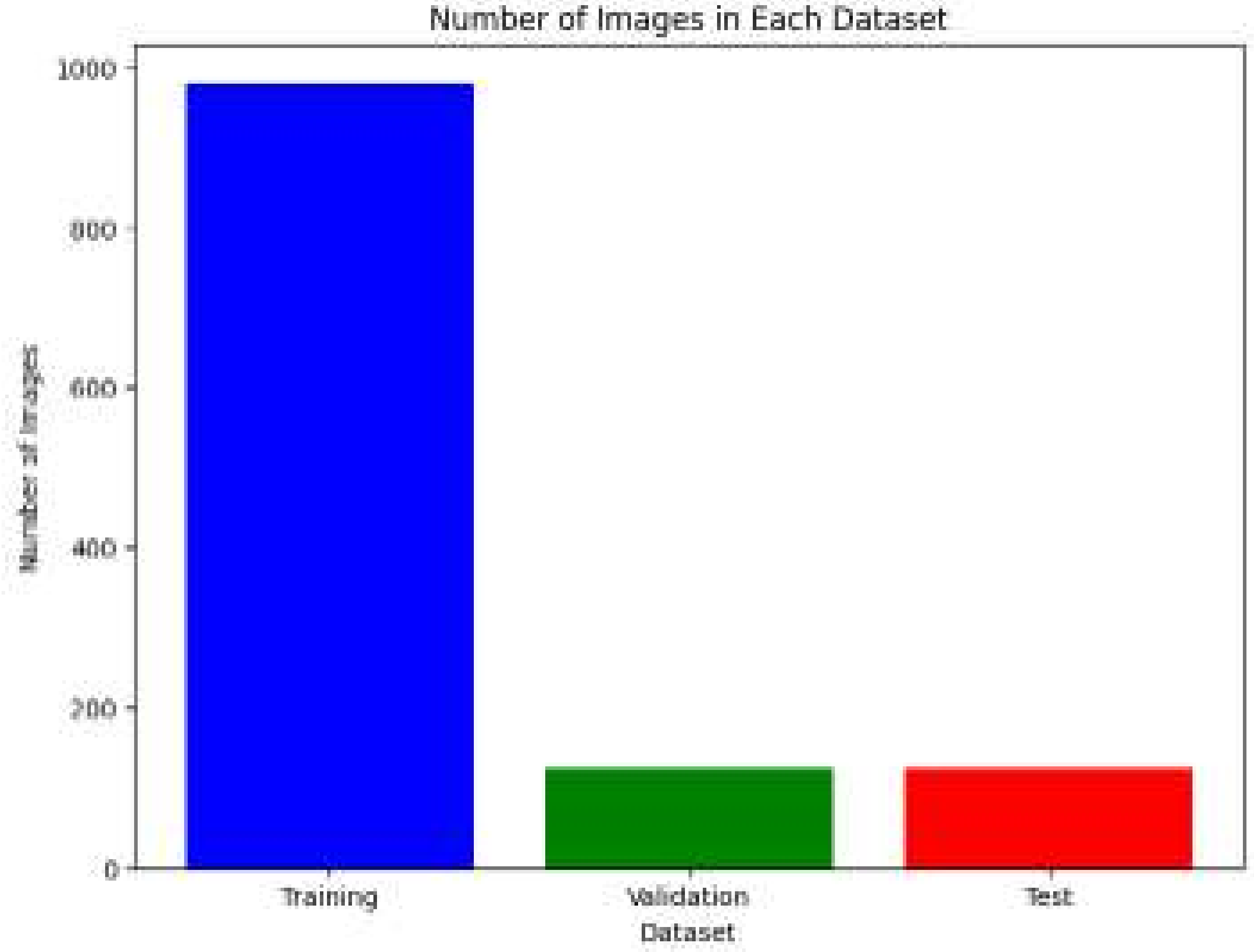
Cropping and resizing masks to match cropped images



Data Preparation

Data Cleaning | Data Transformation | **Data Splitting** | Data management

```
Number of training images: 980
Number of validation images: 123
Number of test images: 123
Shape of training image: (256, 256)
Shape of validation image: (256, 256)
Shape of test image: (256, 256)
```

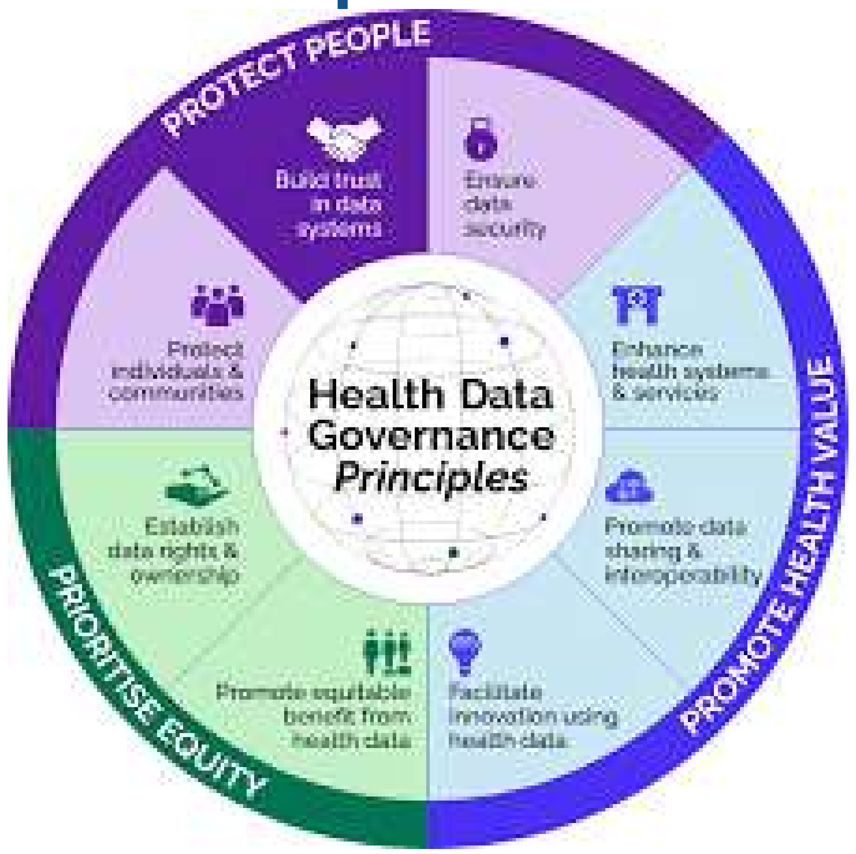


Data Preparation

Data Cleaning | Data Transformation | Data Splitting | **Data Management**

GESTION DES DONNÉES

- Sécurité
  - Anonymisation des Données
  - Stockage Sécurisé
- Organisation
  - Structuration des Données
  - Base de Données Centralisée
- Accès et Partage
  - Contrôle d'Accès
  - Partage Collaboratif



Modeling

1

Connected U-Nets

- Fine Detail Preservation
- Accurate Shape Analysis
- Detailed and Contextual Information
- Sequential Refinement
- Skip Connection
- 2 encoders & 2 decoders

2

Multiscale Approach

- Enhanced Feature Representation
- Contextual Awareness
- Robustness
- Capturing Smaller Details
- GAN

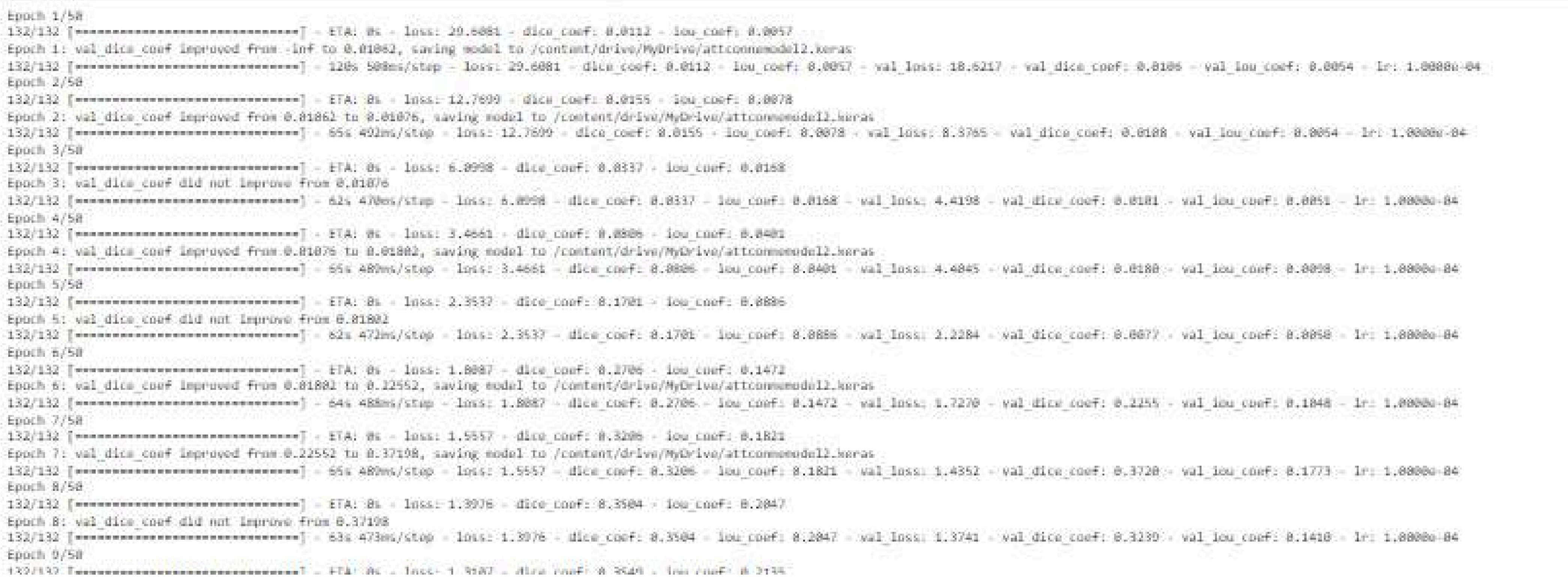
Connected Attention U-Net

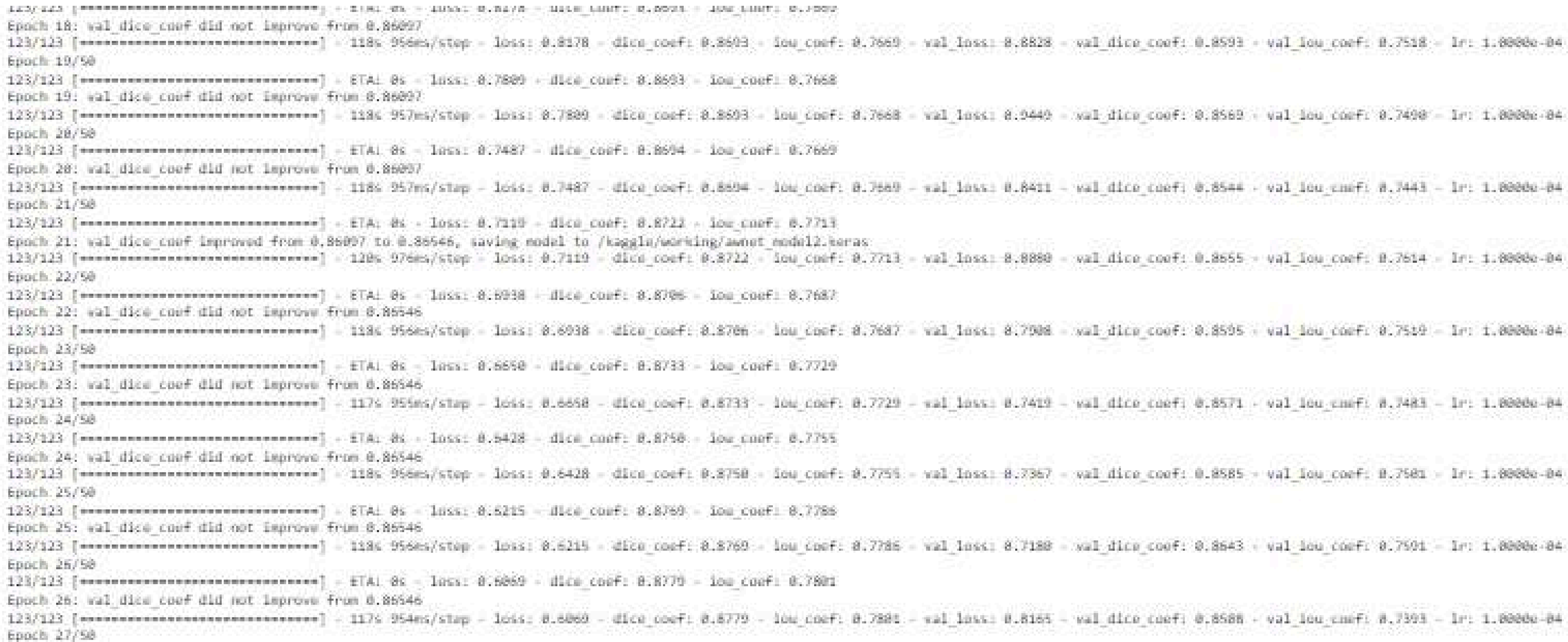
Training techniques

- Early stopping
- Reduce Learning rate on plateau
- Model CheckPoint

Hyperparameters

- Filtres de convolution : 64 à 1024.
- Batch size : 8
- Nombre d'époques : 50

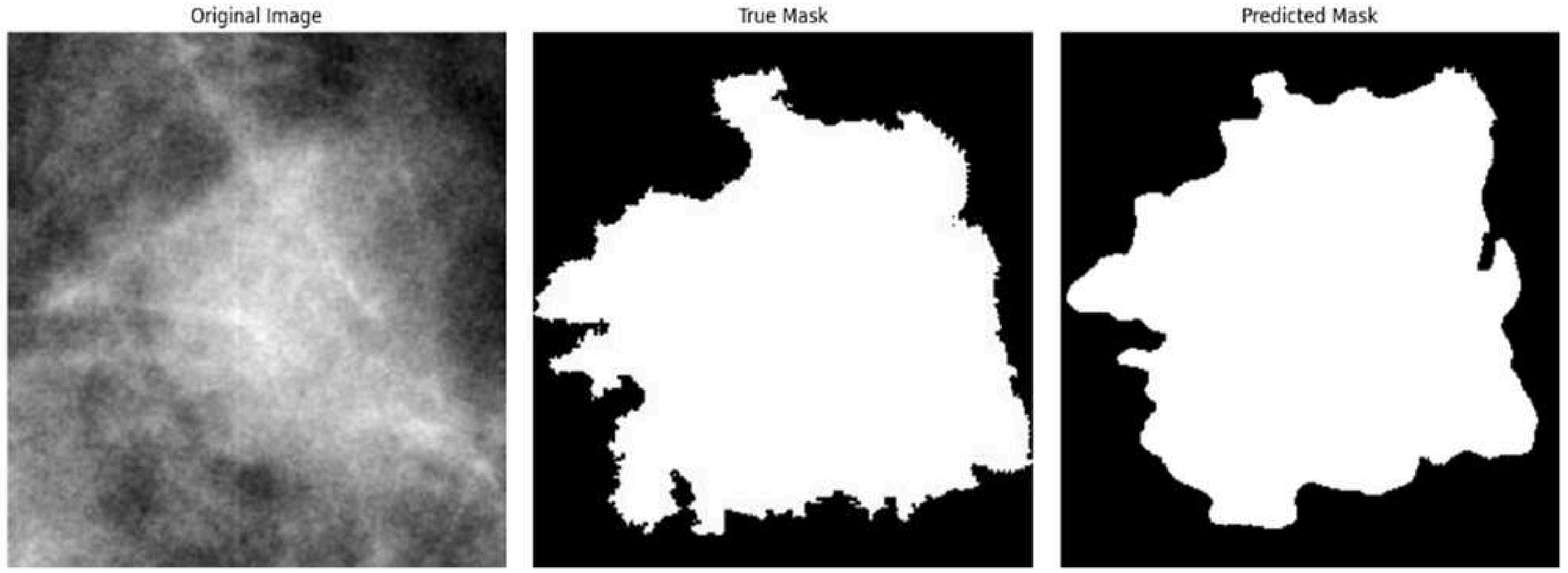




05 Implementation

Modeling

Choice of Models | **Models Training** | Evaluation | Discussion



Connected Attention U-Net for cropped images

Test Metrics Only

Model	Loss	Dice Coefficient	IoU Coefficient
AUNet	0.6794	0.3630	0.2189
Dense UNet	0.6733	0.3665	0.2239
UNet++	0.7008	0.3406	0.2243
CDUNet	0.6890	0.3534	0.2239
CUNet++	0.7060	0.3234	0.3234
CAUNet	1.01	0.3789	0.2458
CDUNet (Cropped)	0.5271	0.8495	0.7360
Dense UNet (Cropped)	0.5904	0.8179	0.6901
CAUNet (Cropped)	0.6999	0.8663	0.7620
AUNet (Cropped)	0.6703	0.8484	0.7344
MSANet (Cropped)	0.4565	0.8556	0.7409
CUNet++ (Cropped)	0.4964	0.8344	0.7577

The Previous table presents the test metrics for various segmentation models, highlighting loss, Dice Coefficient, and IoU Coefficient. Cropped models generally outperform their non-cropped counterparts, with CAUNet (Cropped) achieving the highest Dice Coefficient (0.8663) and IoU Coefficient (0.7620), indicating superior segmentation accuracy. The results suggest that cropping the input images significantly enhances model performance, likely by focusing the model on the relevant regions of interest

Conclusion and Perspectives

Merci pour votre attention !