

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

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- Co-Supervisor: Prof. Najima DAOUDI
- Tutors: Prof & Consultant Naoual EL ABOUDI
Prof & Dr. Nezha ELBAHAOUI

PLAN

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HOST ORGANIZATION

02

CONTEXT AND OBJECTIVES

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IMPLEMENTATION

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SYNTHESIS AND PERSPECTIVES

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.

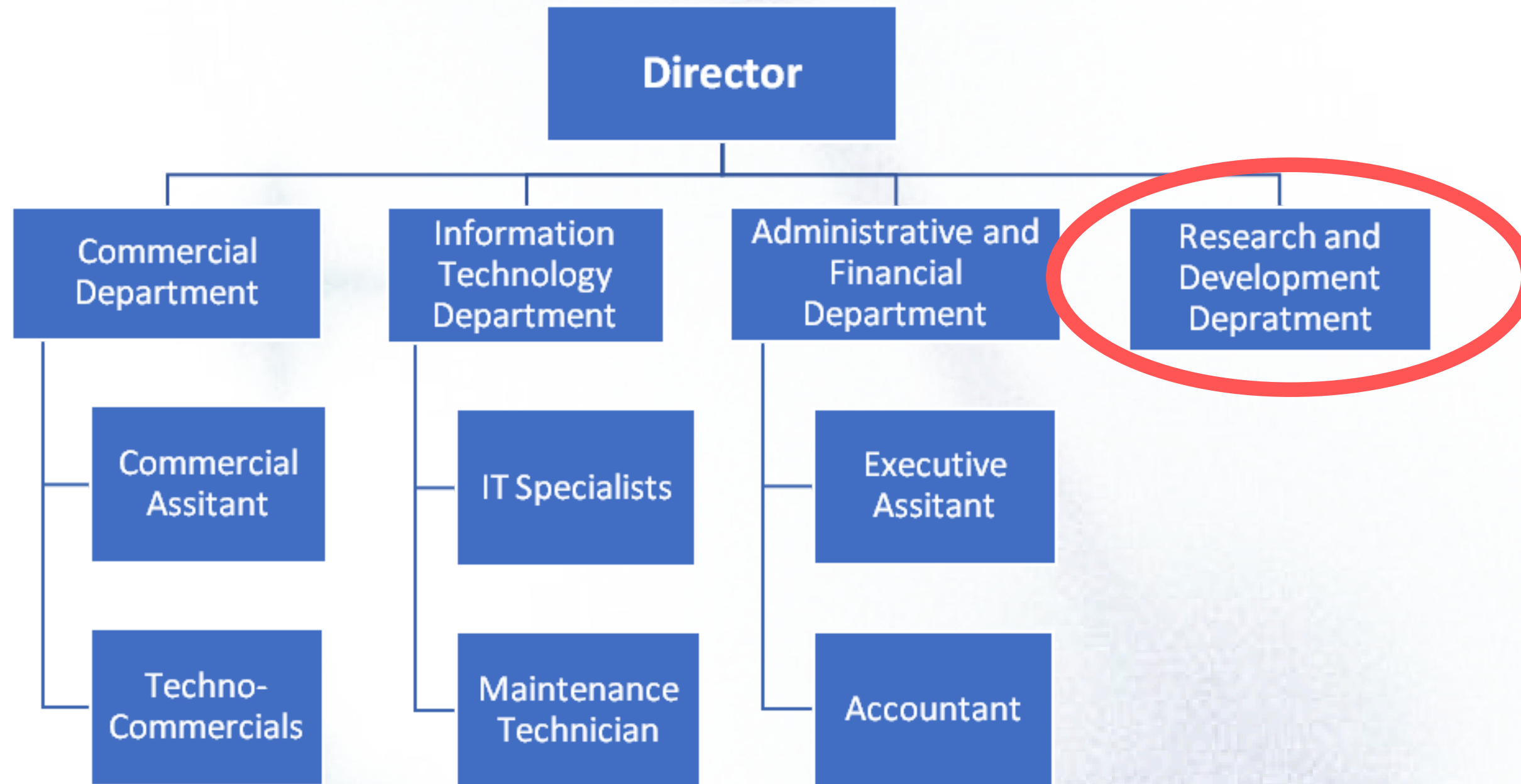


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- Leaders with extensive experience in designing and implementing IT solutions
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- Guarantees the security of IT solutions and facilitates knowledge transfer

01 Host Organization

Presentation of the Organizational Chart





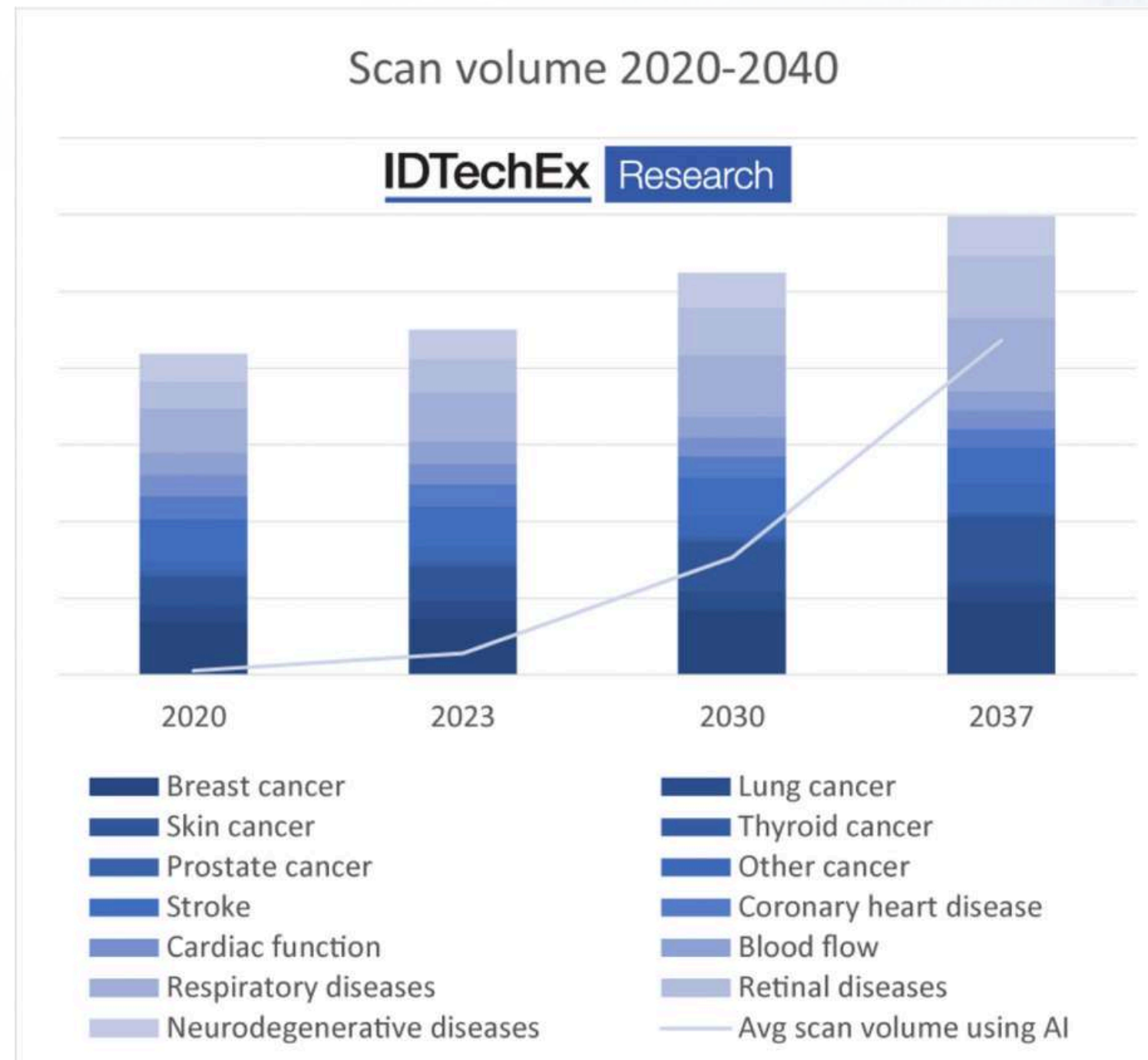
Context and Objectives of the Research



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.

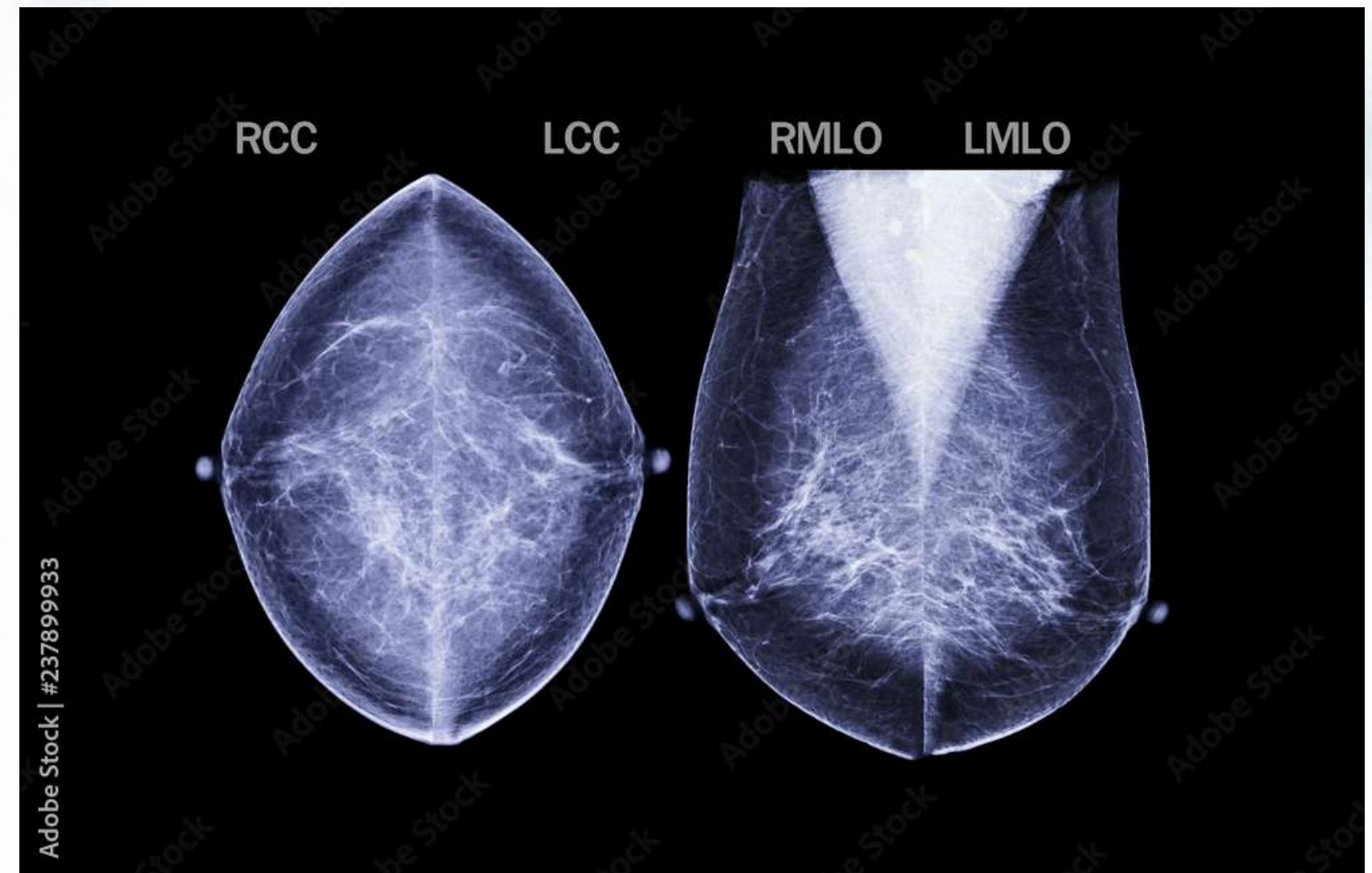
AI in Medical Imaging

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.

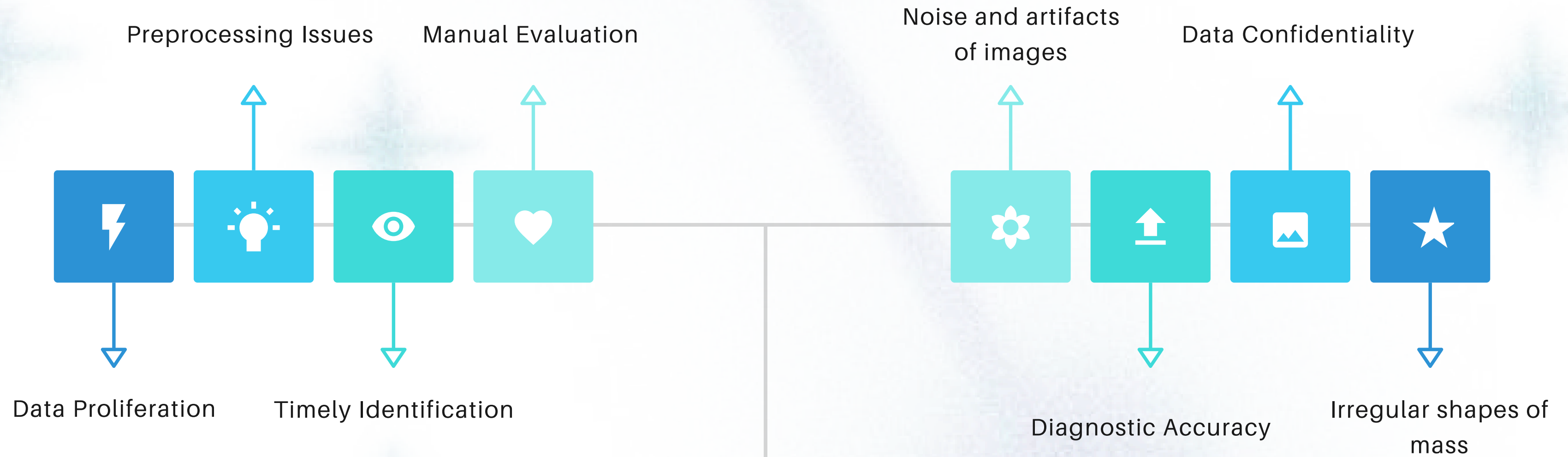


AI in Medical Imaging

Mammography Screening

Problem Statement

Objectives of the Research



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

AI in Medical Imaging

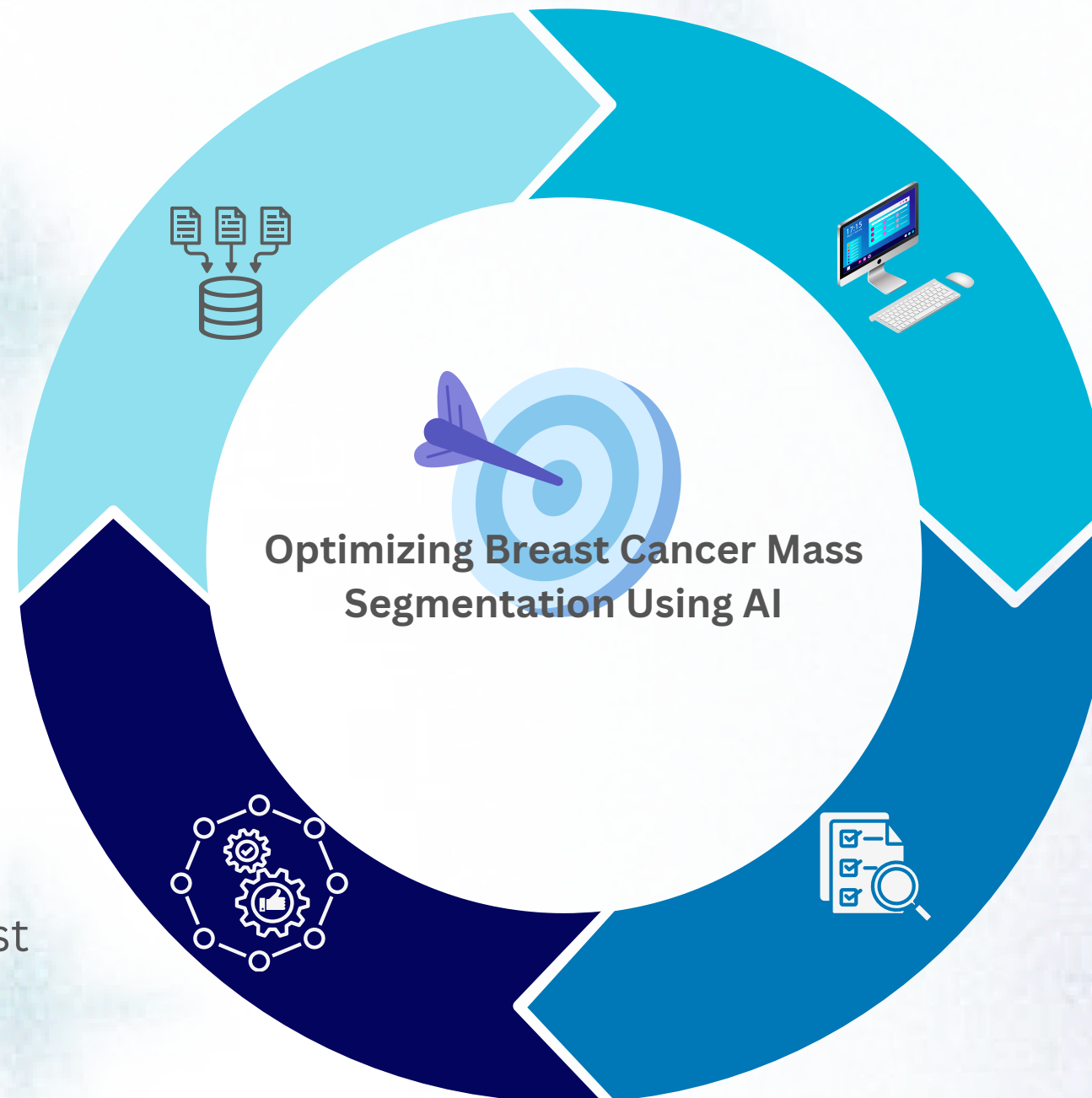
Mammography Screening

Problem Statement

Objectives of the Research

Early breast Cancer
Detection for an
Effective Follow-Up

Fostering IT-Radiologist
Collaboration



Optimizing Breast Cancer Mass
Segmentation Using AI

Developing Automated
Models for Breast
Cancer Mass
Segmentation

Ensuring Accuracy and
Robustness



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

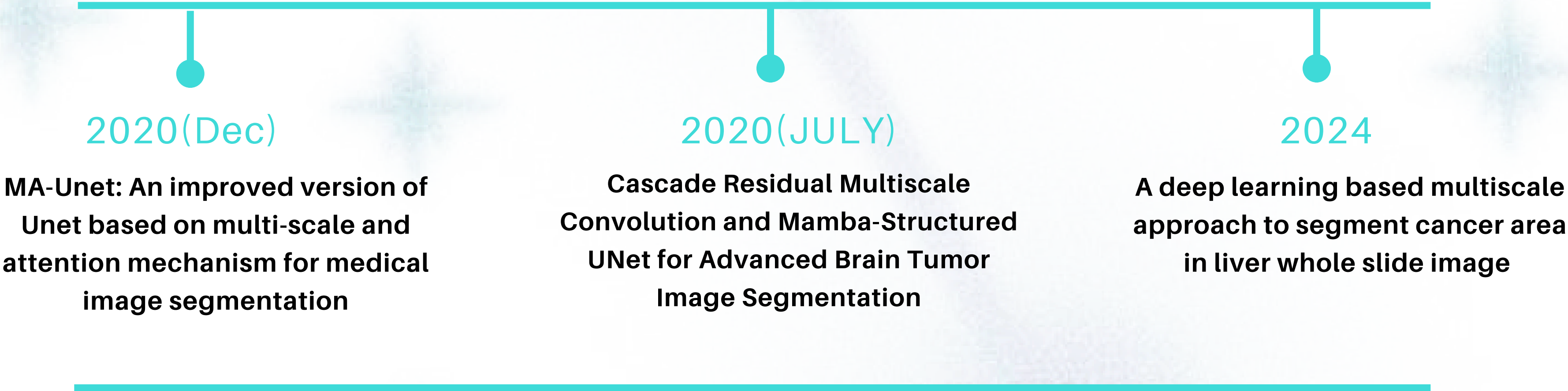
Connected-SegNets: A Deep Learning Model for Breast Tumor Segmentation from X-ray Images

Principal Works

Comparative Table

Connected U-Nets

Multiscale approach



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%

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

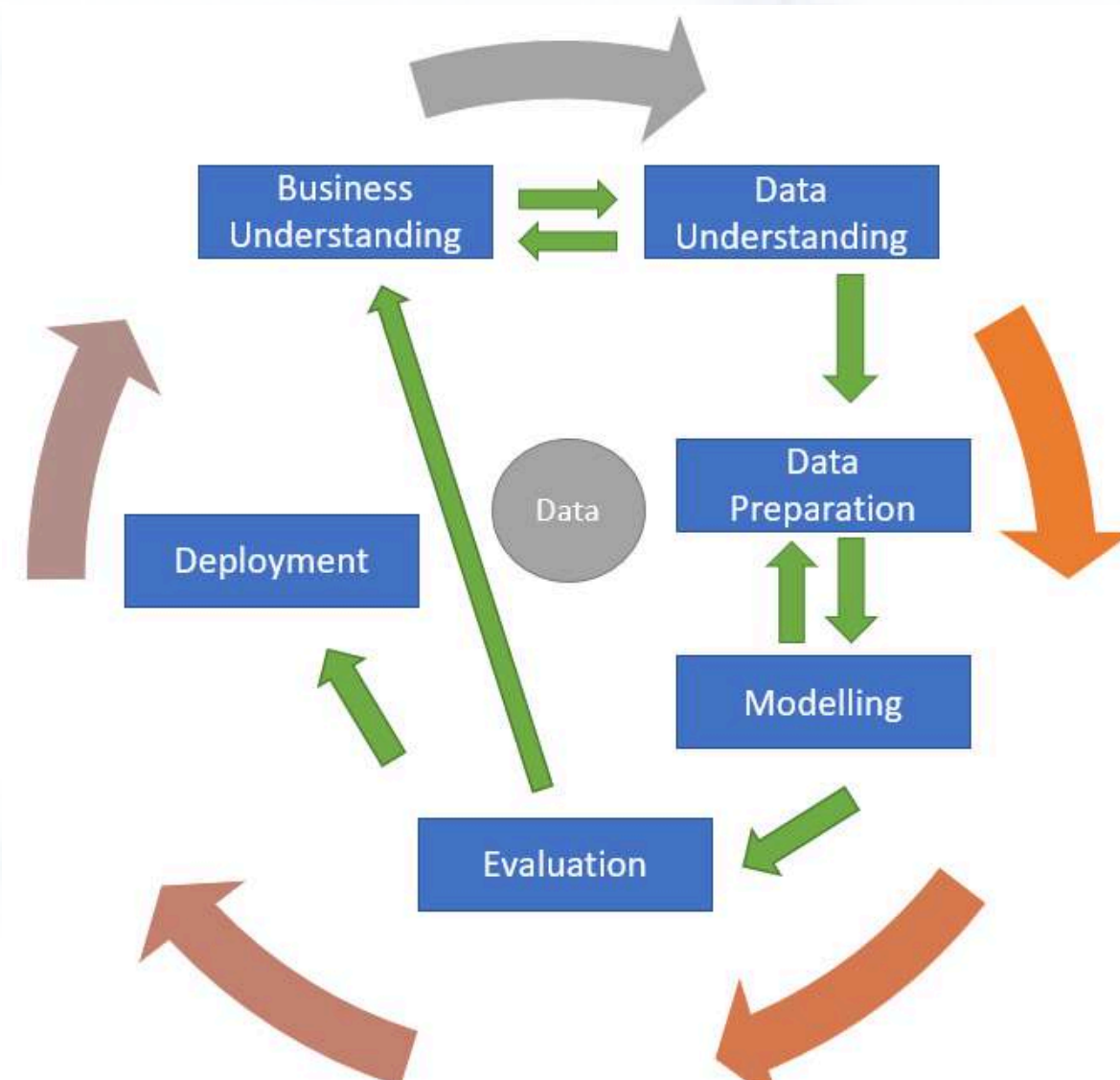
Methodology

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

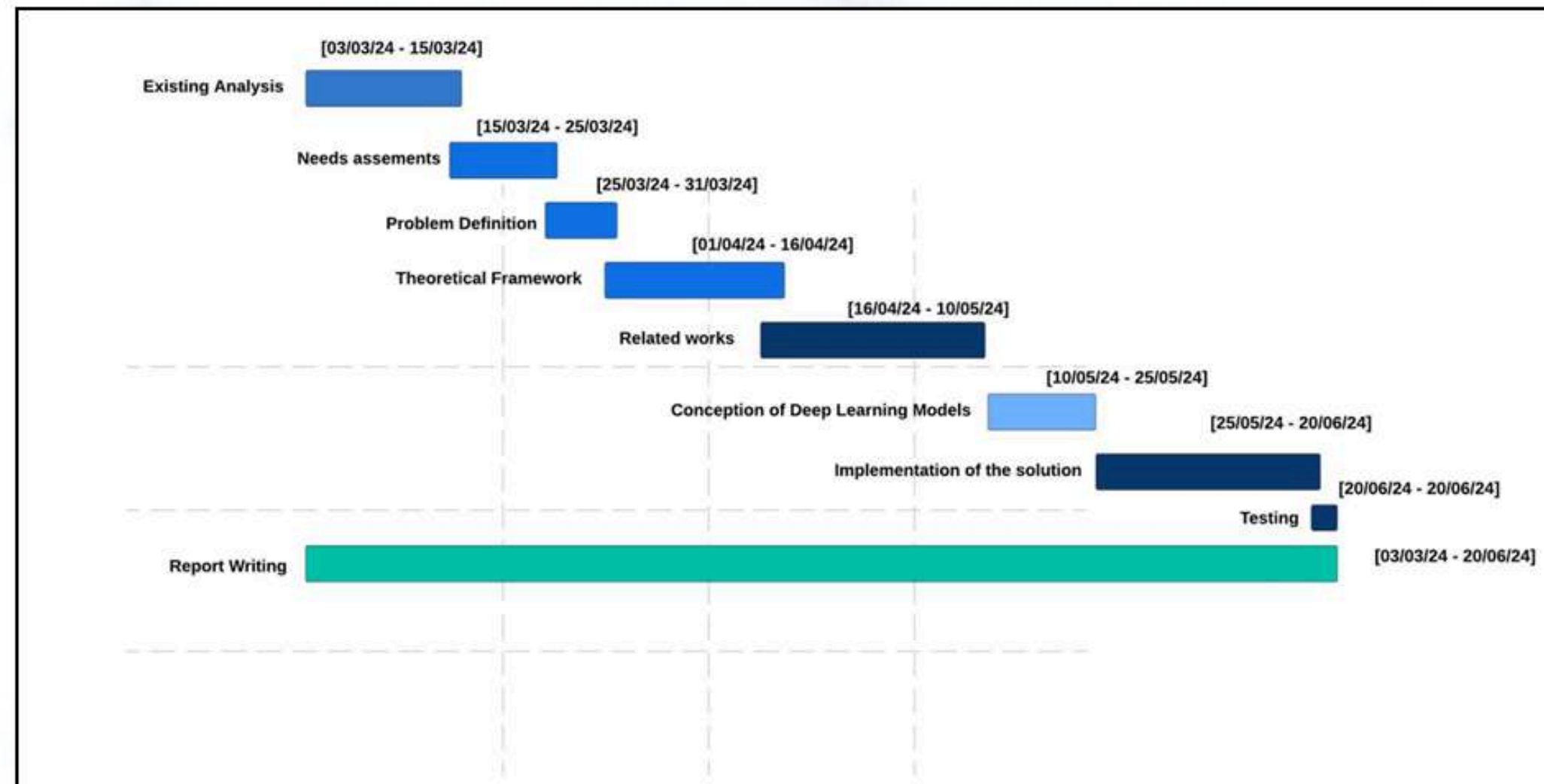
Methodology

Functional Requirements

Conceptual Phase

Techniques and tools used

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

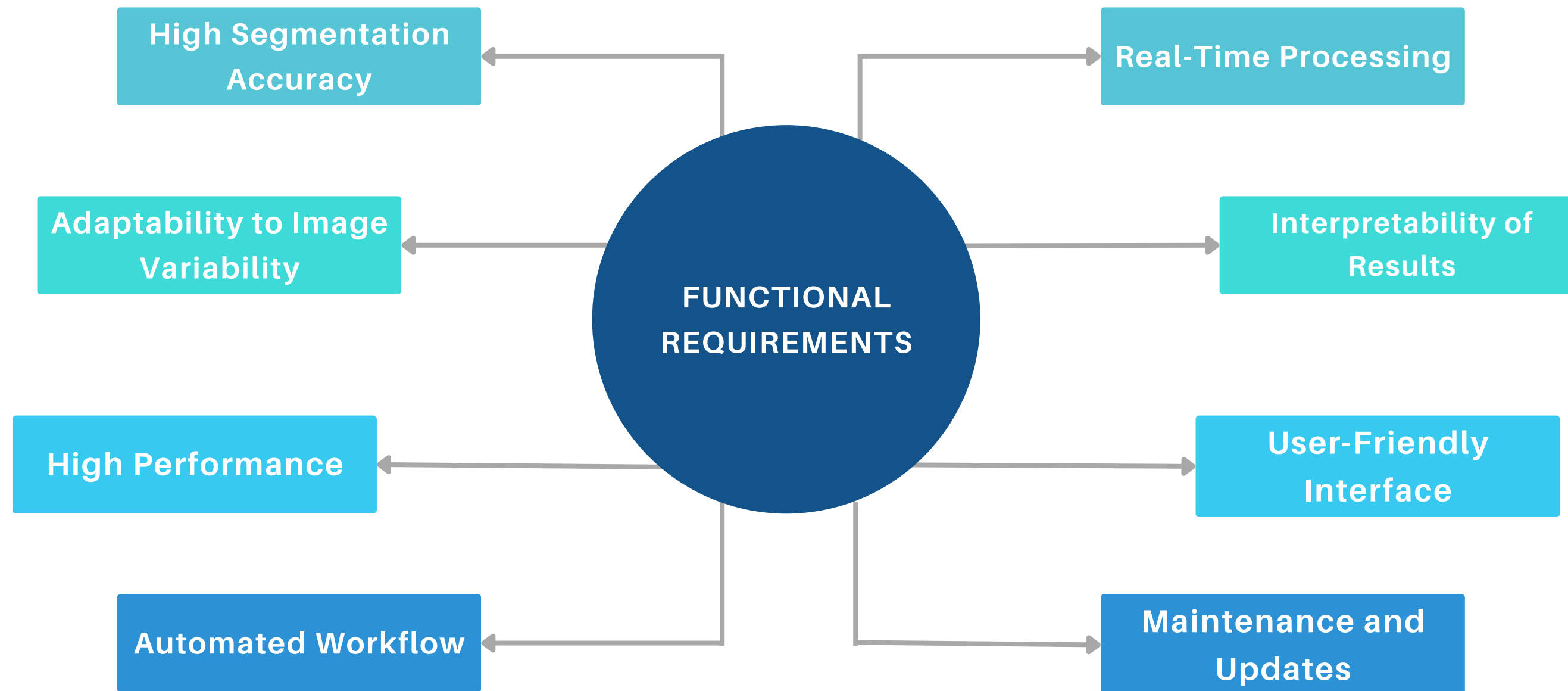


Methodology

Functional Requirements

Conceptual Phase

Techniques and tools used

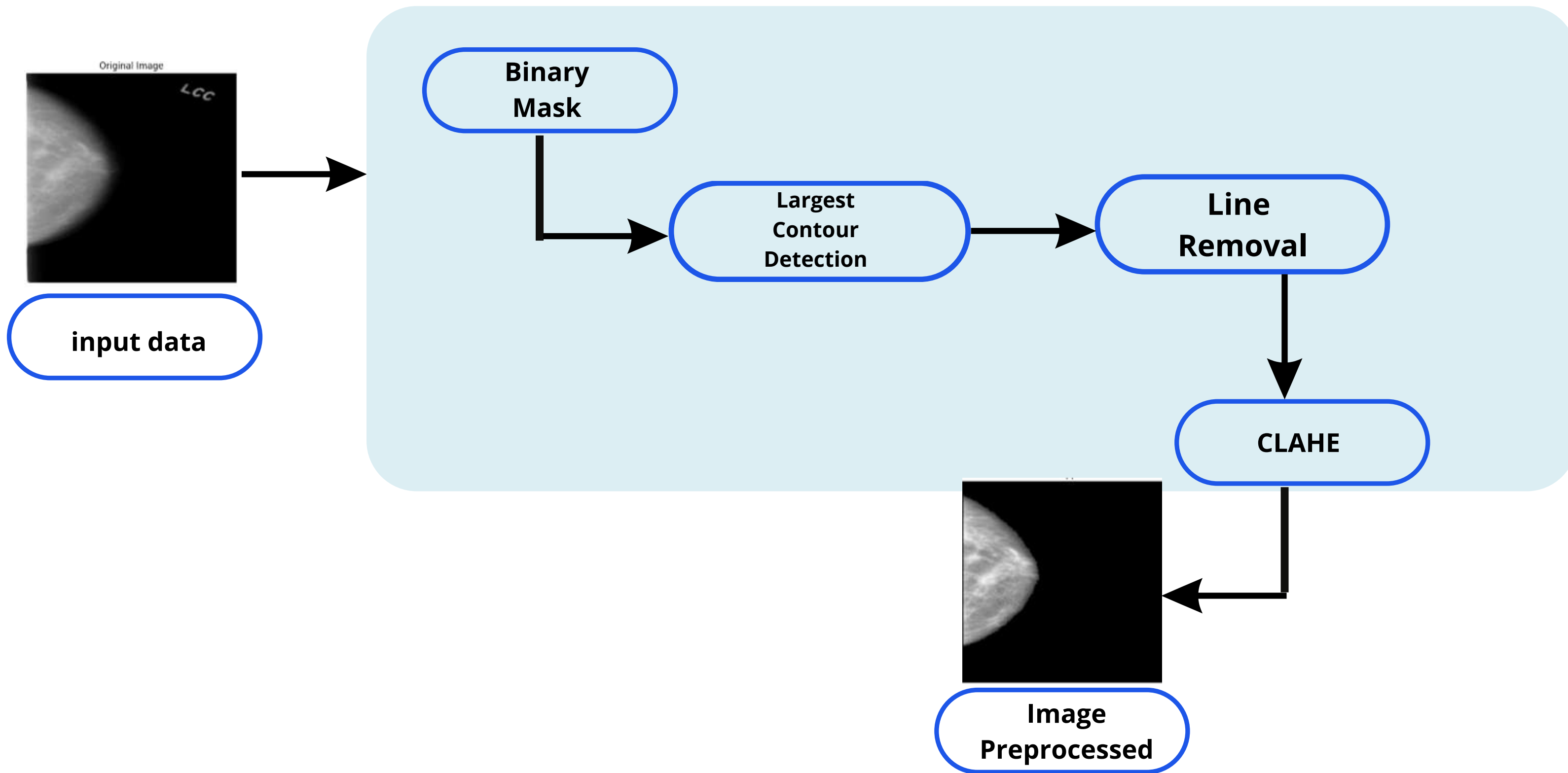


Methodology

Functional Requirements

Conceptual Phase

Techniques and tools used

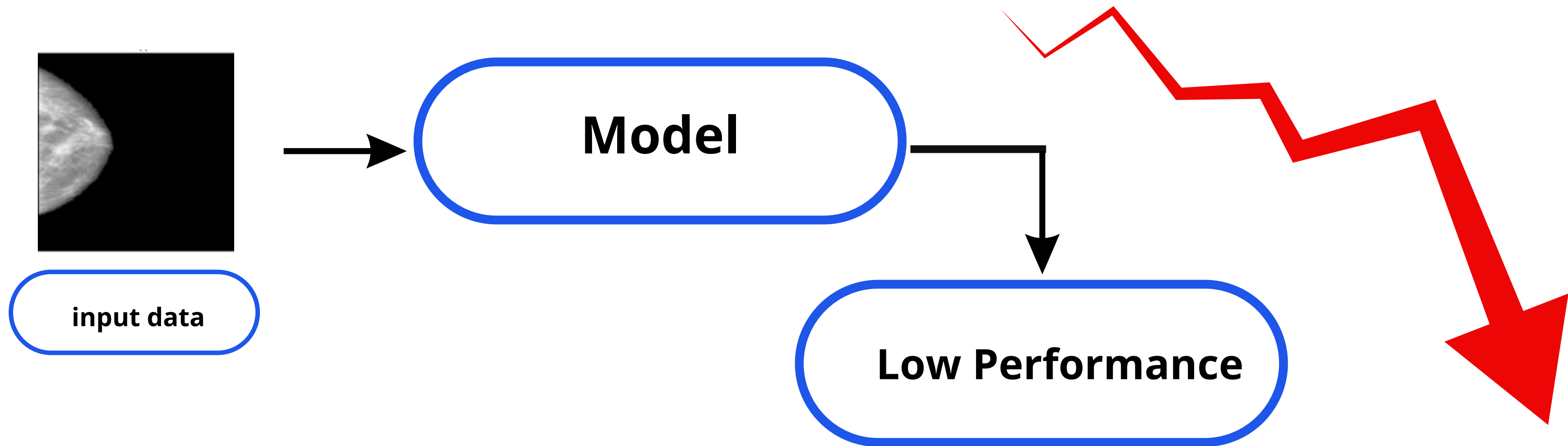


Methodology

Functional Requirements

Conceptual Phase

Techniques and tools used

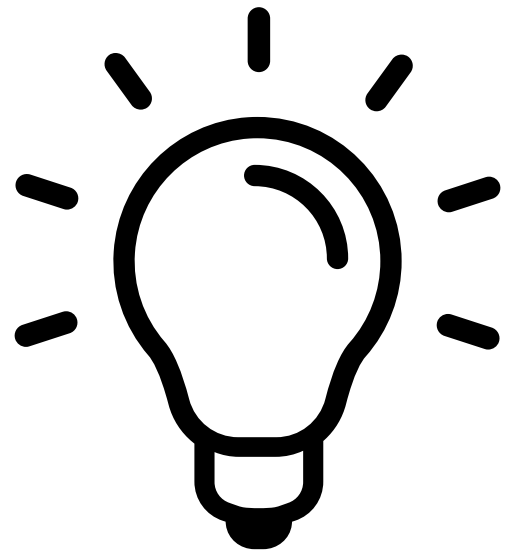


Methodology

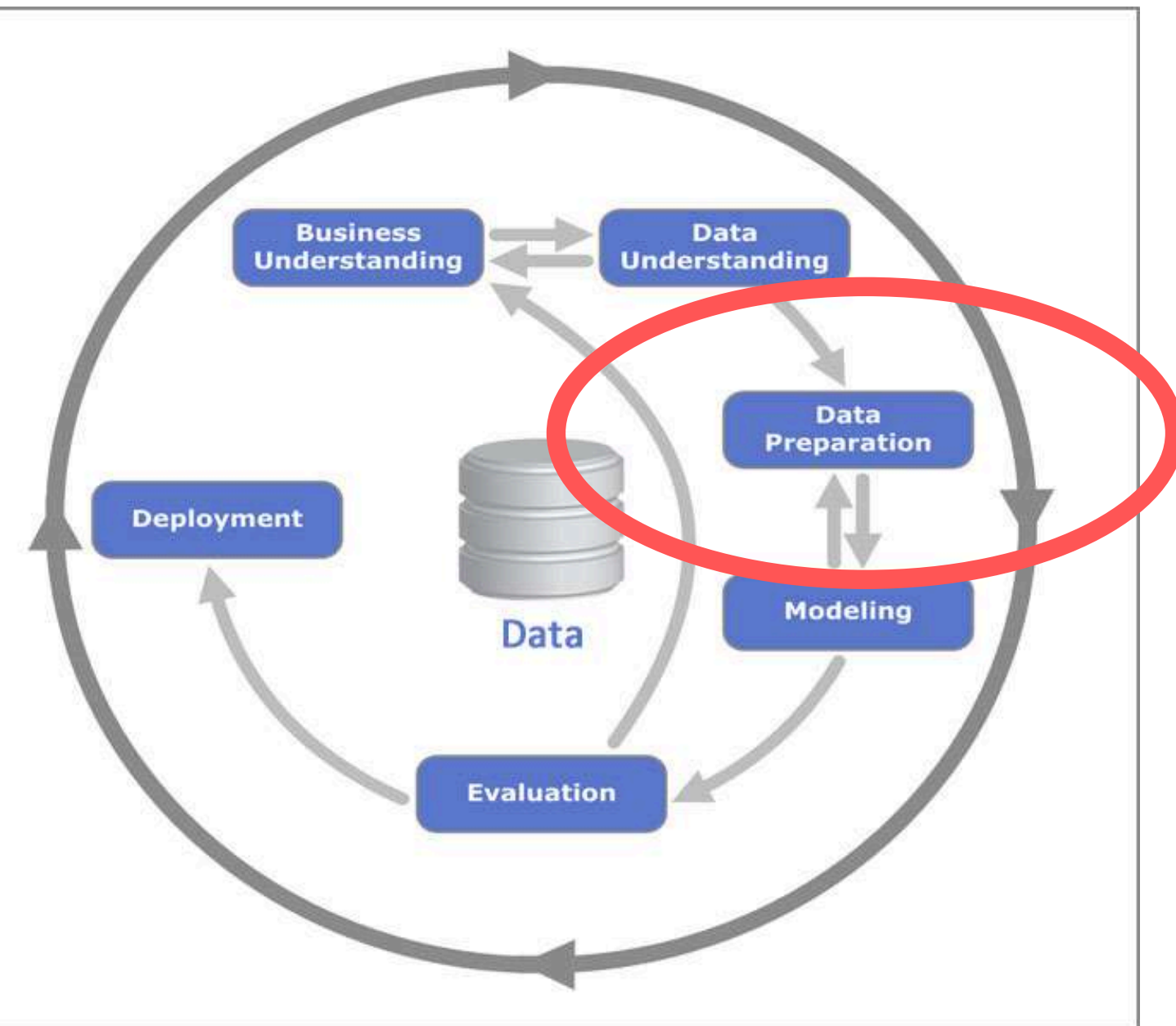
Functional Requirements

Conceptual Phase

Techniques and tools used



**CRISP-DM
Process
Diagram**



Source: Kenneth Jensen

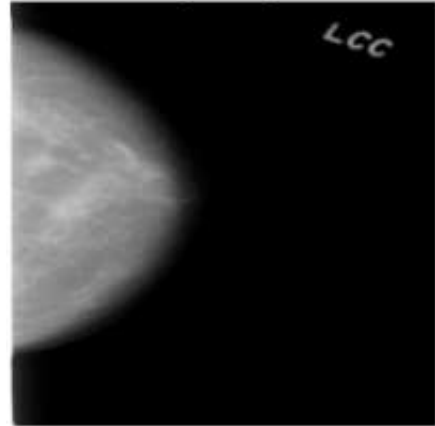
Methodology

Functional Requirements

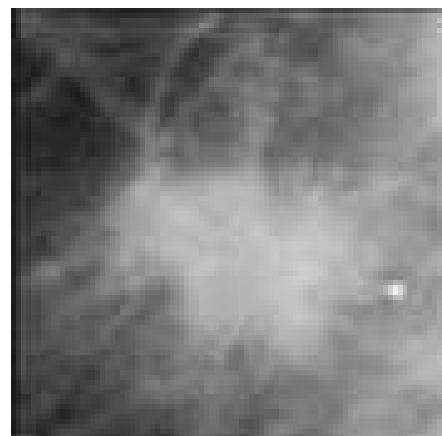
Conceptual Phase

Techniques and tools used

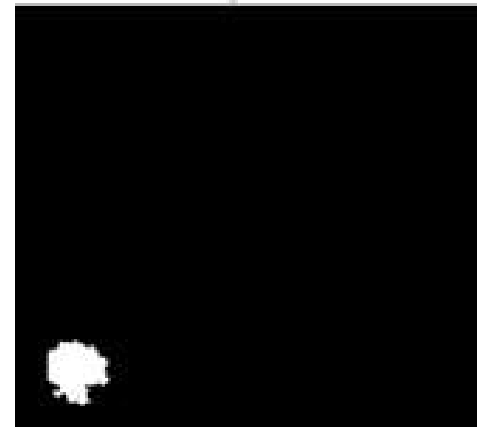
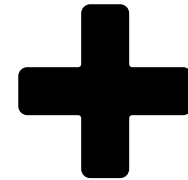
Original Image



input data



Cropped
data



Non cropped
Mask
corresponding



Mismatching
masks and
images

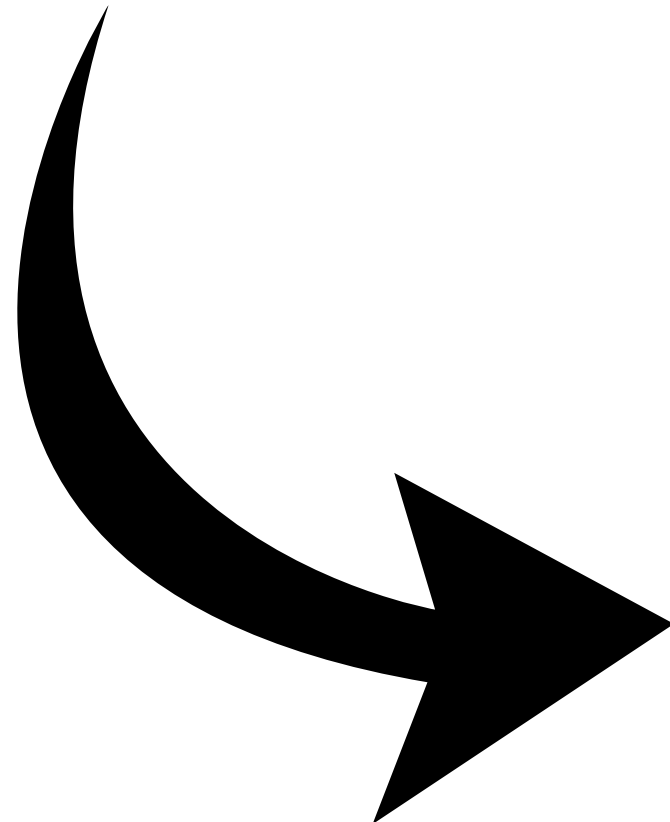
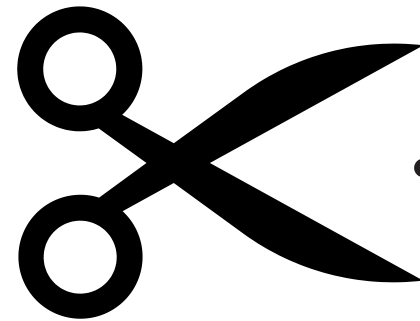
Methodology



Functional Requirements

Conceptual Phase

Techniques and tools used



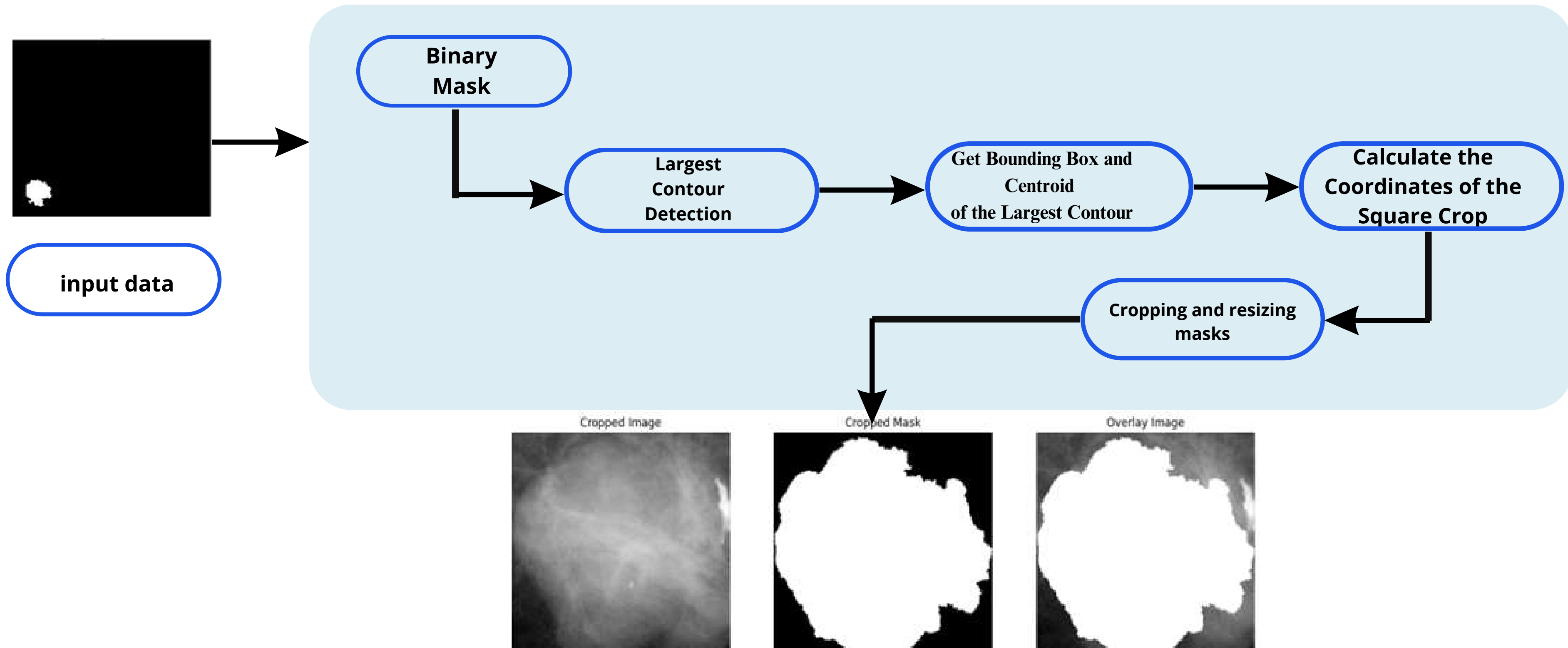
Cropping Masks

Methodology

Functional Requirements

Conceptual Phase

Techniques and tools used

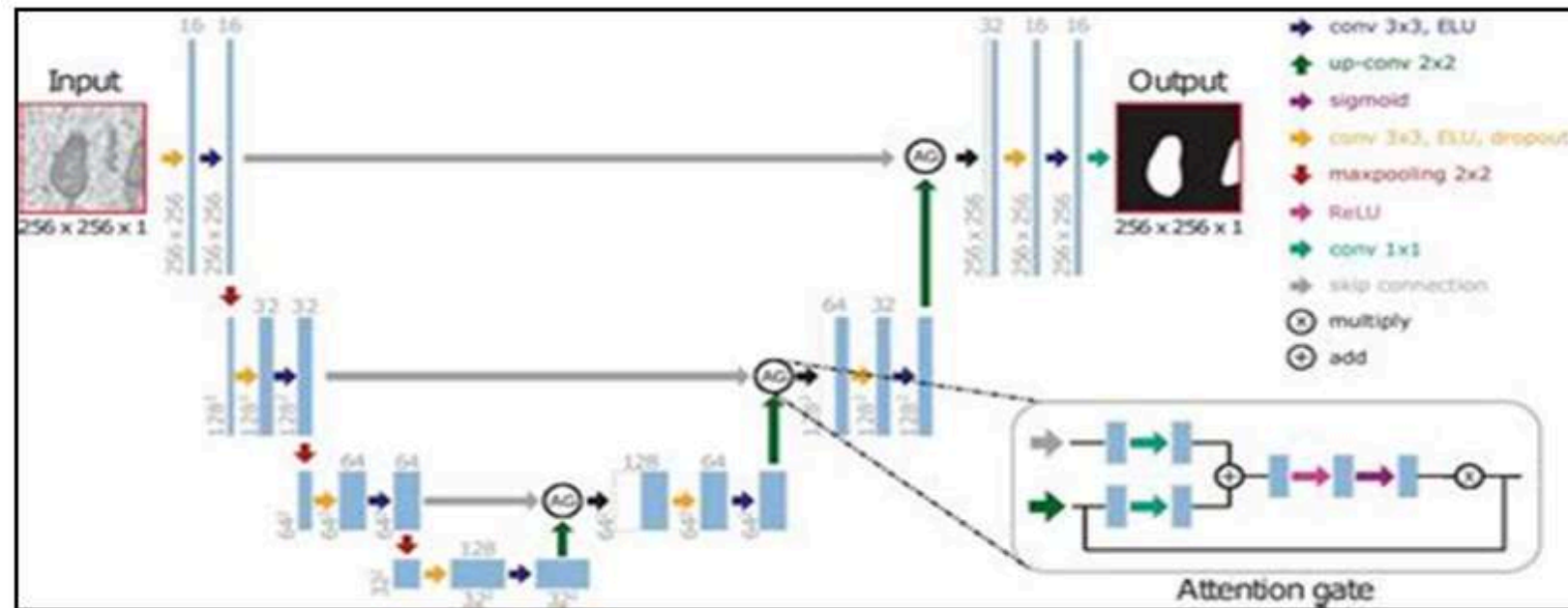


Methodology

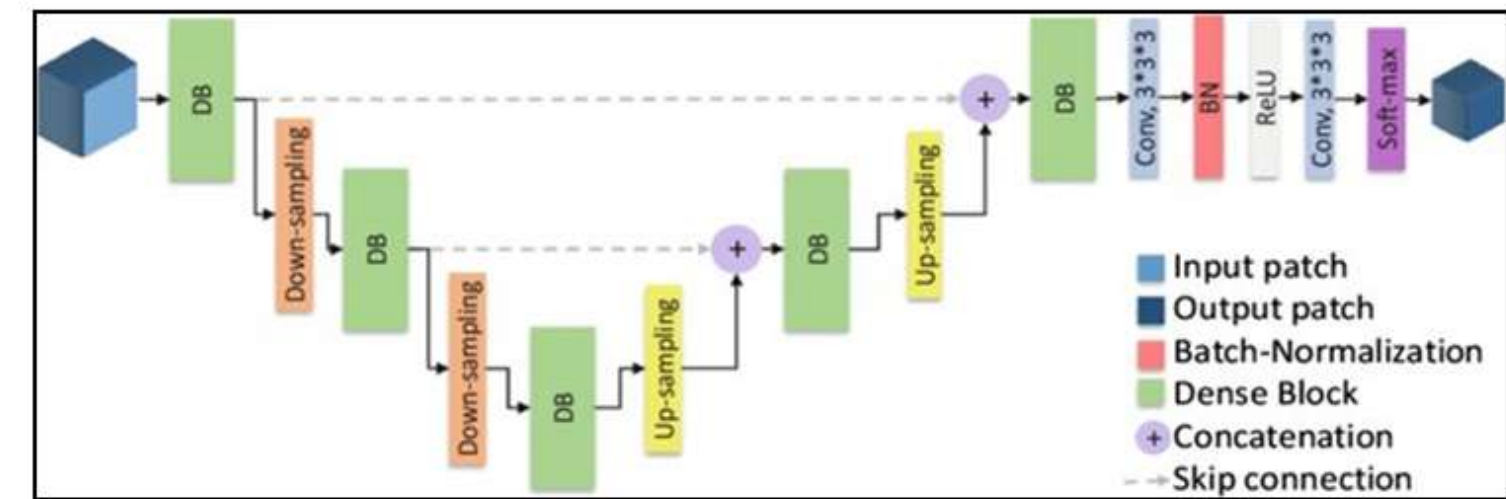
Functional Requirements

Conceptual Phase

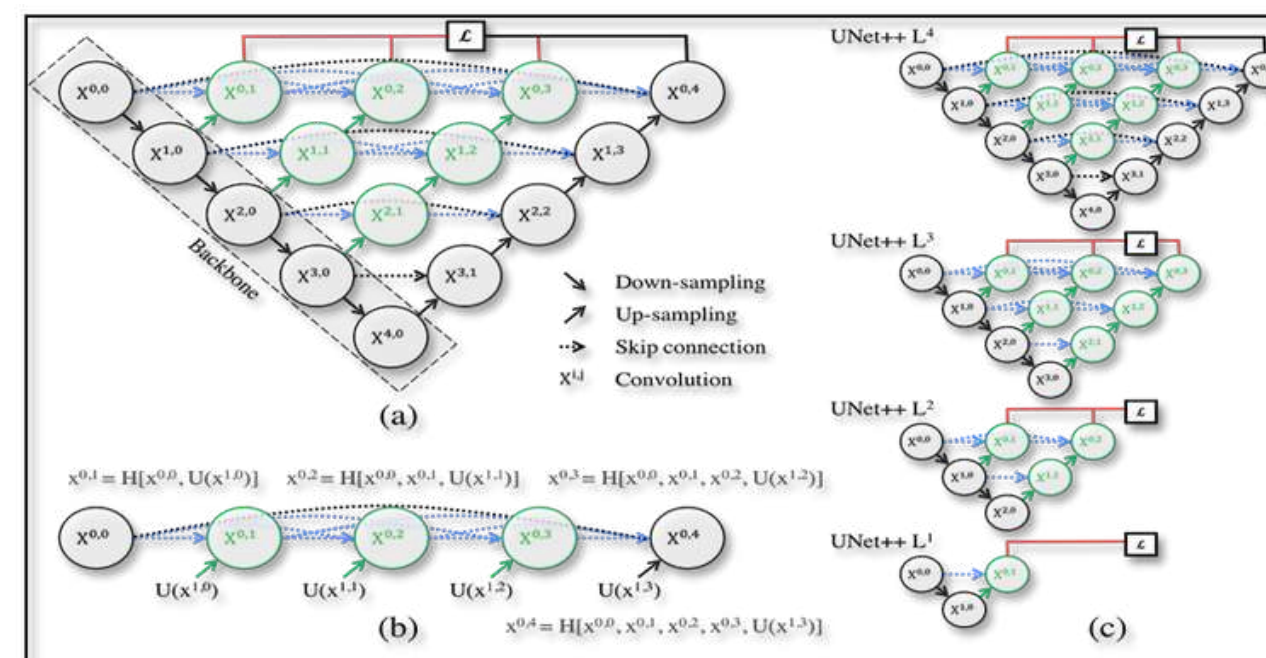
Techniques and tools used



Attention U-Net



Dense U-Net



U-Net plus plus

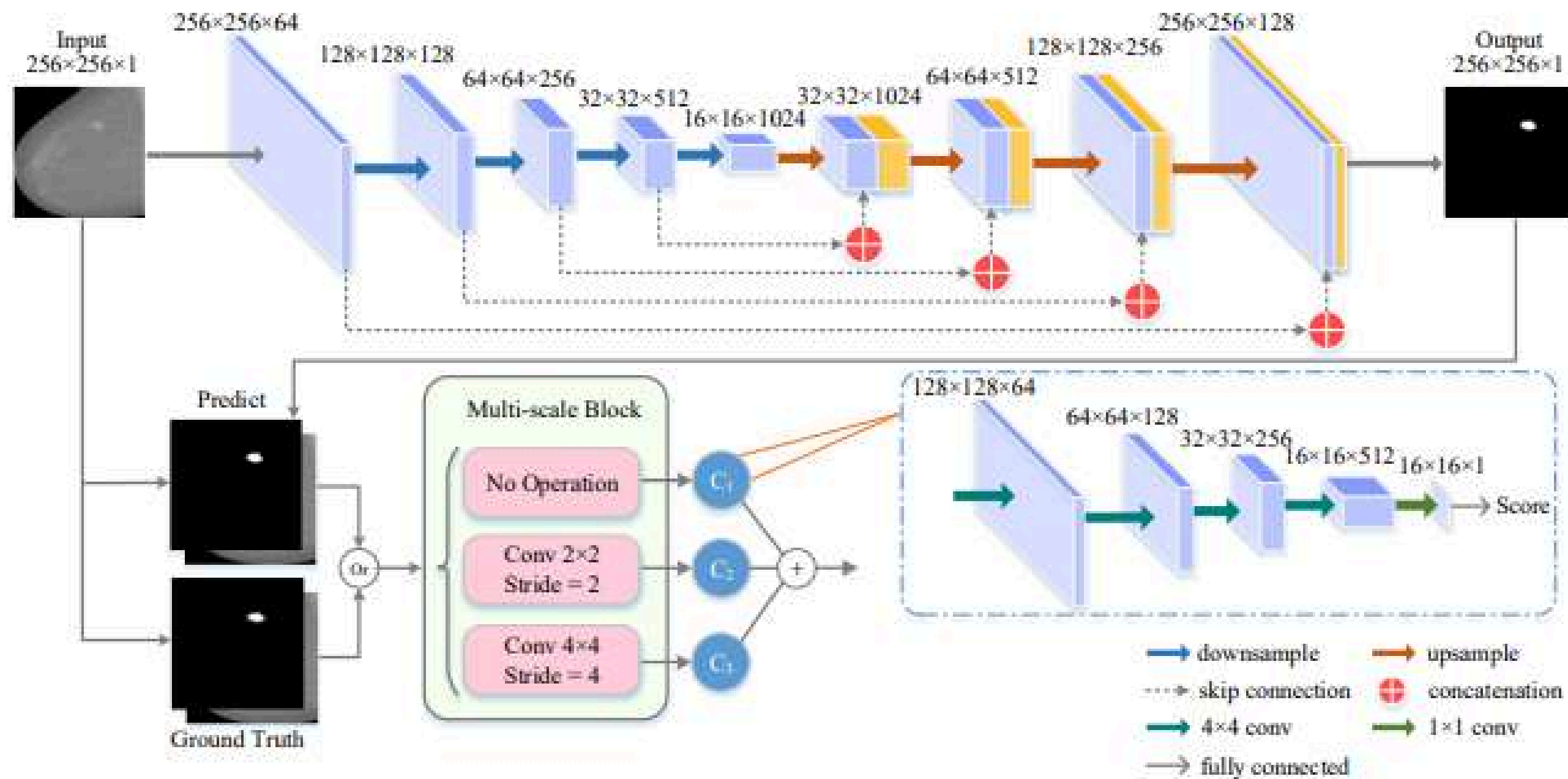


Methodology

Functional Requirements

Conceptual Phase

Techniques and tools used



Multiscale Adversarial Network Architecture

Methodology



Functional Requirements



Conceptual Phase



Techniques and tools used





Implementation

ObjectiveConstraintsRequirements

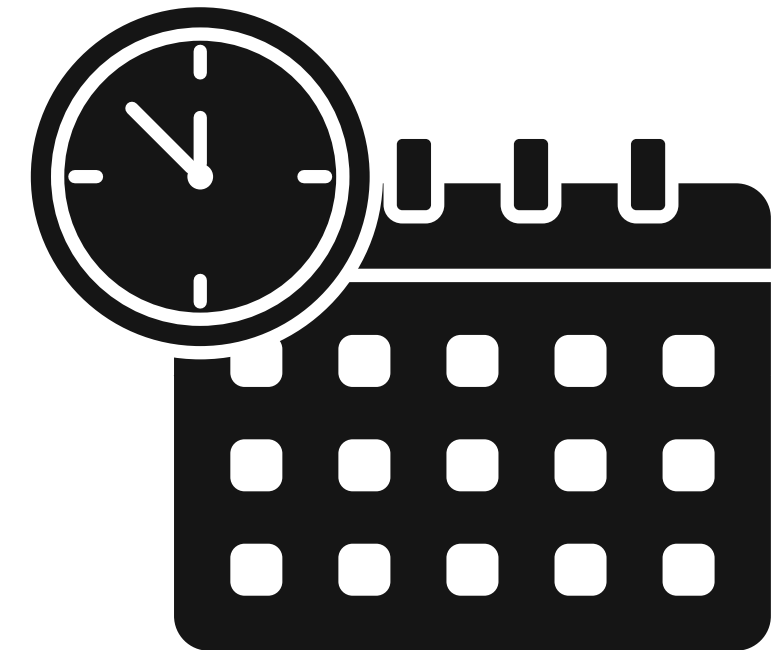
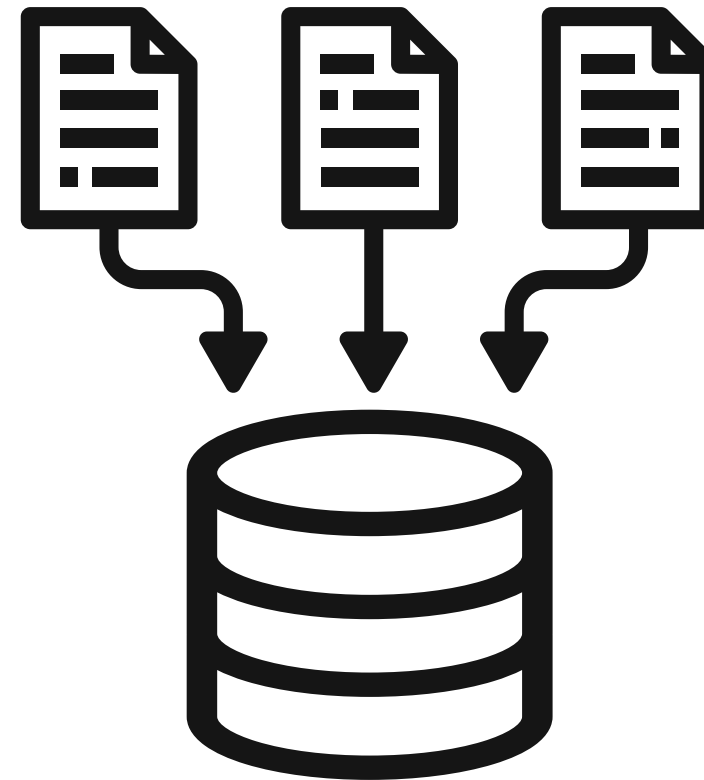
Develop a deep learning model for accurate segmentation of breast cancer masses in mammography images

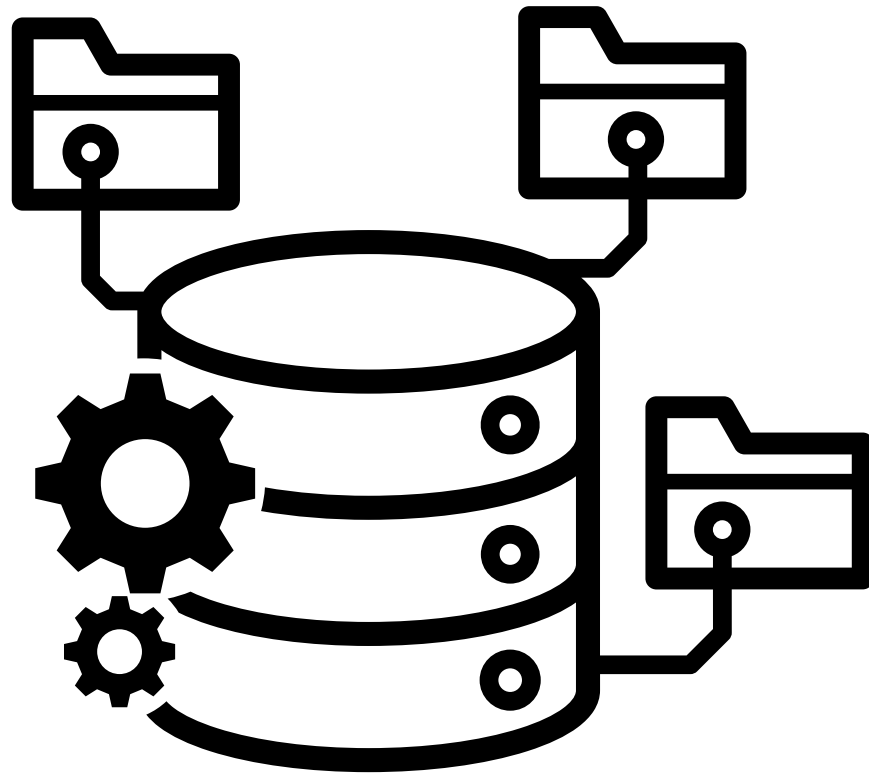


ObjectiveConstraintsRequirements

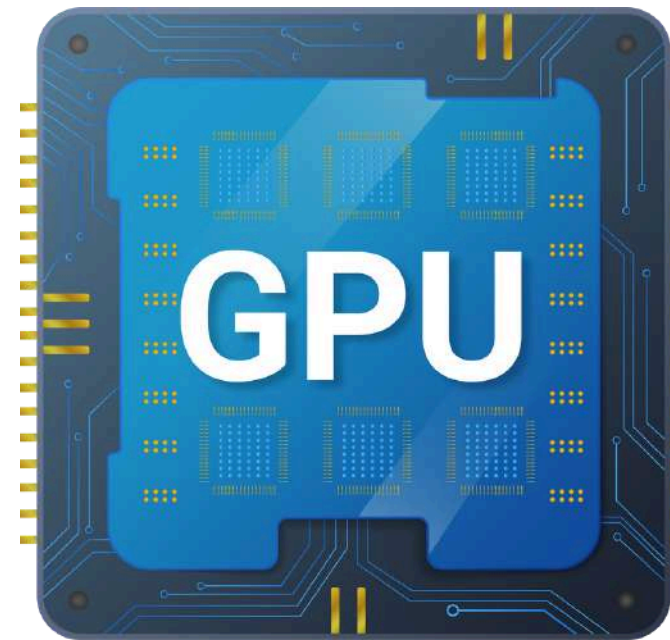
We found the main constraints in deep learning project:

- Budget
- Annotated data
- Time

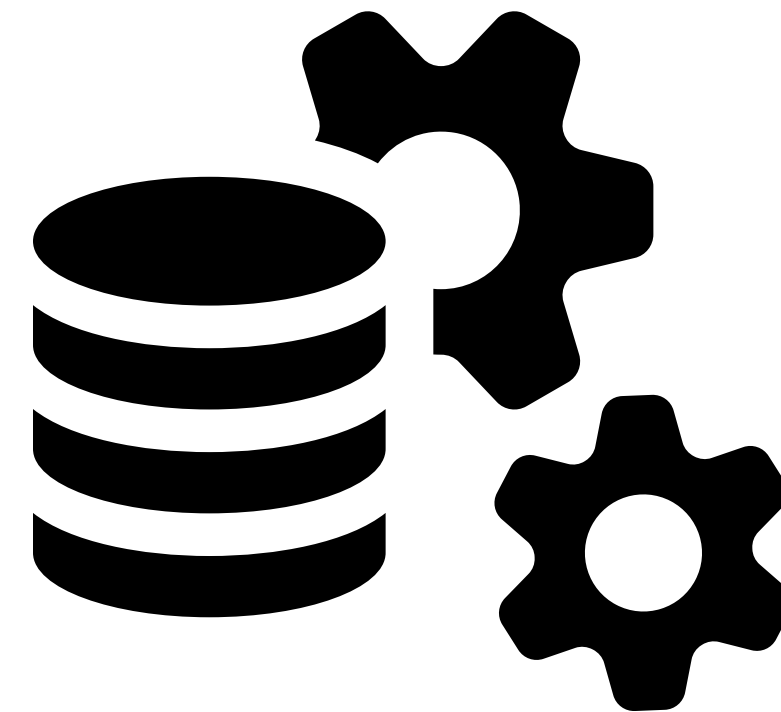


Objective

Data storage

Constraints

Computational resources

Requirements

Annotated data

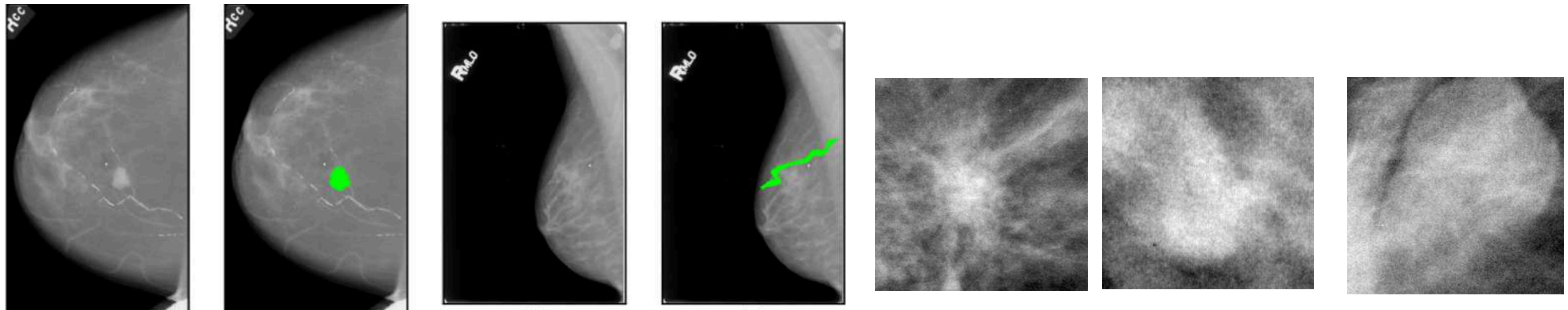
Data Collection

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	RGB
Color Grading Masks	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 CollectionData Explorationdata 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 Collection

Data Exploration

Data source verification



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

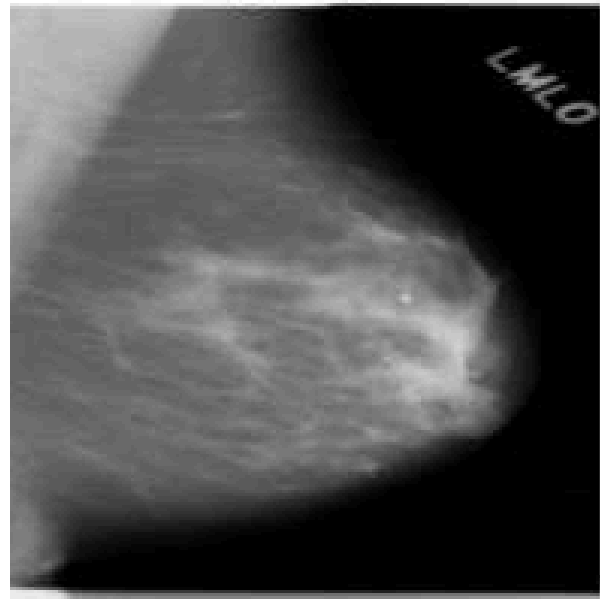
Data Cleaning

Data Transformation

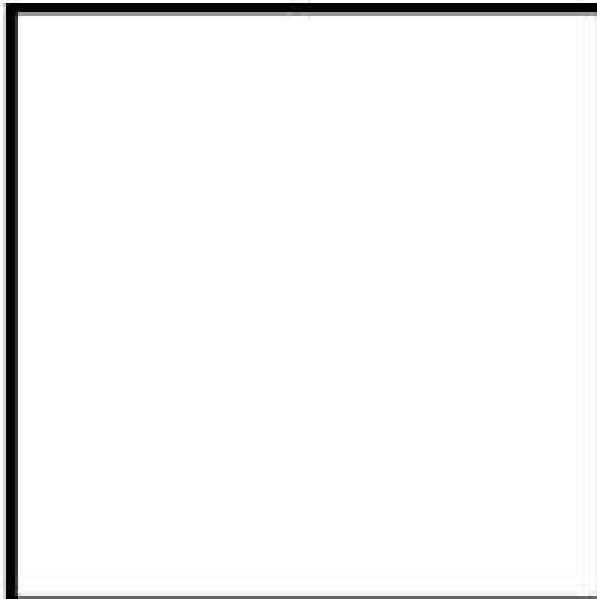
Data splitting

Data management

Original Image



Binary Mask



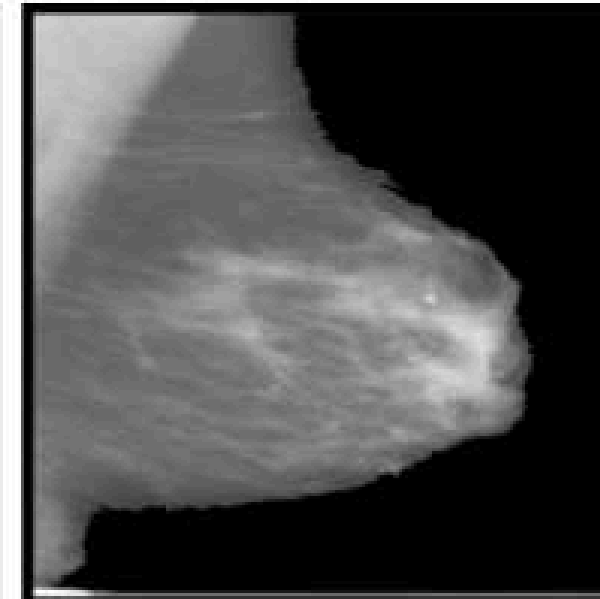
Binary Image



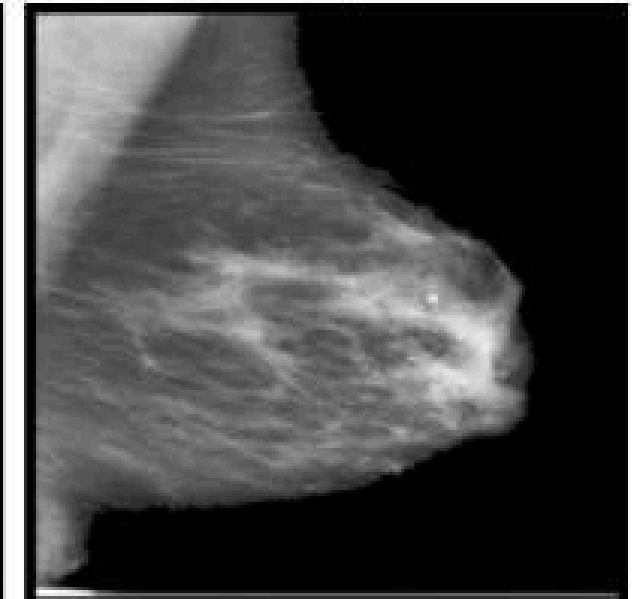
Largest Contour



Vertical Line Removal



CLAHE Applied



Data CleaningData TransformationData splittingData management

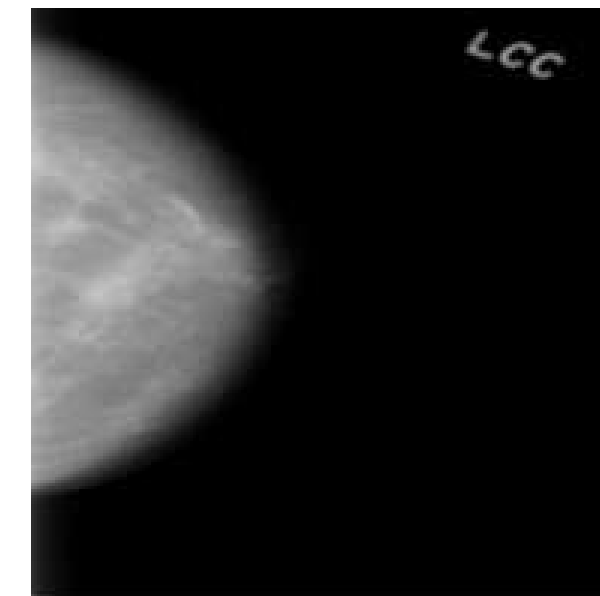
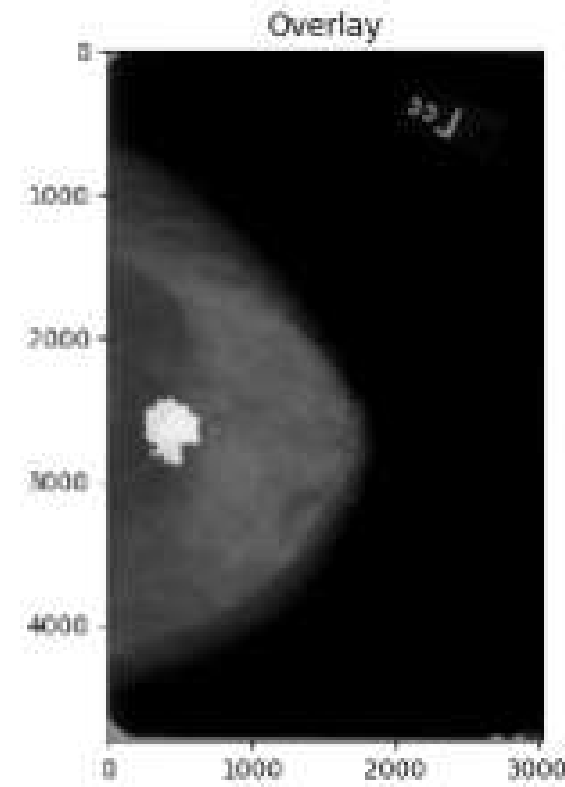
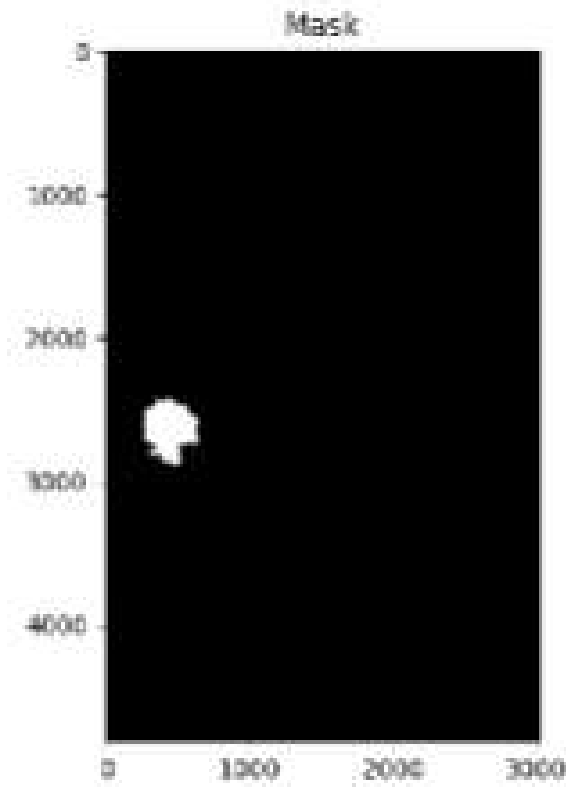
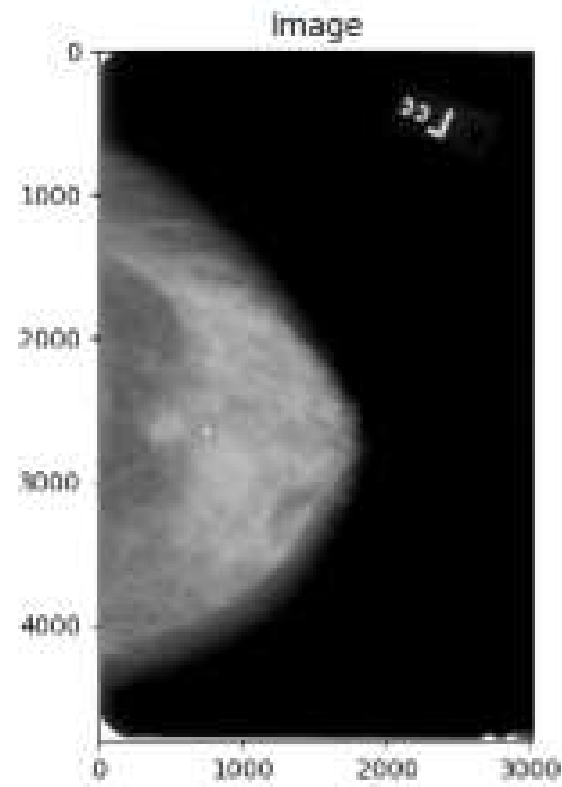
Algorithms	Functions	Values of Parameter
Binary masking	OpenCV rectangle()	Width = 5
Largest contour detection	OpenCV findContours()	Mode for contour approximation = CHAIN_APPROX_SIMPLE Retrieval mode of contour = RETR_EXTERNAL Measure key = contourArea
	max()	Index = largest contour, color of contour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

Data CleaningData TransformationData splittingData management

Data Transformation for Full Mammography

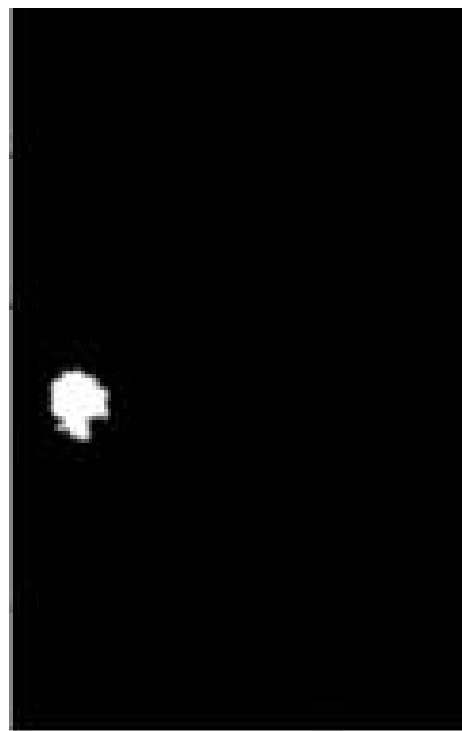
Resizing to 256*256

```
Image: 8888_1-211.jpg, Dimensions: (3024, 4896)  
Mask: 8888_1-250.jpg, Dimensions: (3024, 4896)
```

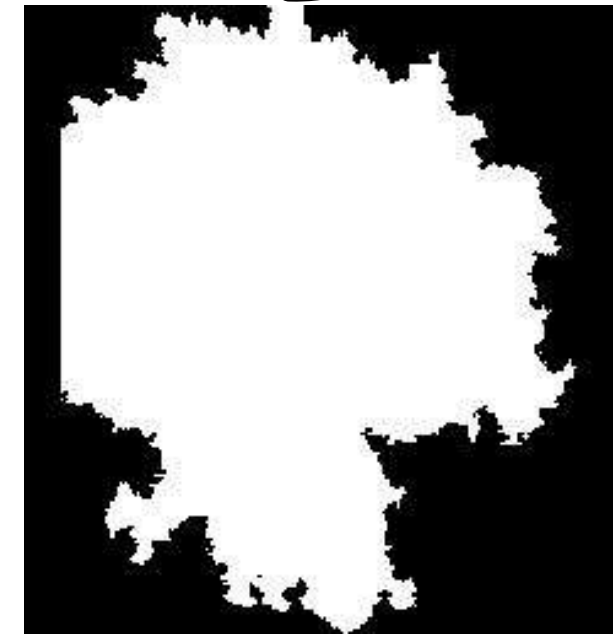
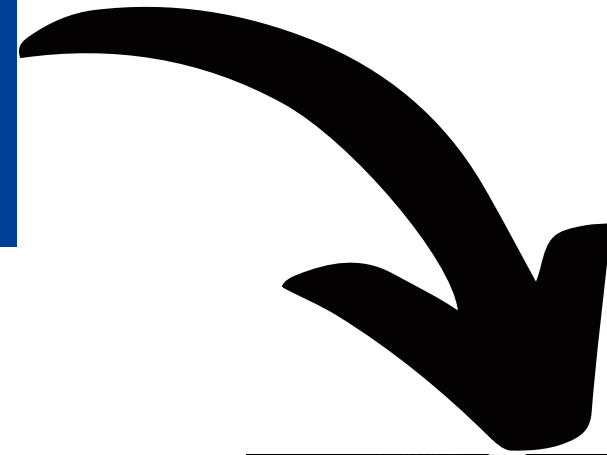


Data CleaningData TransformationData splittingData management

Data Transformation for Cropped images



Cropping and resizing masks to match
cropped images



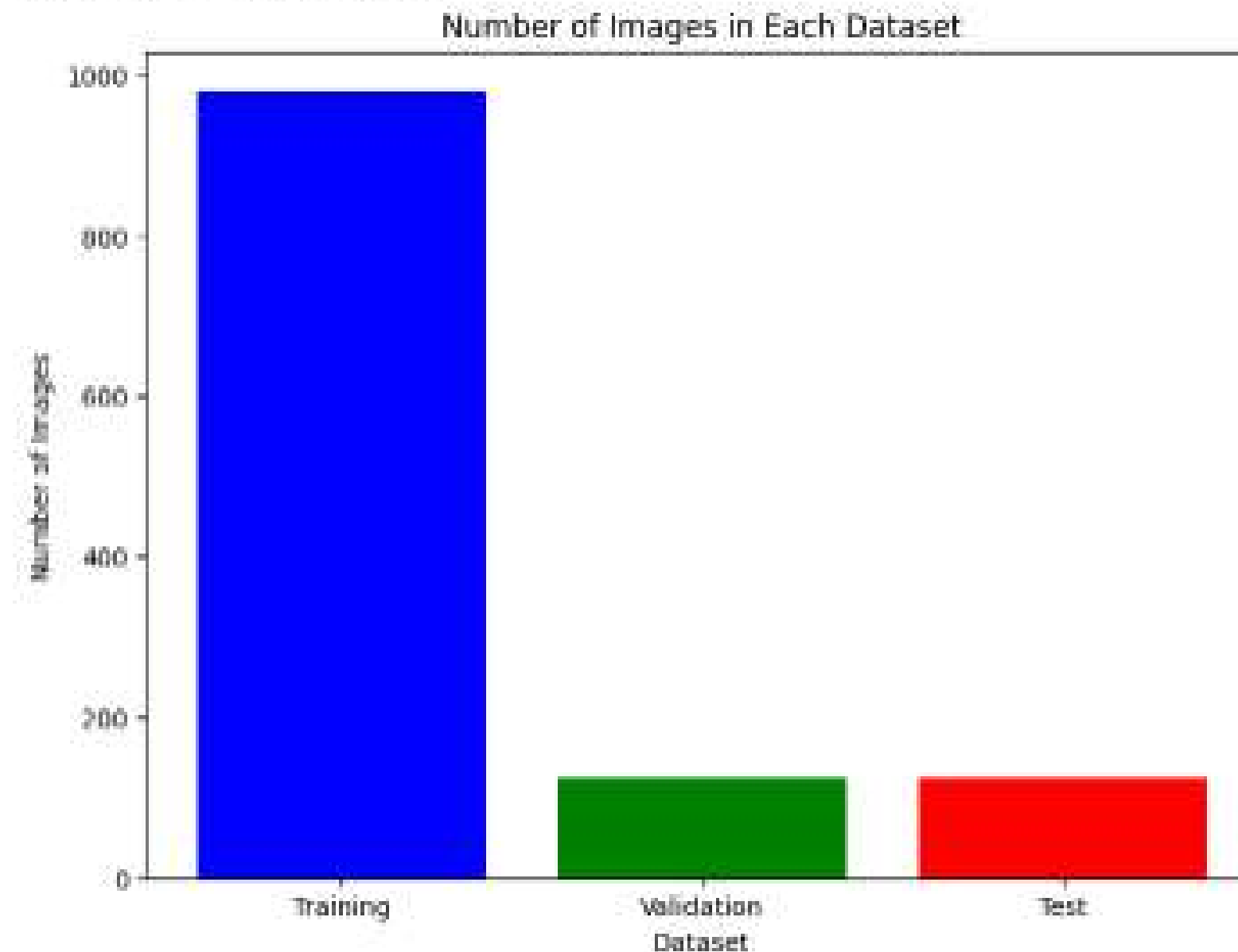
Data Cleaning

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)
```

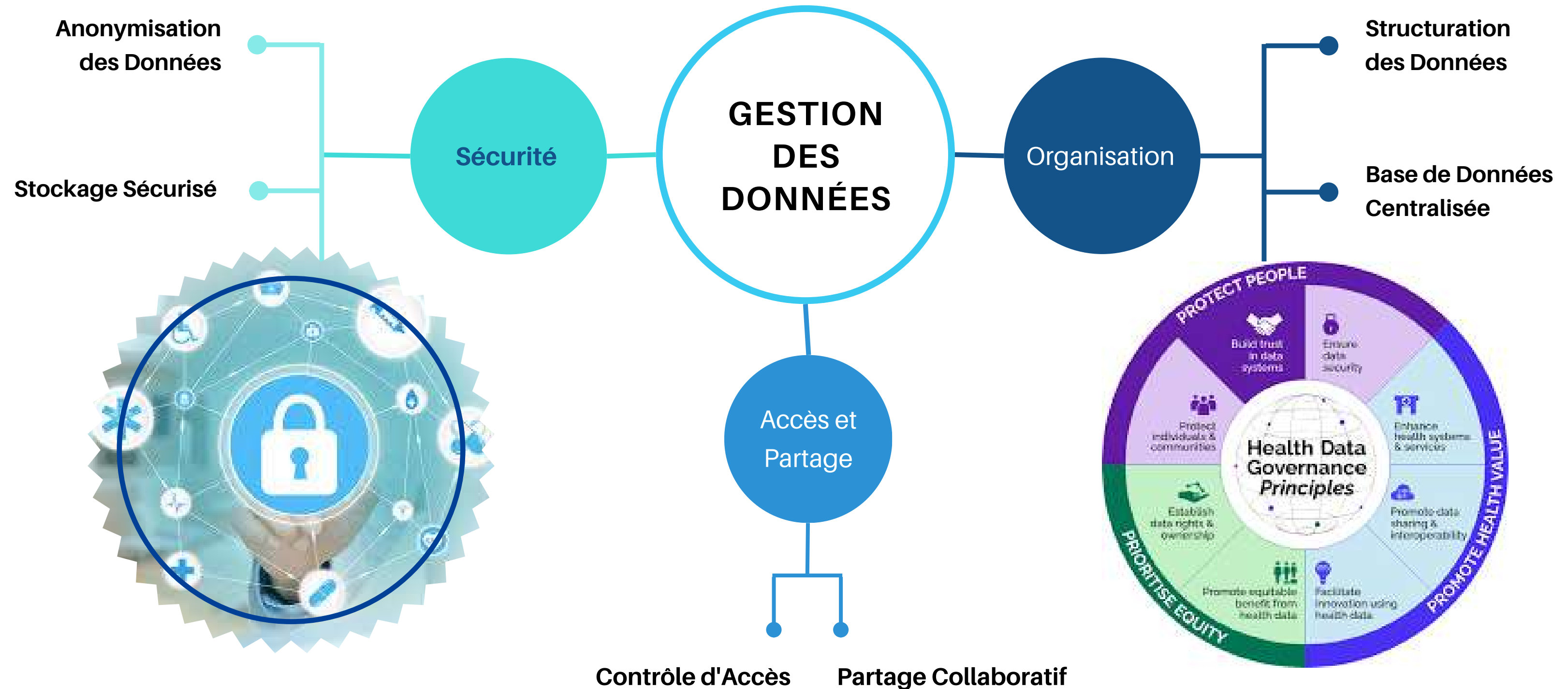


Data Cleaning

Data Transformation

Data Splitting

Data Management



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

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**

Choice of Models

Models Training

Evaluation

Discussion

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

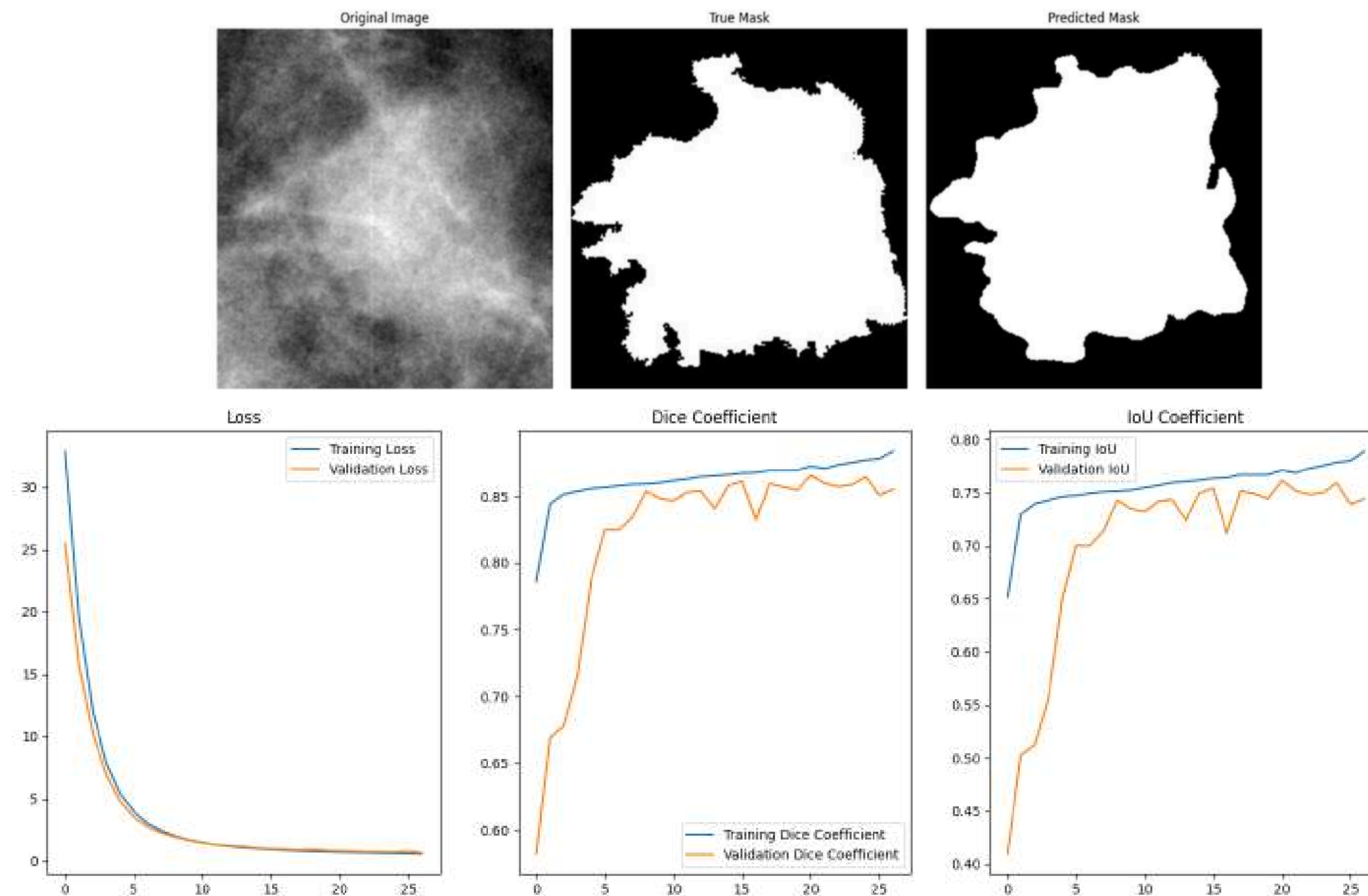
```
Epoch 1/50
132/132 [=====] - ETA: 0s - loss: 29.6881 - dice_coef: 0.0112 - iou_coef: 0.0057
Epoch 1: val_dice_coef improved from -inf to 0.01062, saving model to /content/drive/MyDrive/attconnmodel2.keras
132/132 [=====] - 120s 508ms/step - loss: 29.6881 - dice_coef: 0.0112 - iou_coef: 0.0057 - val_loss: 18.6217 - val_dice_coef: 0.0106 - val_iou_coef: 0.0054 - lr: 1.0000e-04
Epoch 2/50
132/132 [=====] - ETA: 0s - loss: 12.7699 - dice_coef: 0.0155 - iou_coef: 0.0078
Epoch 2: val_dice_coef improved from 0.01062 to 0.01076, saving model to /content/drive/MyDrive/attconnmodel2.keras
132/132 [=====] - 65s 492ms/step - loss: 12.7699 - dice_coef: 0.0155 - iou_coef: 0.0078 - val_loss: 8.3785 - val_dice_coef: 0.0108 - val_iou_coef: 0.0054 - lr: 1.0000e-04
Epoch 3/50
132/132 [=====] - ETA: 0s - loss: 6.0998 - dice_coef: 0.0337 - iou_coef: 0.0168
Epoch 3: val_dice_coef did not improve from 0.01076
132/132 [=====] - 62s 470ms/step - loss: 6.0998 - dice_coef: 0.0337 - iou_coef: 0.0168 - val_loss: 4.4198 - val_dice_coef: 0.0101 - val_iou_coef: 0.0051 - lr: 1.0000e-04
Epoch 4/50
132/132 [=====] - ETA: 0s - loss: 3.4661 - dice_coef: 0.0806 - iou_coef: 0.0401
Epoch 4: val_dice_coef improved from 0.01076 to 0.01082, saving model to /content/drive/MyDrive/attconnmodel2.keras
132/132 [=====] - 55s 489ms/step - loss: 3.4661 - dice_coef: 0.0806 - iou_coef: 0.0401 - val_loss: 4.4845 - val_dice_coef: 0.0108 - val_iou_coef: 0.0058 - lr: 1.0000e-04
Epoch 5/50
132/132 [=====] - ETA: 0s - loss: 2.3537 - dice_coef: 0.1701 - iou_coef: 0.0886
Epoch 5: val_dice_coef did not improve from 0.01082
132/132 [=====] - 62s 472ms/step - loss: 2.3537 - dice_coef: 0.1701 - iou_coef: 0.0886 - val_loss: 2.2284 - val_dice_coef: 0.0677 - val_iou_coef: 0.0058 - lr: 1.0000e-04
Epoch 6/50
132/132 [=====] - ETA: 0s - loss: 1.8087 - dice_coef: 0.2706 - iou_coef: 0.1472
Epoch 6: val_dice_coef improved from 0.01082 to 0.22552, saving model to /content/drive/MyDrive/attconnmodel2.keras
132/132 [=====] - 64s 488ms/step - loss: 1.8087 - dice_coef: 0.2706 - iou_coef: 0.1472 - val_loss: 1.7270 - val_dice_coef: 0.2255 - val_iou_coef: 0.1048 - lr: 1.0000e-04
Epoch 7/50
132/132 [=====] - ETA: 0s - loss: 1.5557 - dice_coef: 0.3206 - iou_coef: 0.1821
Epoch 7: val_dice_coef improved from 0.22552 to 0.37108, saving model to /content/drive/MyDrive/attconnmodel2.keras
132/132 [=====] - 55s 489ms/step - loss: 1.5557 - dice_coef: 0.3206 - iou_coef: 0.1821 - val_loss: 1.4352 - val_dice_coef: 0.3720 - val_iou_coef: 0.1773 - lr: 1.0000e-04
Epoch 8/50
132/132 [=====] - ETA: 0s - loss: 1.3976 - dice_coef: 0.3504 - iou_coef: 0.2047
Epoch 8: val_dice_coef did not improve from 0.37108
132/132 [=====] - 63s 473ms/step - loss: 1.3976 - dice_coef: 0.3504 - iou_coef: 0.2047 - val_loss: 1.3741 - val_dice_coef: 0.3230 - val_iou_coef: 0.1410 - lr: 1.0000e-04
Epoch 9/50
132/132 [=====] - ETA: 0s - loss: 1.3976 - dice_coef: 0.3504 - iou_coef: 0.2047
Epoch 9: val_dice_coef did not improve from 0.37108
132/132 [=====] - 63s 473ms/step - loss: 1.3976 - dice_coef: 0.3504 - iou_coef: 0.2047 - val_loss: 1.3741 - val_dice_coef: 0.3230 - val_iou_coef: 0.1410 - lr: 1.0000e-04
Epoch 10/50
132/132 [=====] - ETA: 0s - loss: 0.8178 - dice_coef: 0.8603 - iou_coef: 0.7669
Epoch 10: val_dice_coef did not improve from 0.86097
132/132 [=====] - 118s 956ms/step - loss: 0.8178 - dice_coef: 0.8603 - iou_coef: 0.7669 - val_loss: 0.8828 - val_dice_coef: 0.8593 - val_iou_coef: 0.7518 - lr: 1.0000e-04
Epoch 11/50
132/132 [=====] - ETA: 0s - loss: 0.7809 - dice_coef: 0.8603 - iou_coef: 0.7668
Epoch 11: val_dice_coef did not improve from 0.86097
132/132 [=====] - 118s 957ms/step - loss: 0.7809 - dice_coef: 0.8603 - iou_coef: 0.7668 - val_loss: 0.9440 - val_dice_coef: 0.8569 - val_iou_coef: 0.7490 - lr: 1.0000e-04
Epoch 12/50
132/132 [=====] - ETA: 0s - loss: 0.7487 - dice_coef: 0.8604 - iou_coef: 0.7669
Epoch 12: val_dice_coef did not improve from 0.86097
132/132 [=====] - 118s 957ms/step - loss: 0.7487 - dice_coef: 0.8604 - iou_coef: 0.7669 - val_loss: 0.8421 - val_dice_coef: 0.8544 - val_iou_coef: 0.7443 - lr: 1.0000e-04
Epoch 13/50
132/132 [=====] - ETA: 0s - loss: 0.7119 - dice_coef: 0.8722 - iou_coef: 0.7713
Epoch 13: val_dice_coef improved from 0.86097 to 0.86546, saving model to /kaggle/working/awnet_model2.keras
132/132 [=====] - 120s 976ms/step - loss: 0.7119 - dice_coef: 0.8722 - iou_coef: 0.7713 - val_loss: 0.8880 - val_dice_coef: 0.8655 - val_iou_coef: 0.7614 - lr: 1.0000e-04
Epoch 14/50
132/132 [=====] - ETA: 0s - loss: 0.6938 - dice_coef: 0.8706 - iou_coef: 0.7687
Epoch 14: val_dice_coef did not improve from 0.86546
132/132 [=====] - 118s 956ms/step - loss: 0.6938 - dice_coef: 0.8706 - iou_coef: 0.7687 - val_loss: 0.7908 - val_dice_coef: 0.8595 - val_iou_coef: 0.7519 - lr: 1.0000e-04
Epoch 15/50
132/132 [=====] - ETA: 0s - loss: 0.6658 - dice_coef: 0.8733 - iou_coef: 0.7729
Epoch 15: val_dice_coef did not improve from 0.86546
132/132 [=====] - 117s 955ms/step - loss: 0.6658 - dice_coef: 0.8733 - iou_coef: 0.7729 - val_loss: 0.7419 - val_dice_coef: 0.8571 - val_iou_coef: 0.7483 - lr: 1.0000e-04
Epoch 16/50
132/132 [=====] - ETA: 0s - loss: 0.6428 - dice_coef: 0.8750 - iou_coef: 0.7755
Epoch 16: val_dice_coef did not improve from 0.86546
132/132 [=====] - 118s 956ms/step - loss: 0.6428 - dice_coef: 0.8750 - iou_coef: 0.7755 - val_loss: 0.7367 - val_dice_coef: 0.8585 - val_iou_coef: 0.7581 - lr: 1.0000e-04
Epoch 17/50
132/132 [=====] - ETA: 0s - loss: 0.6215 - dice_coef: 0.8769 - iou_coef: 0.7786
Epoch 17: val_dice_coef did not improve from 0.86546
132/132 [=====] - 118s 956ms/step - loss: 0.6215 - dice_coef: 0.8769 - iou_coef: 0.7786 - val_loss: 0.7188 - val_dice_coef: 0.8643 - val_iou_coef: 0.7501 - lr: 1.0000e-04
Epoch 18/50
132/132 [=====] - ETA: 0s - loss: 0.6069 - dice_coef: 0.8779 - iou_coef: 0.7801
Epoch 18: val_dice_coef did not improve from 0.86546
132/132 [=====] - 117s 954ms/step - loss: 0.6069 - dice_coef: 0.8779 - iou_coef: 0.7801 - val_loss: 0.8165 - val_dice_coef: 0.8588 - val_iou_coef: 0.7393 - lr: 1.0000e-04
Epoch 19/50
132/132 [=====] - ETA: 0s - loss: 0.6178 - dice_coef: 0.8603 - iou_coef: 0.7669
Epoch 19: val_dice_coef did not improve from 0.86097
132/132 [=====] - 118s 956ms/step - loss: 0.6178 - dice_coef: 0.8603 - iou_coef: 0.7669 - val_loss: 0.8828 - val_dice_coef: 0.8593 - val_iou_coef: 0.7518 - lr: 1.0000e-04
Epoch 20/50
132/132 [=====] - ETA: 0s - loss: 0.7809 - dice_coef: 0.8603 - iou_coef: 0.7668
Epoch 20: val_dice_coef did not improve from 0.86097
132/132 [=====] - 118s 957ms/step - loss: 0.7809 - dice_coef: 0.8603 - iou_coef: 0.7668 - val_loss: 0.9440 - val_dice_coef: 0.8569 - val_iou_coef: 0.7490 - lr: 1.0000e-04
Epoch 21/50
132/132 [=====] - ETA: 0s - loss: 0.7487 - dice_coef: 0.8604 - iou_coef: 0.7669
Epoch 21: val_dice_coef did not improve from 0.86097
132/132 [=====] - 118s 957ms/step - loss: 0.7487 - dice_coef: 0.8604 - iou_coef: 0.7669 - val_loss: 0.8421 - val_dice_coef: 0.8544 - val_iou_coef: 0.7443 - lr: 1.0000e-04
Epoch 22/50
132/132 [=====] - ETA: 0s - loss: 0.7119 - dice_coef: 0.8722 - iou_coef: 0.7713
Epoch 22: val_dice_coef improved from 0.86097 to 0.86546, saving model to /kaggle/working/awnet_model2.keras
132/132 [=====] - 120s 976ms/step - loss: 0.7119 - dice_coef: 0.8722 - iou_coef: 0.7713 - val_loss: 0.8880 - val_dice_coef: 0.8655 - val_iou_coef: 0.7614 - lr: 1.0000e-04
Epoch 23/50
132/132 [=====] - ETA: 0s - loss: 0.6938 - dice_coef: 0.8706 - iou_coef: 0.7687
Epoch 23: val_dice_coef did not improve from 0.86546
132/132 [=====] - 118s 956ms/step - loss: 0.6938 - dice_coef: 0.8706 - iou_coef: 0.7687 - val_loss: 0.7908 - val_dice_coef: 0.8595 - val_iou_coef: 0.7519 - lr: 1.0000e-04
Epoch 24/50
132/132 [=====] - ETA: 0s - loss: 0.6658 - dice_coef: 0.8733 - iou_coef: 0.7729
Epoch 24: val_dice_coef did not improve from 0.86546
132/132 [=====] - 117s 955ms/step - loss: 0.6658 - dice_coef: 0.8733 - iou_coef: 0.7729 - val_loss: 0.7419 - val_dice_coef: 0.8571 - val_iou_coef: 0.7483 - lr: 1.0000e-04
Epoch 25/50
132/132 [=====] - ETA: 0s - loss: 0.6428 - dice_coef: 0.8750 - iou_coef: 0.7755
Epoch 25: val_dice_coef did not improve from 0.86546
132/132 [=====] - 118s 956ms/step - loss: 0.6428 - dice_coef: 0.8750 - iou_coef: 0.7755 - val_loss: 0.7367 - val_dice_coef: 0.8585 - val_iou_coef: 0.7581 - lr: 1.0000e-04
Epoch 26/50
132/132 [=====] - ETA: 0s - loss: 0.6215 - dice_coef: 0.8769 - iou_coef: 0.7786
Epoch 26: val_dice_coef did not improve from 0.86546
132/132 [=====] - 118s 956ms/step - loss: 0.6215 - dice_coef: 0.8769 - iou_coef: 0.7786 - val_loss: 0.7188 - val_dice_coef: 0.8643 - val_iou_coef: 0.7501 - lr: 1.0000e-04
Epoch 27/50
132/132 [=====] - ETA: 0s - loss: 0.6069 - dice_coef: 0.8779 - iou_coef: 0.7801
Epoch 27: val_dice_coef did not improve from 0.86546
132/132 [=====] - 117s 954ms/step - loss: 0.6069 - dice_coef: 0.8779 - iou_coef: 0.7801 - val_loss: 0.8165 - val_dice_coef: 0.8588 - val_iou_coef: 0.7393 - lr: 1.0000e-04
```


Choice of Models

Models Training

Evaluation

Discussion



Connected Attention U-Net for cropped images

Choice of Models

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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

Choice of Models

Model Training

Evaulation

Discussion

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

A large blue hexagon is positioned in the top left corner. Below it and to the left is a smaller purple hexagon. Both are partially cut off by the left edge of the frame.

**Merci pour votre
attention !**