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The International Workshop on Advanced Image Technology (IWAIT 2025)

"A YOLO-based Model for Breast Calcification Areas Detection in Screening Mammography"

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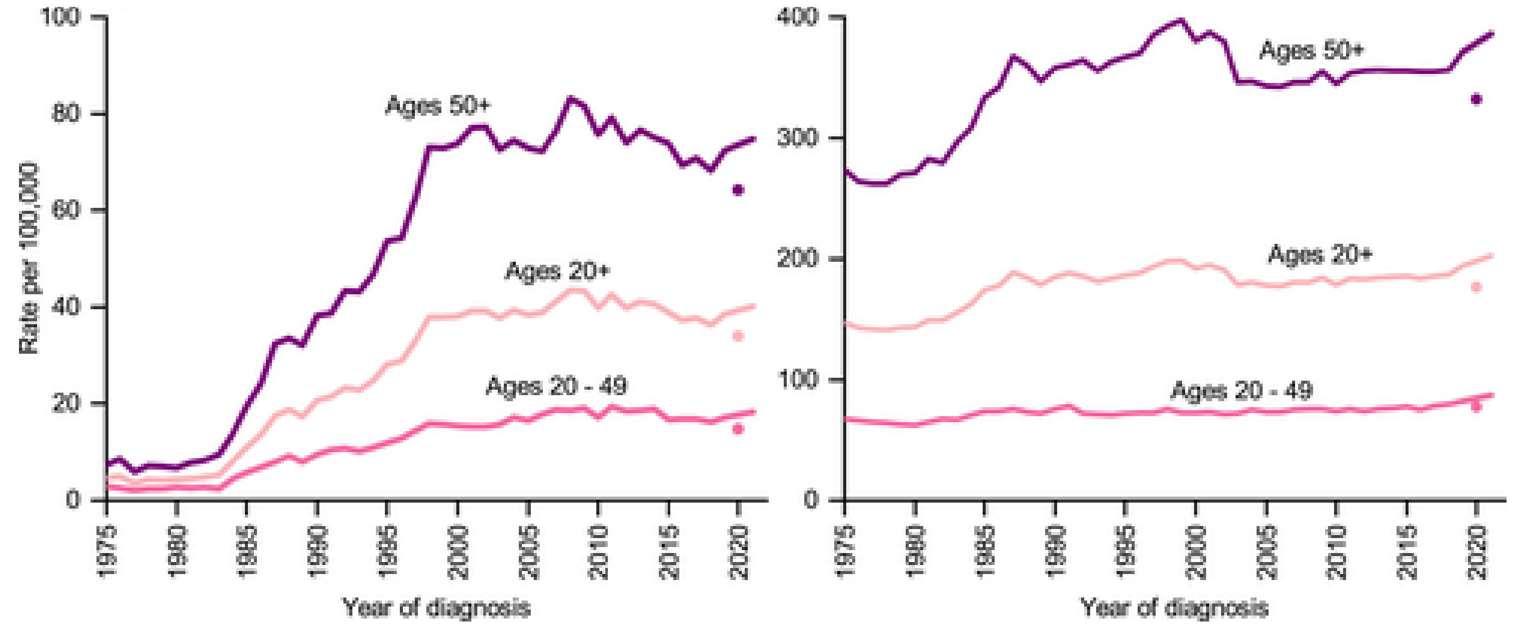
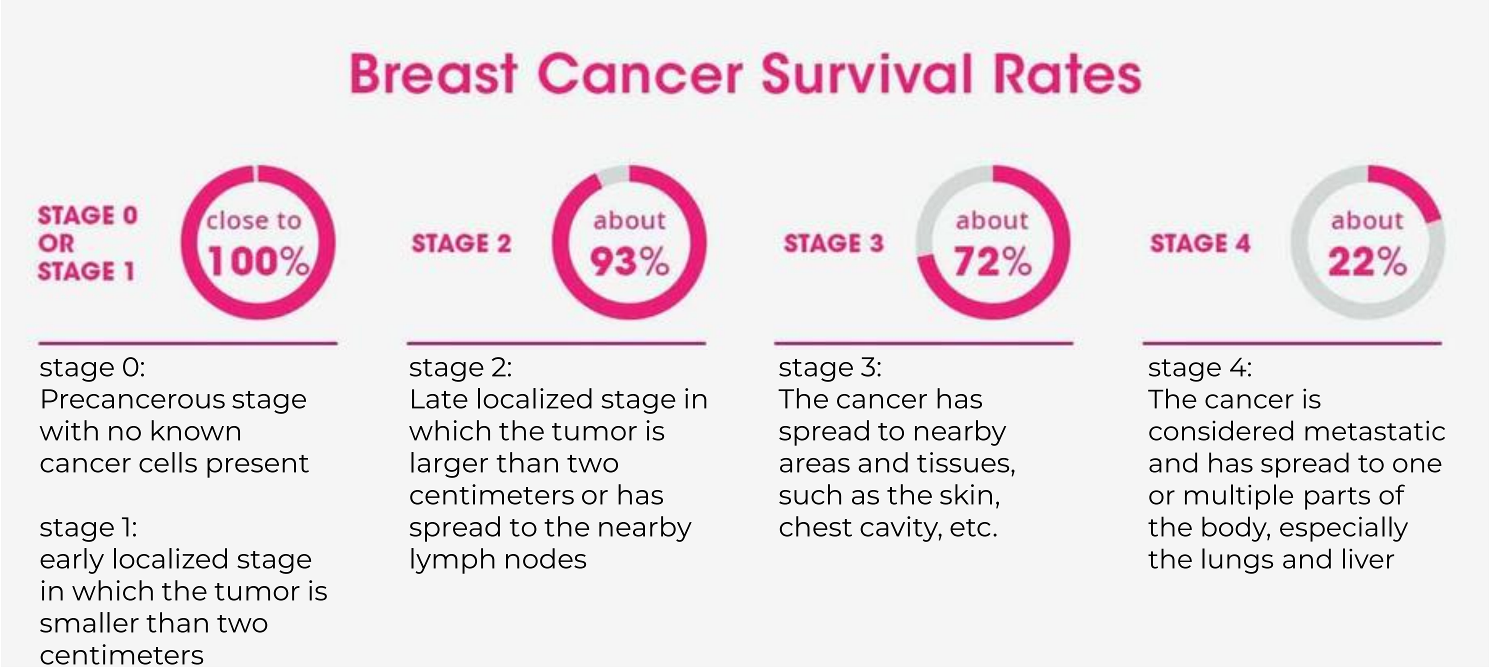
主辦單位 | YunTech 國立雲林科技大學 資訊工程系 Computer Science and Information Engineering 協辦單位 | IRIS 智慧辨識產業服務研究中心 Intelligent Recognition Industry Service Research Center ETPC 工程科技推展中心 ENGINEERING & TECHNOLOGY PROMOTION CENTER 指導單位 | NSTC 國家科學及技術委員會 National Science and Technology Council 教育部

1. Background

1. Noticeable shift toward younger ages of breast cancer onset



2. Early treatment of breast cancer enhances five-year survival rates



3. The critical importance of early detection of breast cancer

Especially for the earliest signs of non-palpable breast cancer, which often manifest as calcification.

2. Research Problem

Breast Cancer Detection (BCD)

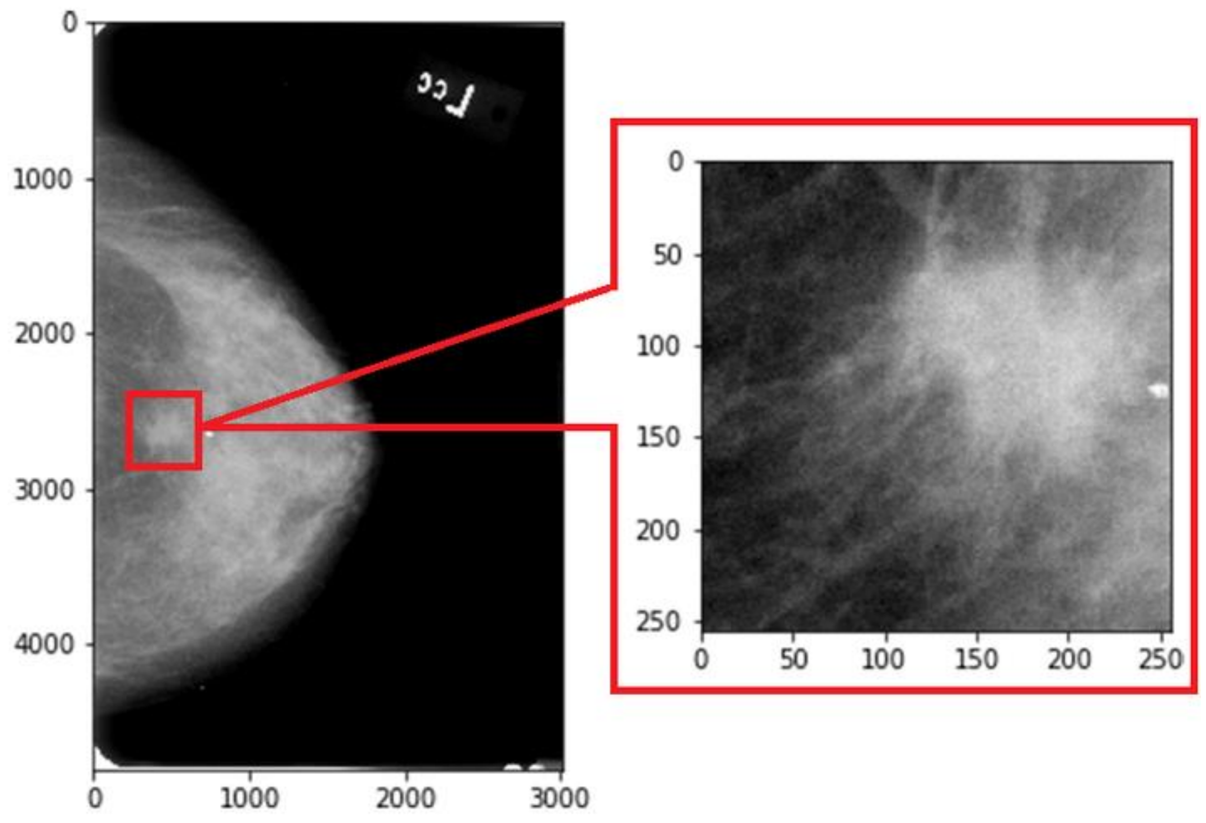
BCD with Machine Learning
involves using advanced imaging techniques and machine learning models to identify early signs of breast cancer within mammography images.

It has become an increasingly important area of research and application in medical imaging and diagnostics.

Our goal was to improve the instance detection of breast calcification based on machine learning and deep learning architectures.

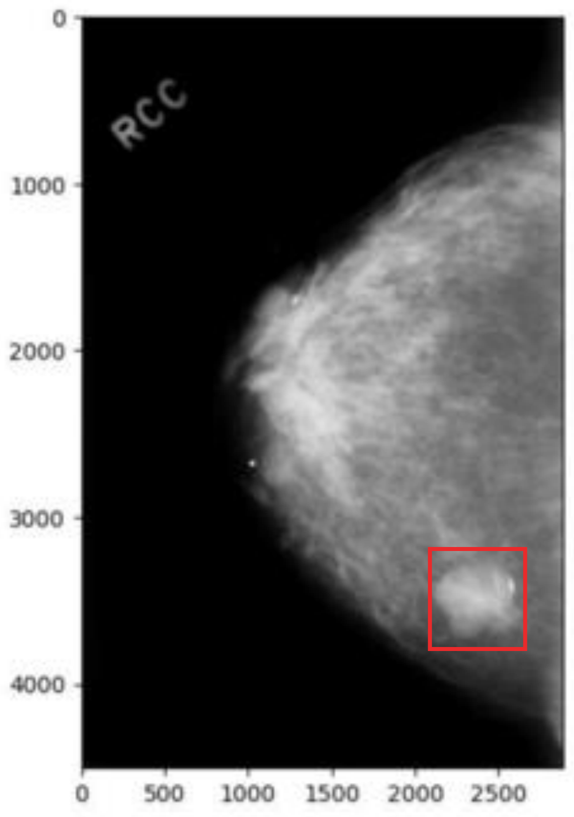
3. Materials

CBIS-DDSM



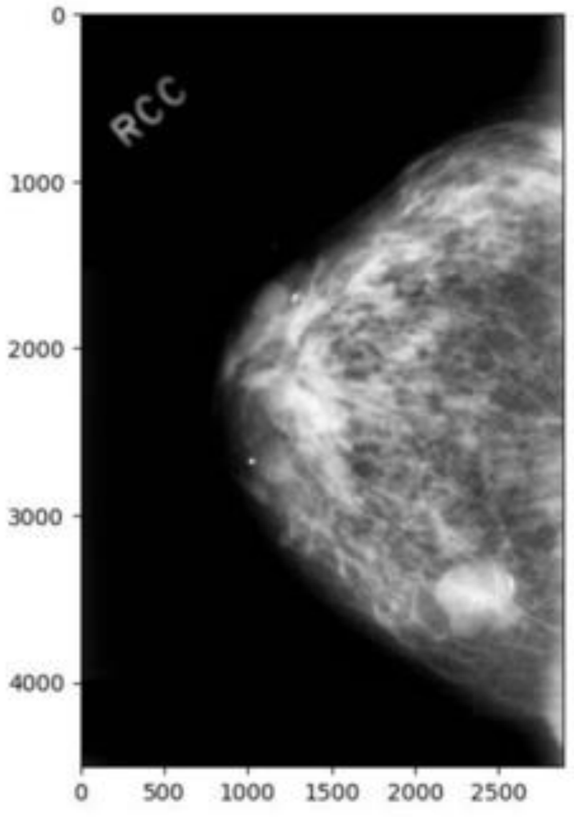
A well-established **benchmark** in digital mammogram-based breast cancer screening.
Used a subset of 1,806 craniocaudal images focused on **calcification**.

Annotation

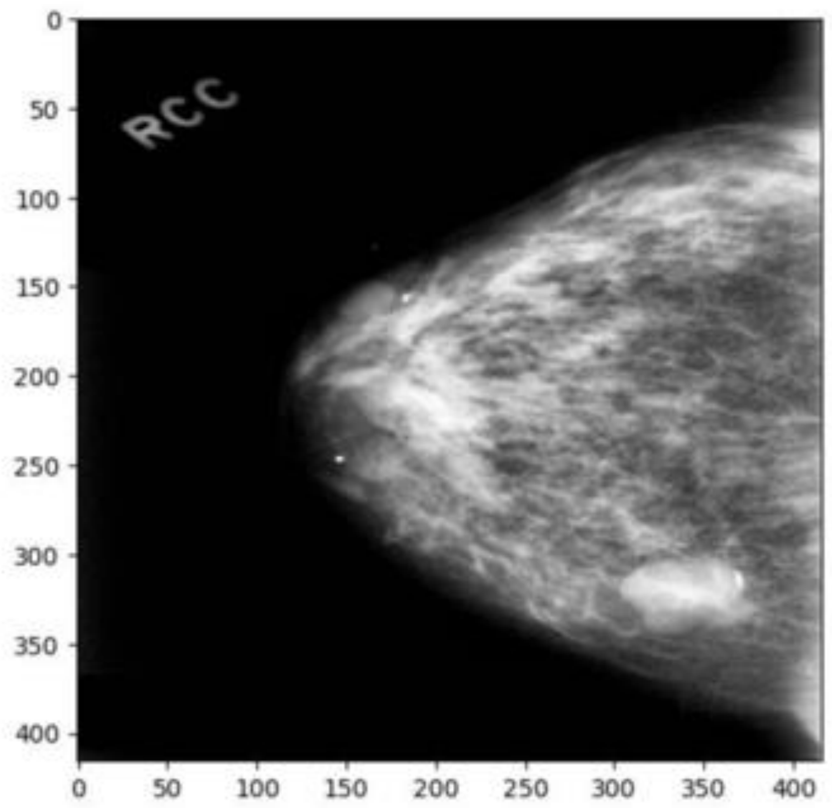


Manually annotated with LabelImg in **YOLO** format as text files.

Image Preprocessing



Each image was **enhanced contrast** and **standardized** for consistency.



All images were **resized** to a fixed resolution of 640×640 pixels.

4. Methodology

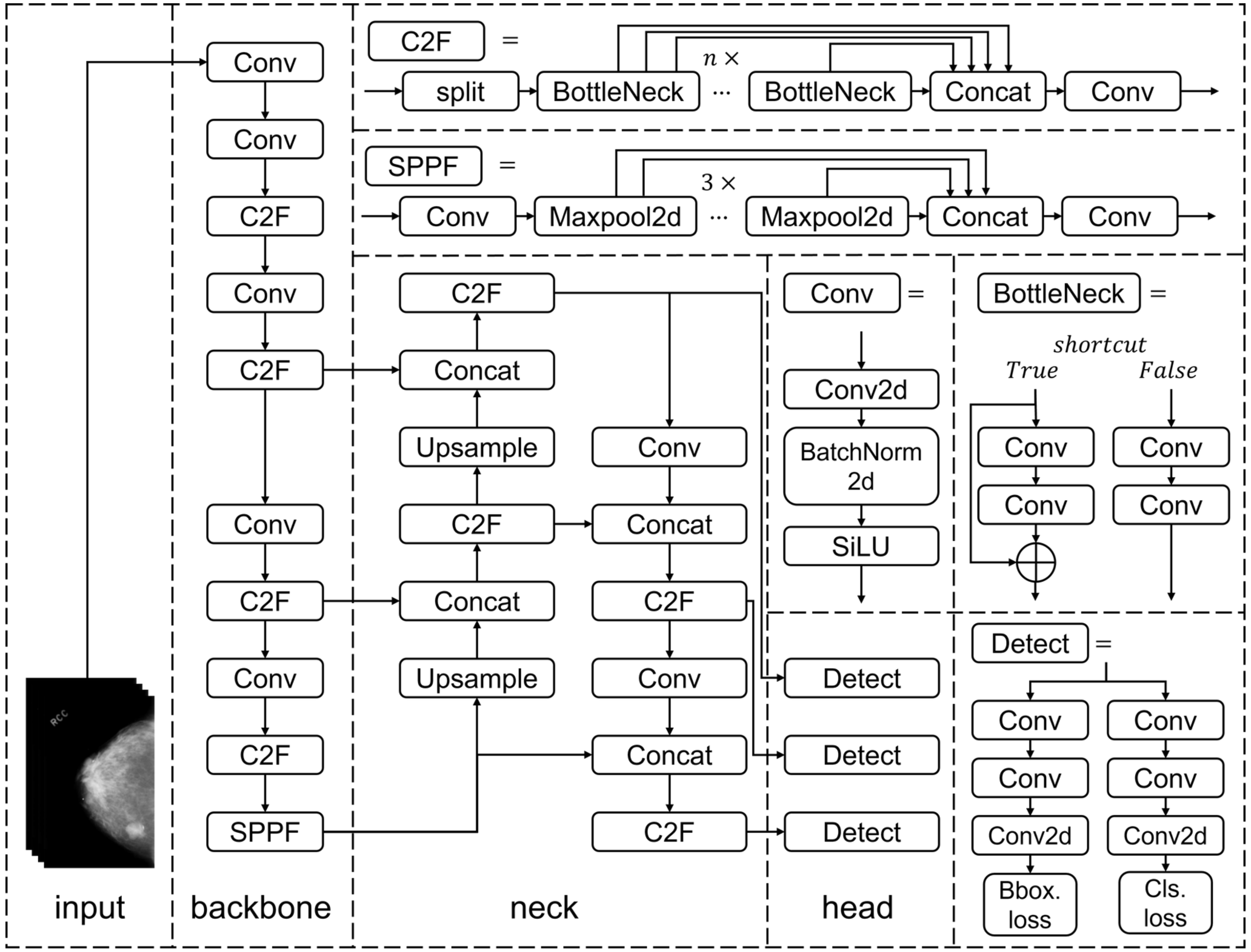
YOLO (You Only Look Once)

YOLO is a real-time object detection model renowned for its speed and accuracy. It divides images into grids and predicts bounding boxes and class probabilities in a single pass, making it ideal for fast, large-scale object detection tasks.

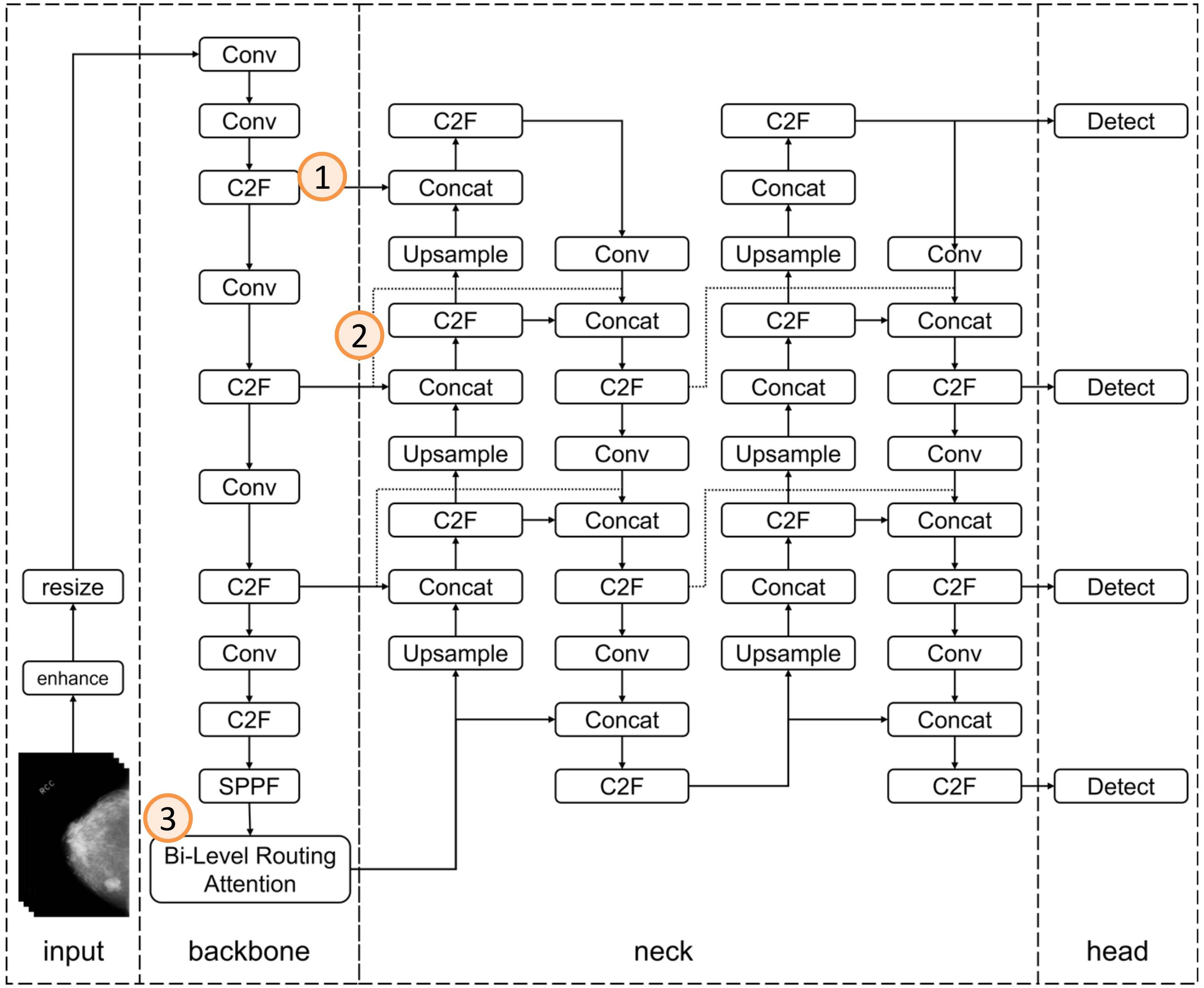
YOLOv8 Introduction

YOLOv8 is the eighth iteration, enhancing the YOLO architecture with advanced features like the CSPNet backbone, improved FPN+PAN neck, and more efficient head design. This results in better detection performance, speed, and accuracy, making it suitable for complex tasks like breast cancer detection in medical imaging.

4. Methodology



(a) YOLOv8



(b) The proposed network

4. Methodology

01

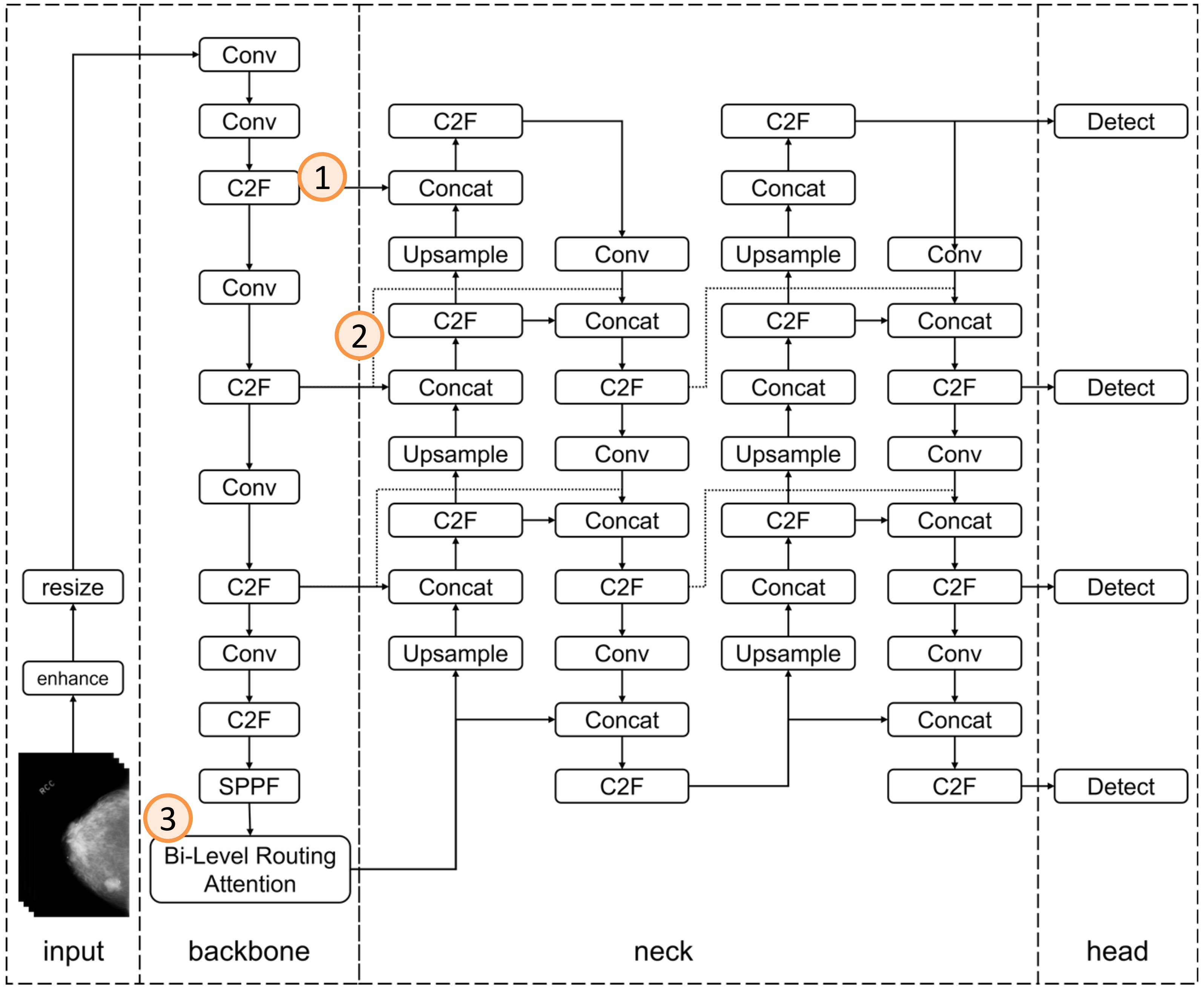
Small Object Detection Layer
P2

02

Multi-Level Feature Fusion Networks
BiFPN

03

Self-Attention Guidance Mechanism
BRA



(b) The proposed network

4. Methodology

01

Small Object Detection Layer
P2

→ Enhances fine-grained feature recognition.

02

Multi-Level Feature Fusion Networks
BiFPN

→ Improves multi-scale feature fusion.

03

Self-Attention Guidance Mechanism
BRA

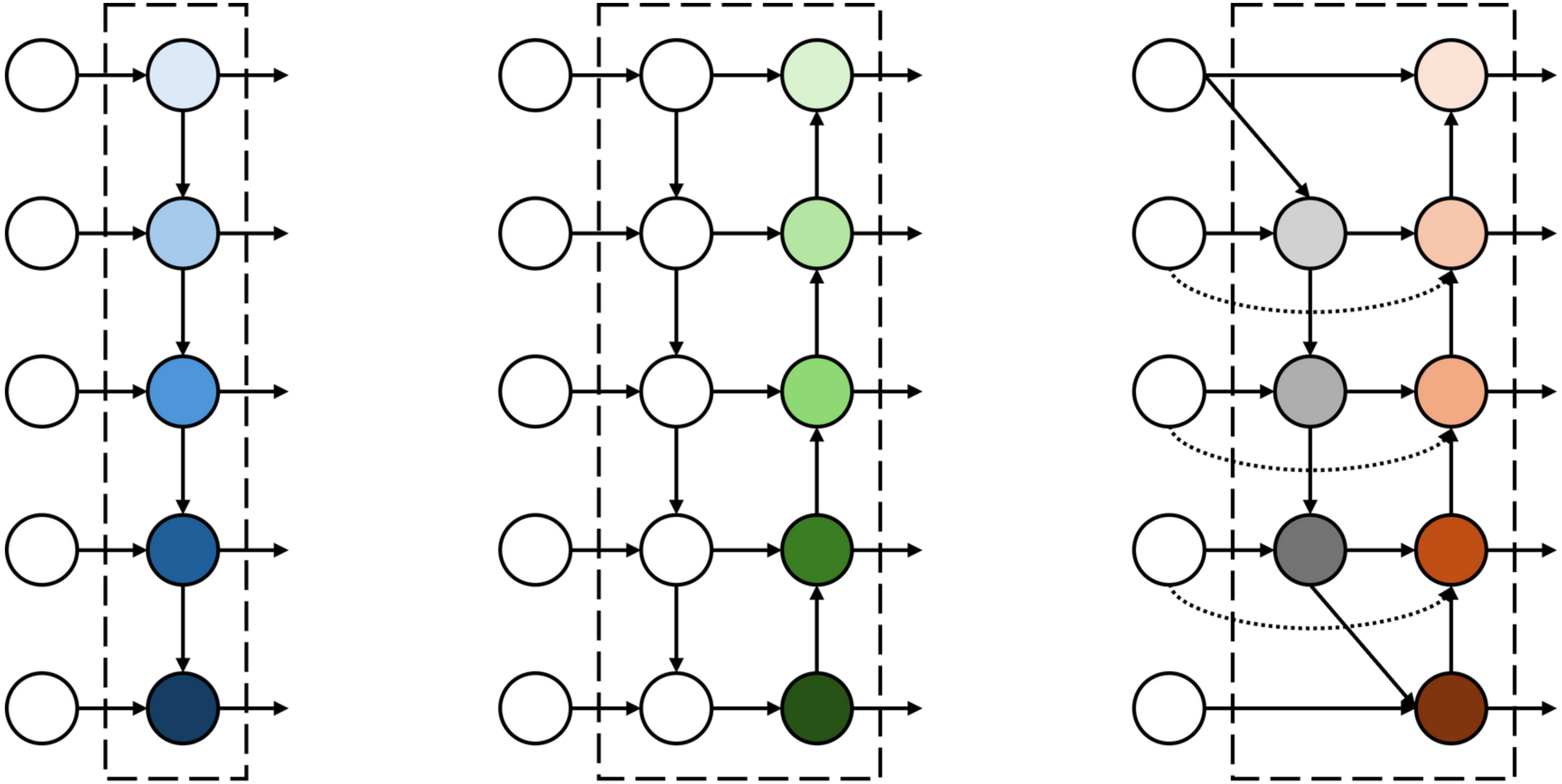
→ Selective focus on relevant regions.

4. Methodology

02

Multi-Level Feature Fusion Networks

Bi-directional Feature Pyramid Network



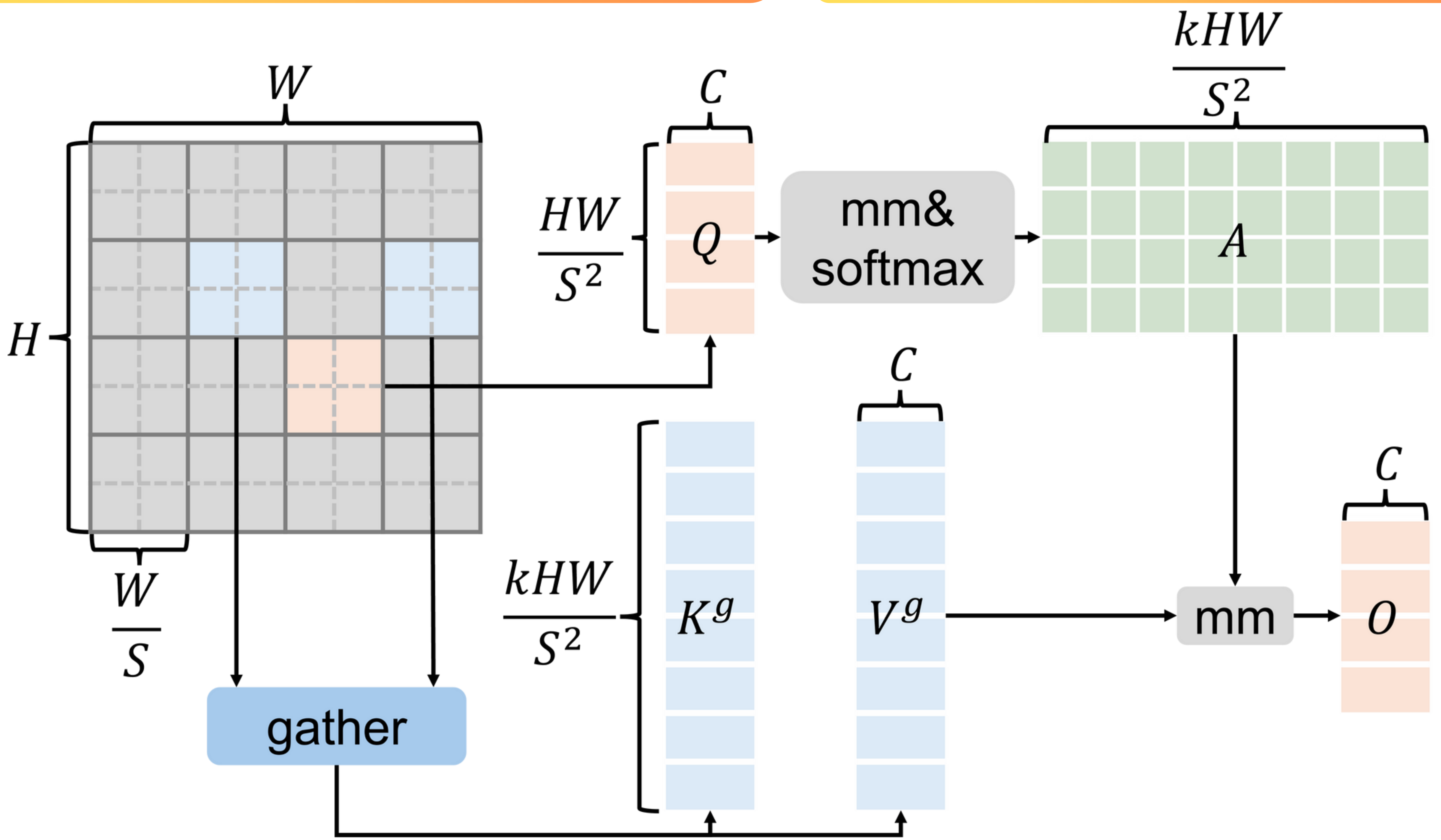
(a) FPN (b) PAN (c) BiFPN

4. Methodology

03

Self-Attention Guidance Mechanism

Bi-Level Routing Attention



5. Experiment and Results

Hardware

CPU: Intel Core i5-10400 CPU @ 2.90GHz × 12
GPU: NVIDIA GeForce RTX 3090
Memory: 32GB
Framework: Pytorch YOLO
Operating system: Ubuntu 20.04.6 LTS

Parameters

Input image size: 640 x 640 pixels
Batch size: 4
Optimizer: Adam, with lr0 of 0.001 and lrf of 0.0005
Trained: 300 epochs via 5-fold cross-validation

5. Experiment and Results

99.32%
Precision

85.0%
Recall

91.59%
F1-score

89.86%
mAP@0.5

5-fold cross-validation

For comparison, all models listed below are modified versions based on the YOLOv8 architecture.

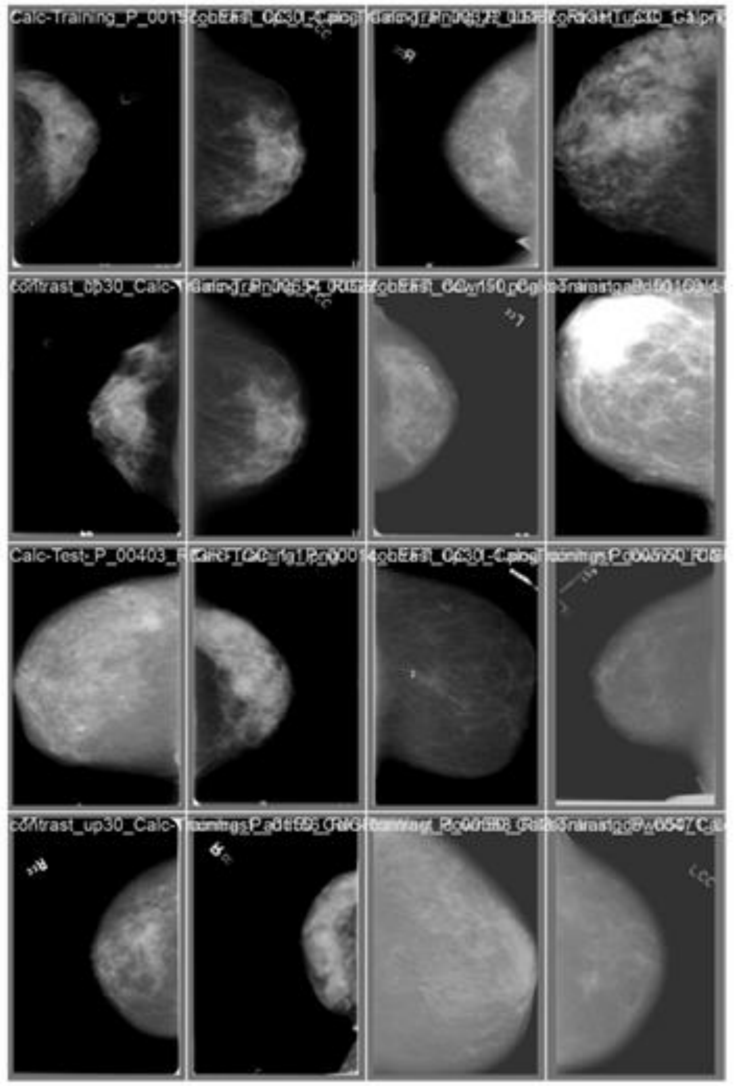
Table 1. Result of the proposed network throughout the k-fold cross validation. (K=5)

Fold Number	Precision	Recall	mAP50	mAP50-95	F1 Score
1	**1.0000**	0.8140	0.8730	0.7570	0.8975
2	0.9870	0.8550	0.8970	0.7780	0.9163
3	0.9910	**0.8780**	**0.9210**	**0.8200**	**0.9311**
4	**1.0000**	0.8620	0.9130	0.8050	0.9259
5	0.9880	0.8410	0.8890	0.7760	0.9086
✔ Average Value	0.9932	0.8500	0.8986	0.7872	0.9159
Standard Deviation	0.0064	0.0241	0.0191	0.0251	0.0135

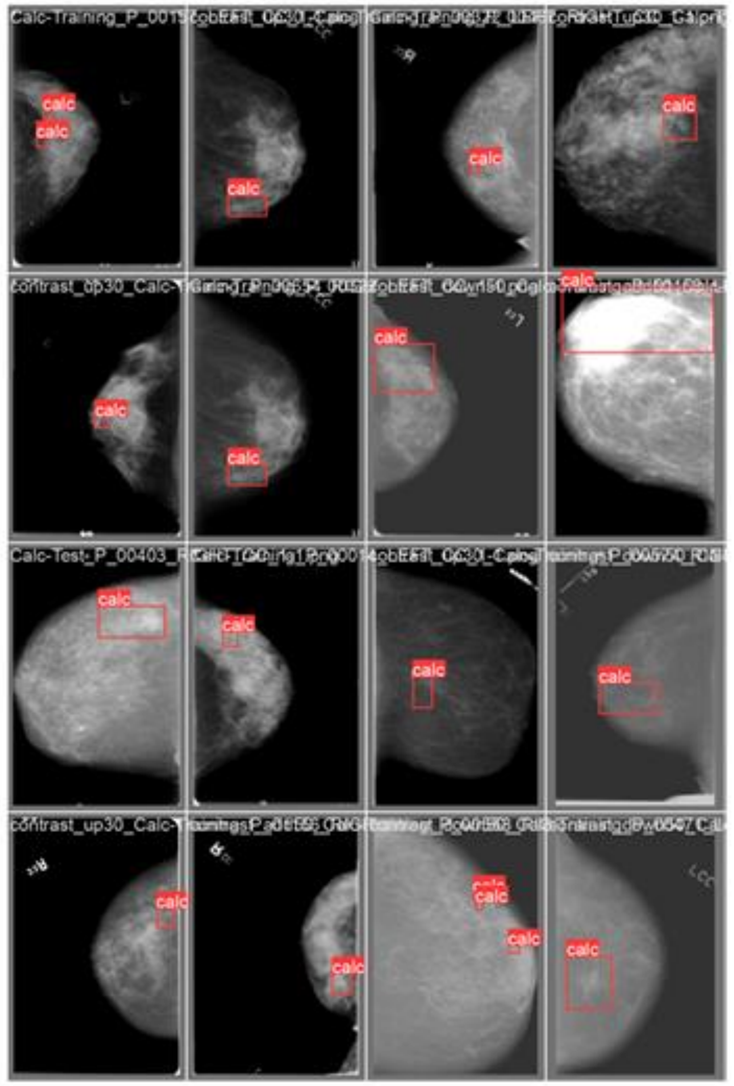
Table 2. Average performance comparison across several network with multi-level features BiFPN.

Backbone	Attention	Precision	Recall	mAP50	mAP50-95	F1 Score
✔ **YOLOv8**	**BRA**	**0.9932**	**0.8500**	**0.8986**	**0.7872**	**0.9159**
YOLOv8	✗	0.9316	0.7906	0.8408	0.7252	0.8552
YOLOv10	✗	0.7154	0.4714	0.5416	0.2532	0.5679
SwinTransformer	✗	0.4492	0.3396	0.3446	0.2434	0.3834
ConvNeXtv2	✗	0.0007	0.0489	0.0012	0.0004	0.0014

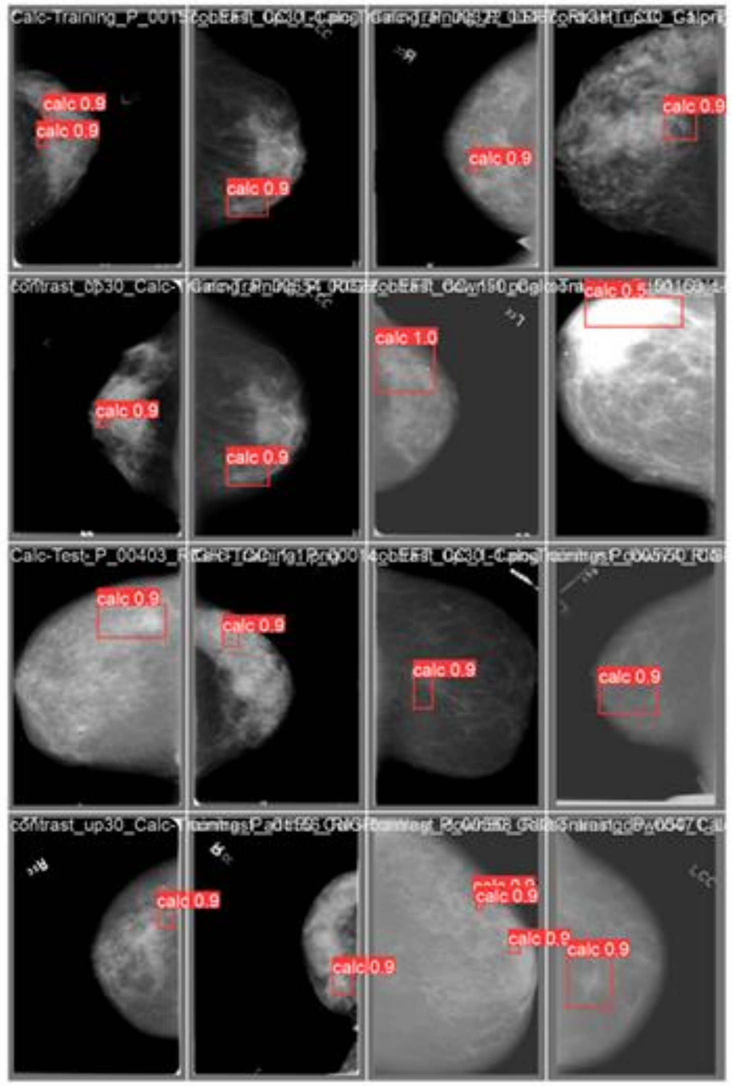
5. Experiment and Results



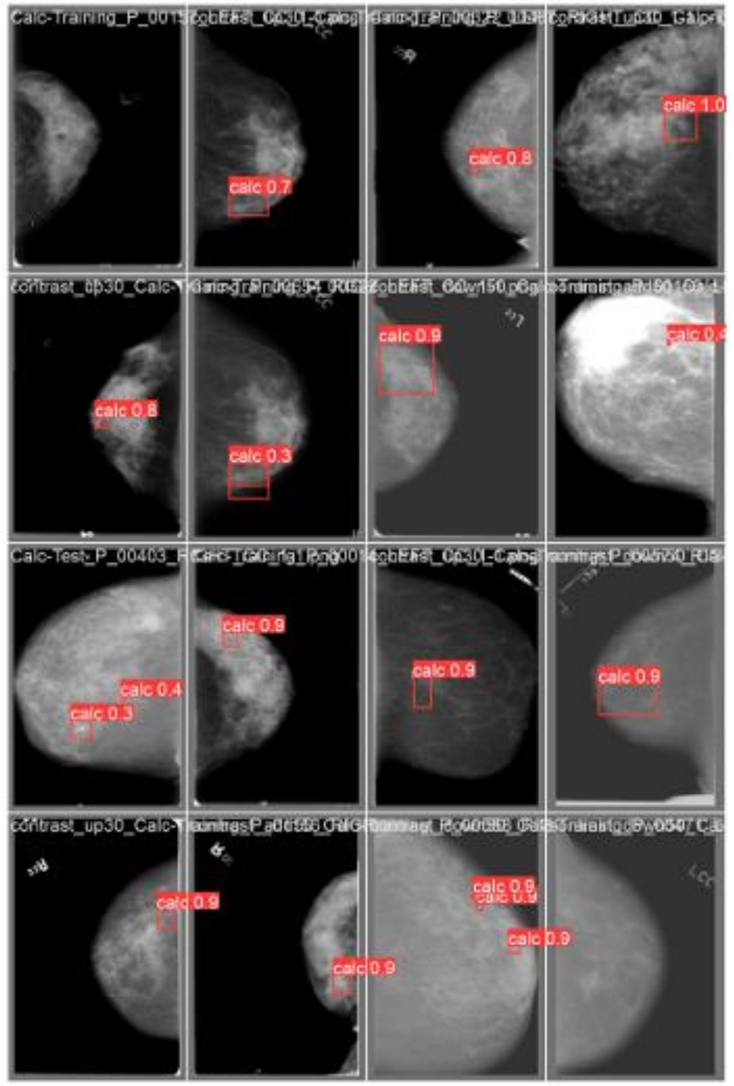
(a) Inputs



(b) Inputs with ground truth

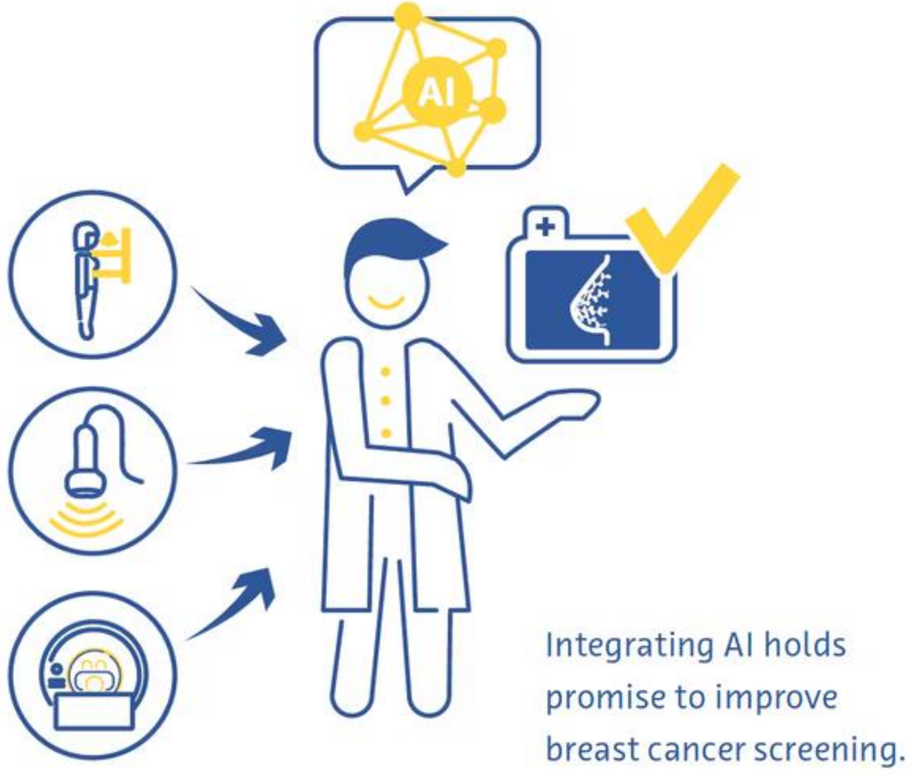


(c) Prediction by the proposed networks



(d) Prediction by YOLOv8

6. Conclusions

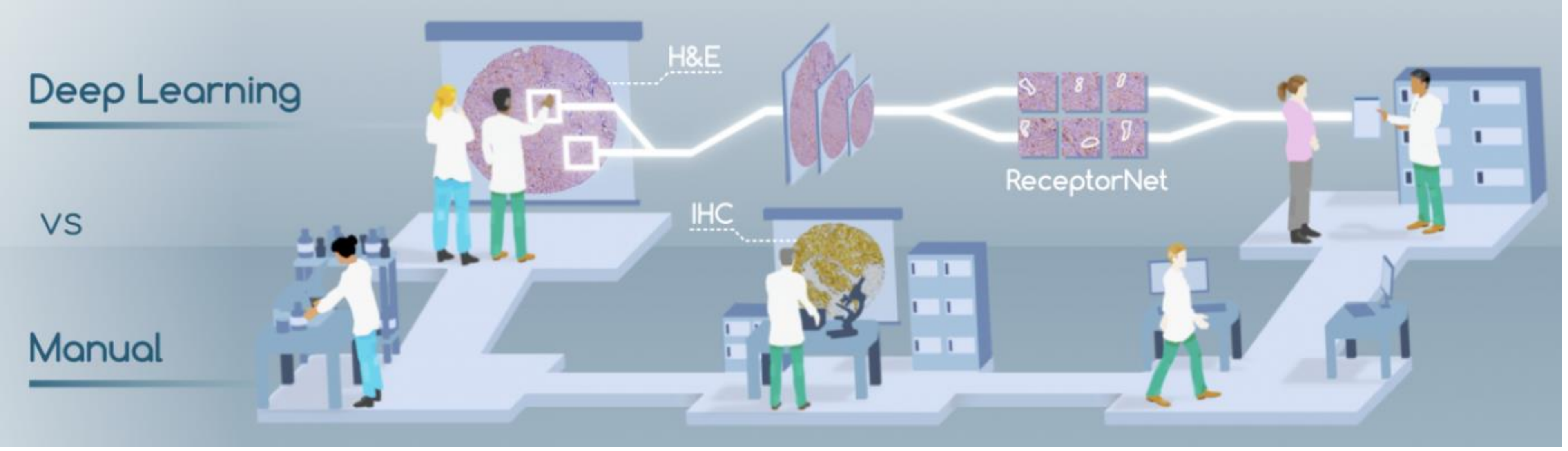


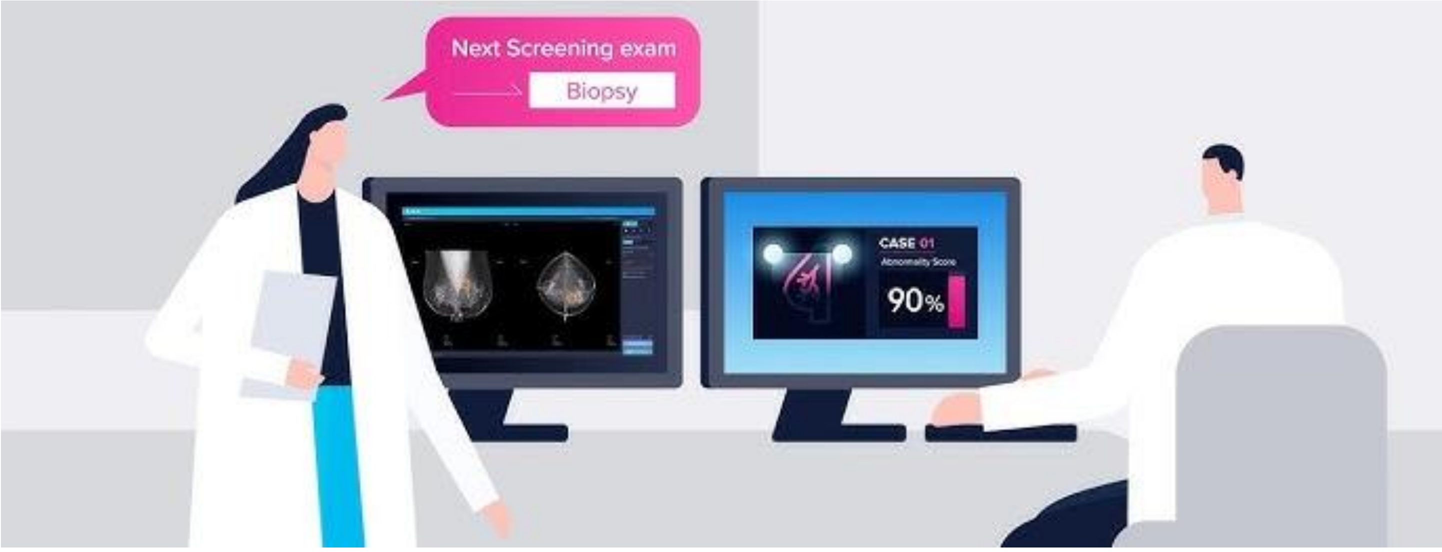
- Utilizing the lightweight as **YOLOv8** to reduce the computational resources required for detecting large mammographic images.
- To strengthen **fine-grained feature** recognition, a small objects detection layer **P2** is added, and the feature fusion network is improved following the **BiFPN** link idea.
- The **BRA module** is introduced to improve the ability to capture multi-scale contextual information effectively.

- Tested on the **CBIS-DDSM** dataset for calcifications, results show improved **accuracy**, **recall**, and **stability**.
- Accelerated training process and met the **real-time** requirements of **medical inspection**.

7. Future Direction

- Extend our model to detect other breast lesion types.
- Explore domain adaptation techniques for generalizing across datasets.
- Develop a complete medical system.
- Create a 3D breast cancer imaging model.





8. Q & A

THANK YOU