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Multimodal AI for Breast Cancer Diagnosis:

Precision Segmentation and Comprehensive Report Generation from Mammograms

Mohammad Monir Uddin
North South University

Joint Work

Istiak Ahmed	Department of Electrical & Computer Engineering, North South University
Kazi Shahriar Sanjid	Department of Electrical & Computer Engineering, North South University
Md. Tanzim Hossain	Department of Computer Science, Friedrich-Alexander University, Germany
Galib Ahmed	Department of Applied Mathematics & Computational Science
Md. Nishan Khan	Department of Electrical & Computer Engineering, North South University
Md. Misbah Khan	Department of Electrical & Computer Engineering, North South University
Dr. Sheikh Anisul Haque	Department of Transfusion & Medicine, Bangladesh Specialized Hospitals Limited
Dr. Md. Arifur Rahman	Department of Oncology & Radiotherapy, Bangladesh Specialized Hospitals Limited

Introduction

Objectives

To develop a multimodal AI-based tool for breast cancer diagnosis that generates comprehensive clinical reports and segments various key structures of the breast from mammogram images.

Tasks

Data Preparation → Algorithm Development → Model Training → Model Prediction → Model Deployment

Background

Artificial Intelligence (AI):

AI is the simulation of human intelligence in machines, enabling them to perform tasks like problem-solving, learning, and decision-making.

◈ Example: AI-powered chatbots assist doctors by answering patient queries and scheduling appointments in hospitals.

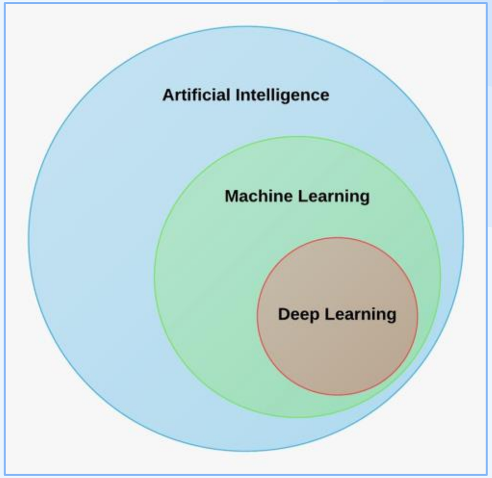
Machine Learning (ML):

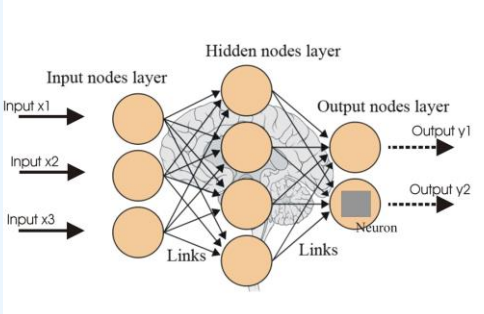
ML is a subset of AI that enables machines to learn from data and improve performance without being explicitly programmed.

Deep Learning (DL):

DL is a subset of ML that uses neural networks with multiple layers (deep neural networks) to learn complex patterns from large datasets.

Multimodal-AI: AI systems that integrate and process data from multiple sources or types (e.g., images, text, audio) to improve decision-making and predictions.





Advancement of AI in Medical Diagnosis

AI, especially **machine learning and deep learning** , has **enabled** the **automation and enhancement** of **medical imaging** (CT, MRI, X-Ray, ECG, EEG, US, PET etc.) **analysis**, which plays a crucial role in the **early detection, diagnosis, and treatment of various diseases**.

- Automated Image Analysis and Segmentation
- Classification and Detection of Pathologies
- Predictive and Prognostic Analysis
- AI-Assisted Radiology
- Improved Disease Detection and Diagnosis
- Reducing Human Error and Bias

Advancement of AI in Breast Cancer Diagnosis

Early Detection: AI has significantly improved early breast cancer detection through the analysis of mammograms, ultrasound, and MRI images, enabling earlier and more accurate diagnoses (Yu et al., 2020).

Risk Prediction: AI models now integrate clinical data, such as age, genetic information, and lifestyle factors, to predict the risk of breast cancer, allowing for personalized screening and prevention strategies (Chen et al., 2020).

Radiomics: AI-driven radiomics is used to extract detailed features from medical images, helping in the differentiation of benign and malignant tumors (Liu et al., 2020).

Deployment in Rural Areas: Efforts are being made to deploy AI tools in underserved regions, providing access to breast cancer detection in remote areas (Smith et al., 2021).

Main Works

Multimodal Fusion Approach: Developed a state-of-the-art multimodal fusion framework that seamlessly integrates breast mammography segmentation with comprehensive clinical report generation, enhancing diagnostic accuracy and interpretability.

Comprehensive Clinical Report Prediction: Simultaneously predicts multiple clinical attributes (e.g., mass presence, density, BIRADS category), unlike existing methods that focus on isolated tasks.

Integrated Segmentation & Classification: Bridges the gap between breast structure segmentation and clinical report generation, leading to a more holistic analysis.

Enhanced Interpretability: Utilizes XAI tools like GRAD-CAM and saliency maps to improve model transparency and trustworthiness for clinicians.

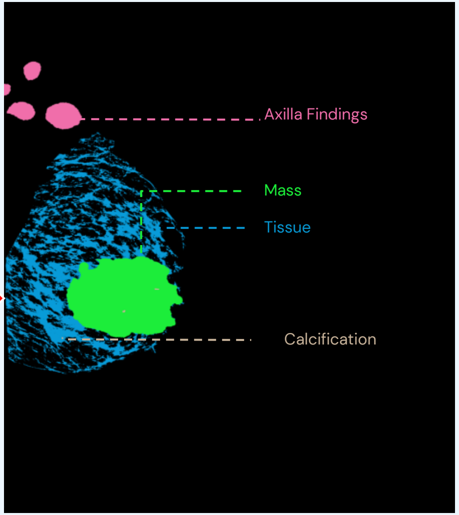
Improved Accessibility: Designed with potential deployment in rural areas and medical camps, addressing AI accessibility challenges in underserved regions.

Main Works

1. Data Preprocessing

Step-1

Breast Mammogram



Annotated Breast Mask

Step-2

Breast Mammogram Report

Name:---   ID: ----

Findings:

- **Breast Composition:** The breast tissue is [heterogeneously dense/scattered areas of fibroglandular density/fatty/almost entirely fatty].
- **Masses:** No suspicious masses were identified. (If present: "A [size] mm mass was noted in the [location] of the [left/right] breast.")
- **Calcifications:** No suspicious calcifications were observed. (If present: "Suspicious calcifications were noted in the [location].")
- **Architectural Distortion:** No evidence of architectural distortion.
- **Asymmetries:** No significant asymmetries were detected.
- **Other Findings:** No skin thickening, nipple retraction, or axillary lymphadenopathy was observed.

Impression/Conclusion:

- BI-RADS Category [0-6]: [e.g., BI-RADS 1: Negative, no significant findings; BI-RADS 4: Suspicious abnormality, biopsy recommended].
- Recommendations: [e.g., Routine follow-up in 1 year; Additional imaging recommended; Biopsy recommended].

Generated

ID	mass	Mass Shape	Mass Definition	BI-RADS	- - -	- - -
P1	yes	oval	well	3	- - -	- - -
P2	no	-	-	1	- - -	- - -

Tabular Data

Step-3: Validation of Annotated image by experts

Main Works

2. Develop the Mathematical Algorithm and Codes

Algorithm 1 Multimodal Deep Learning for Breast Cancer Analysis

Input: Mammogram image I_i, Tabular data X_i
Output: Segmentation mask $\hat{M}_i$, Clinical feature predictions $\hat{Y}$
1. Segmentation Model:
Encode image features:

$$Z_s = E_s(I_i; \theta_{E_s})$$

Decode to segmentation mask:

$$M_i = D_s(Z_s; \theta_{D_s})$$

Apply softmax:

$$\hat{M}_i = \arg\max \mathrm{Softmax}(M_i)$$

2. Clinical Feature Prediction Model:
Compute feature transformation:

$$Z_c = \sigma(W_c X_i + b_c)$$

Predict clinical features:

$$\hat{Y} = \mathrm{Softmax}(W_f Z_c + b_f)$$

3. Multimodal Fusion
Early Fusion:
Concatenate image and tabular features:

$$Z_{\text{early}} = \Phi([Z_s, X_i]; \theta_f)$$

Predict features:

$$\hat{Y}_{\text{early}} = f_c(Z_{\text{early}})$$

Late Fusion:
Compute weighted sum of predictions:

$$\hat{Y}_{\text{final}} = \alpha f_s(I_i) + (1-\alpha) f_c(X_i)$$

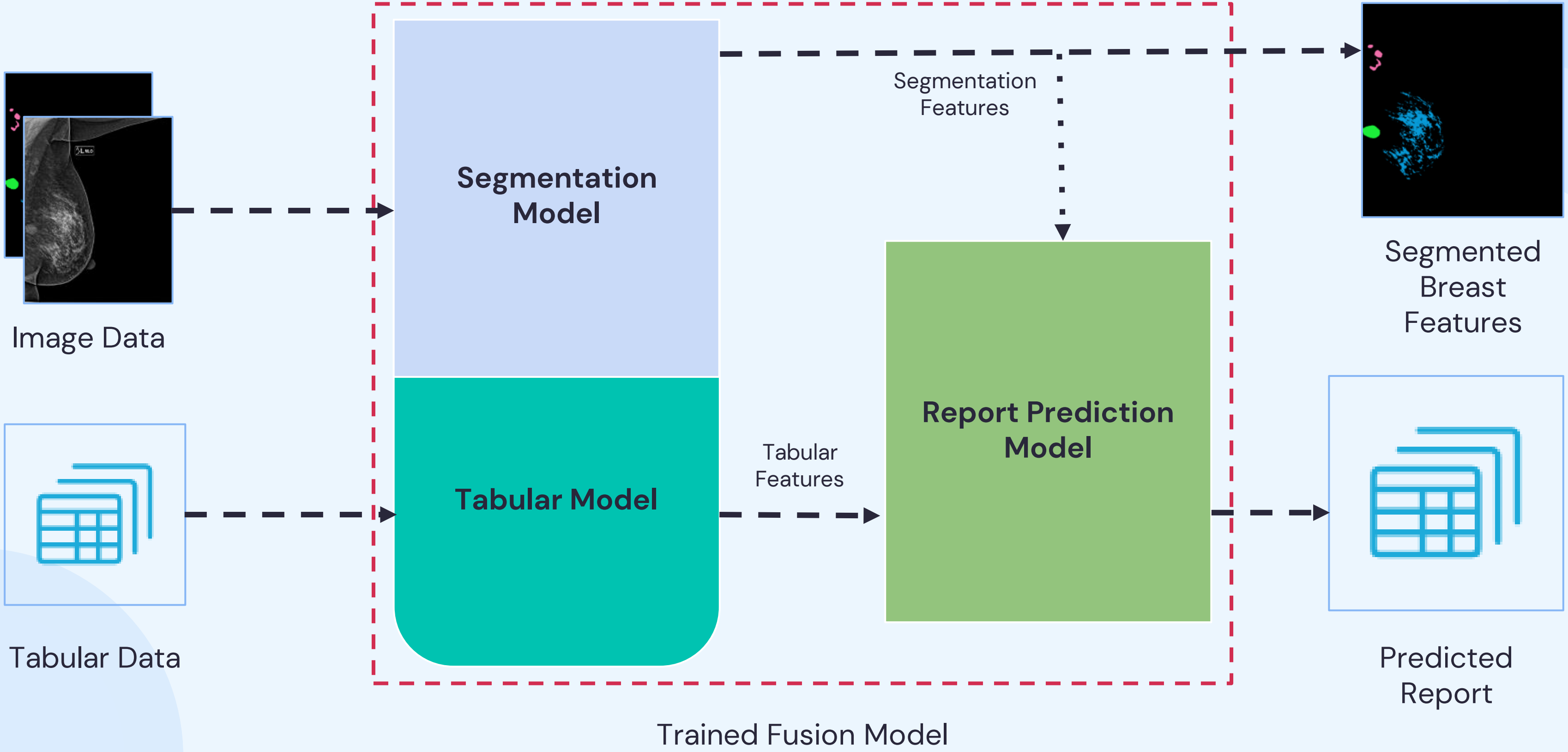
where α is a trainable fusion weight.
4. Model Optimization:
Update parameters using gradient descent:

$$\theta \leftarrow \theta - \eta \cdot \mathbb{E}\left[\nabla_\theta \mathcal{L}(\hat{Y}, Y)\right]$$

```
import tensorflow as tf

def focal_loss(y_true, y_pred, gamma=2.0):
    epsilon = tf.keras.backend.epsilon()
    y_pred = tf.clip_by_value(y_pred, epsilon, 1.0 - epsilon)
    cross_entropy = -y_true * tf.math.log(y_pred)


    loss = tf.pow(1 - y_pred, gamma) * cross_entropy
    return tf.reduce_mean(loss, axis=-1)


def soft_dice_coefficient(y_true, y_pred, smooth=1):
    intersection = tf.reduce_sum(y_true * y_pred, axis=(1, 2, 3))
    sum_true = tf.reduce_sum(y_true, axis=(1, 2, 3))
    sum_pred = tf.reduce_sum(y_pred, axis=(1, 2, 3))
    dice_coefficient = (2. * intersection + smooth) / (sum_true + sum_pred + smooth)
    return tf.reduce_mean(dice_coefficient)


def soft_dice_loss(y_true, y_pred, smooth=1):
    intersection = tf.reduce_sum(y_true * y_pred, axis=(1, 2, 3))
    sum_true = tf.reduce_sum(y_true, axis=(1, 2, 3))
    sum_pred = tf.reduce_sum(y_pred, axis=(1, 2, 3))
    dice_coefficient = (2. * intersection + smooth) / (sum_true + sum_pred + smooth)
    dice_loss = 1 - dice_coefficient
    return tf.reduce_mean(dice_loss)
```

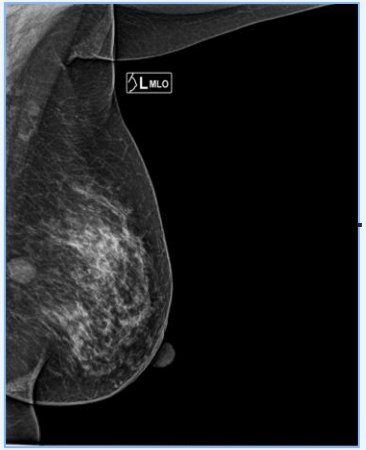
Main Works

3. Model Development



Main Works

4. Model Prediction

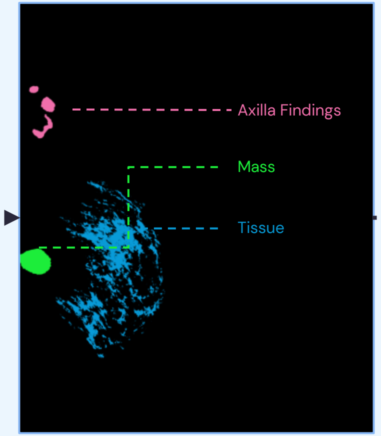


Input Image

Multimodal Fusion

Model

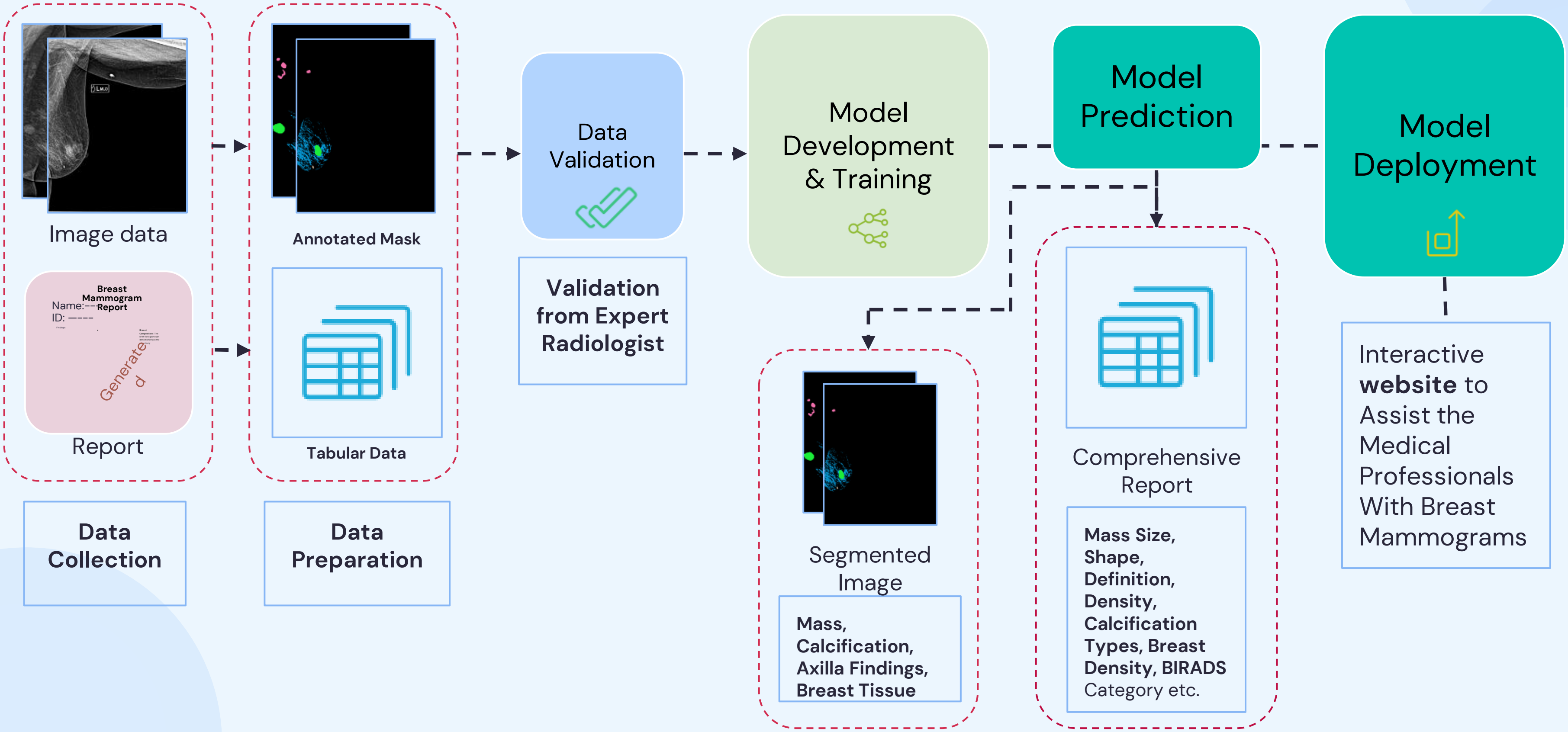
Predicted Breast Features



Mass **Definition:** Ill-defined **Shape:** Oval **Density:** Isodense **Mass Size:** 22 mm x 19 mm	**Calcification:** No **Breast Density:** Heterogeneous breast tissue (c). **Axilla Findings:** Multiple Fatty Hilum **BI-RADS: 3**

Predicted Report

Main Works (Whole Picture)



Big-Matrix Lab Research & Development

BANGLADESH SOCIETY FOR BREAST CANCER STUDY BSBCS

Result Discussion

Segmentation Features	IoU	Dice Score	Accuracy	Precision	Recall	F1 Score	ASD	NSD
Mass	92%	94%	98%	97%	98%	97%	1.23	93
Calcification	91%	93%	95%	95%	95%	95%	1.78	92
Axilla Findings	90%	91%	95%	95%	95%	95%	1.84	92
Breast Tissue	87%	89%	93%	93%	92%	92%	2.13	89

Table1: Detail segmentation result of Mass, Calcification, Axilla Findings, and Breast Tissue.

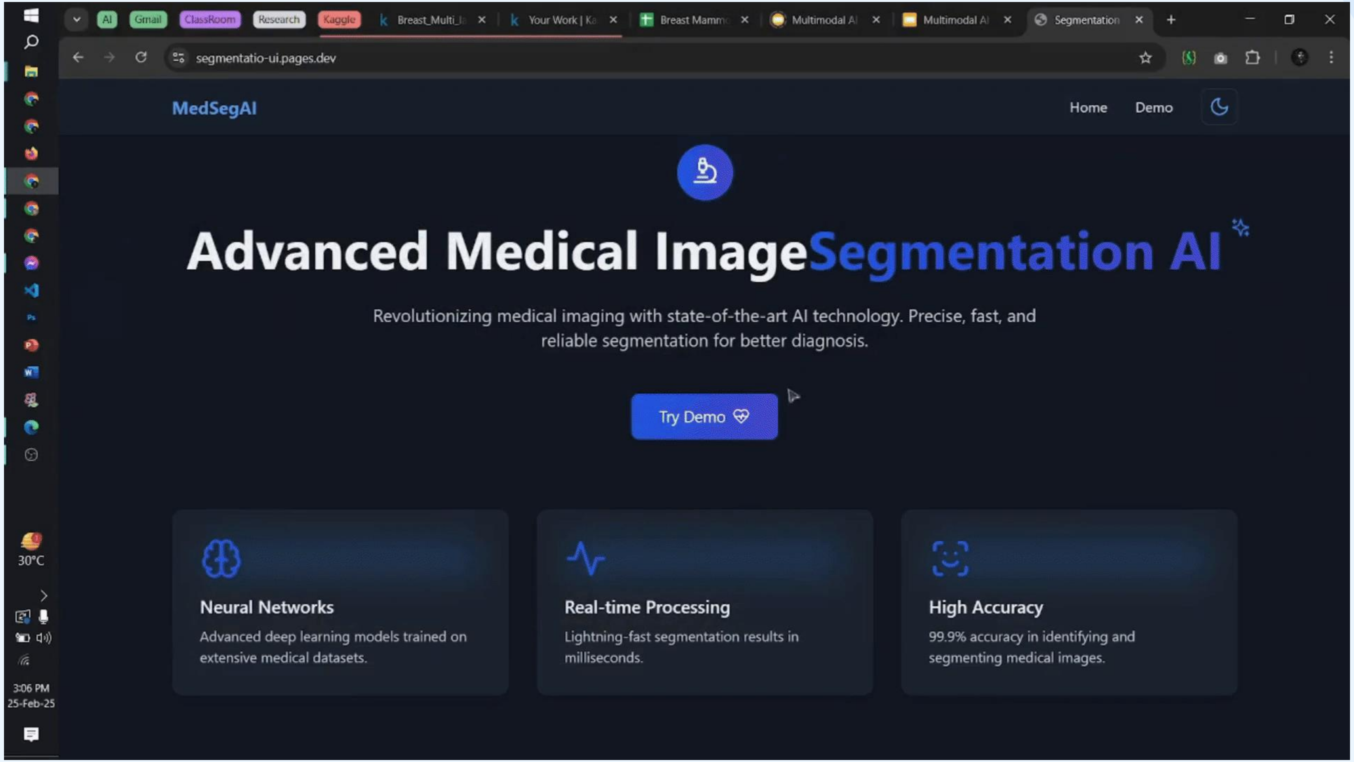
IoU = Intersection over union, ASD= Average surface distance, NSD= Normalized Surface distance

Result Discussion

Clinical Features	Accuracy	Precision	Recall	F1 Score
Mass (shape, definition, density, calcification)	92%	91%	93%	92%
Calcification (types of calcification)	93%	93%	93%	93%
Axilla Findings	91%	91%	92%	91%
Breast Density	85%	83%	87%	85%
BI-RADS	88%	88%	89%	88%

Detail clinical report prediction result of Mass, Calcification, Axilla Findings, and Breast Density, and BI-RADS

Web Platform



https://segmentatio-ui.pages.dev/

Conclusion, Remarks, and Future Work

Conclusion:

- This research developed multimodal AI-based tool for breast cancer diagnosis and report generation using Bangladeshi mammogram images and clinical data.
- Results shows good accuracy of the predicted segmentaion images and reports

Remarks:

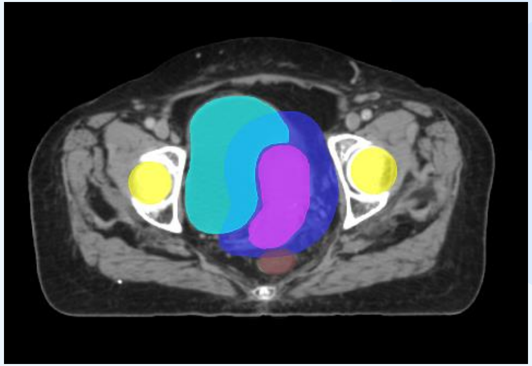
- It can help the experts enhances diagnostic accuracy, interpretability, and accessibility, assisting radiologists in breast cancer detection

Conclusion, Remarks, and Future Work

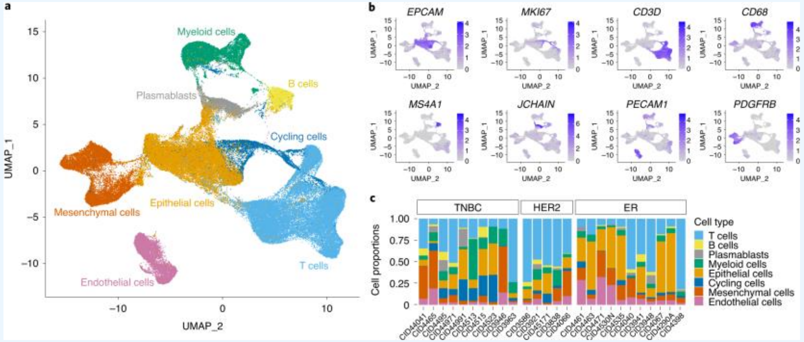
Current Works:

- Multimodal based Lung Cancer Detection from CT-Scan and Report Generation
- Auto contouring of CT-Scan for radiotherapy
- Single Cell Sequencing Analysis for Cancer detection

Model performance improves with more data, increasing accuracy and robustness in real-world applications.



Radiotherapy Auto Contouring



Single Cell RNA Sequencing: Breast Cancer

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Office of Research
North South University

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Scan to Analyze

Thank You!