# Computer-Aided System for Breast Cancer Lesion Segmentation and Classification Using Ultrasound Images.

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# Introduction

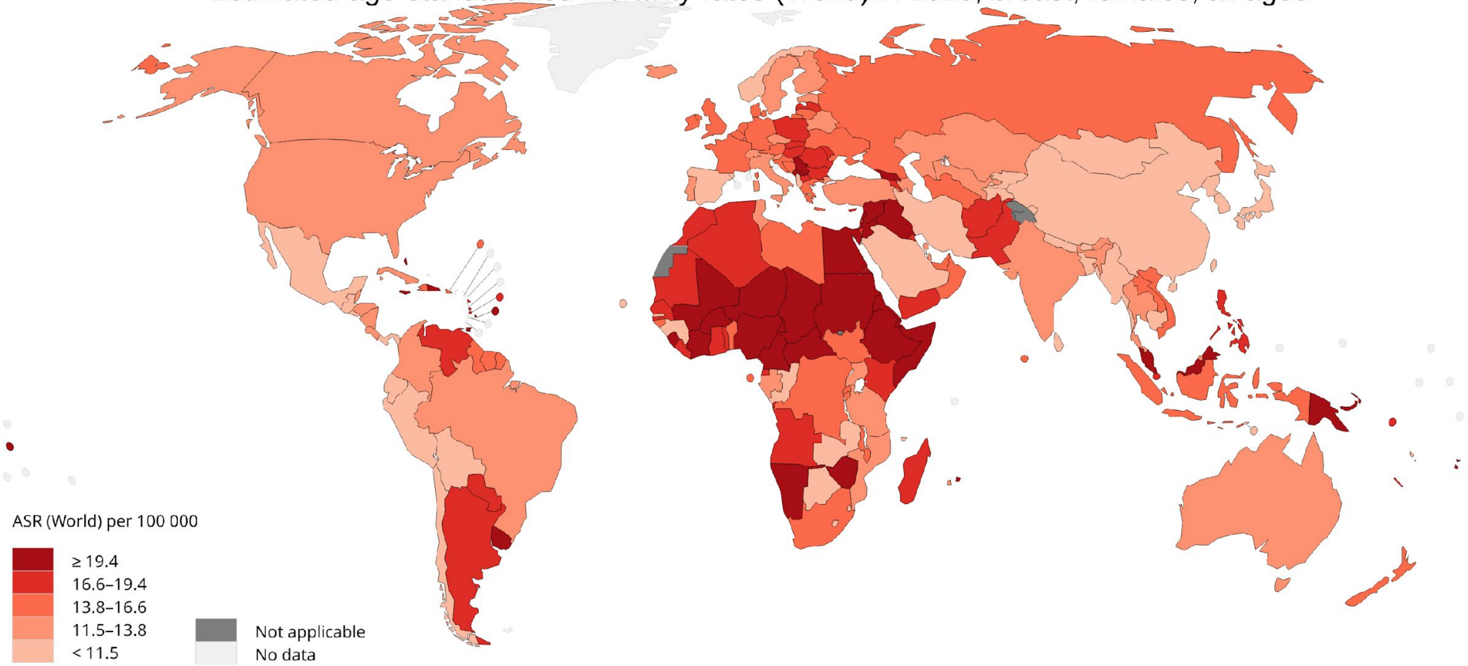
# Incidence, Prevalence & Mortality

- **Breast Cancer** Was Ranked **1st** in **Incidence Rates & Prevalence** Among Other Cancer Types In The **World** in **2020 By WHO**

- **Breast Cancer** Also Was Ranked **5th** in **Mortality Rates** Among Other Cancer Types In The **World** in **2020 By WHO**

Global Cancer Statistics 2020: GLOBOCAN Estimates of Incidence and Mortality Worldwide for 36 Cancers in 185 Countries - Sung - 2021 - CA: A Cancer Journal for Clinicians - Wiley Online Library

## Estimated age-standardized mortality rates (World) in 2020, breast, females, all ages






Data source: GLOBOCAN 2020
Map production: IARC
(http://gco.iarc.fr/today)
World Health Organization

World Health Organization

# Problem


- Although breast cancer **incidence rate** is **higher in developed countries**, the problem lies within **developing countries** where the **mortality rates** are **higher than usual**, which means **less treatment or lack of resources for it.**

# Objective

- Develop a CAD for healthcare providers to improve the screening and diagnosis of breast cancer using ultrasound imaging.

- Decrease the need for unnecessary biopsies and/or x-ray imaging methods.

# Why Ultrasound?

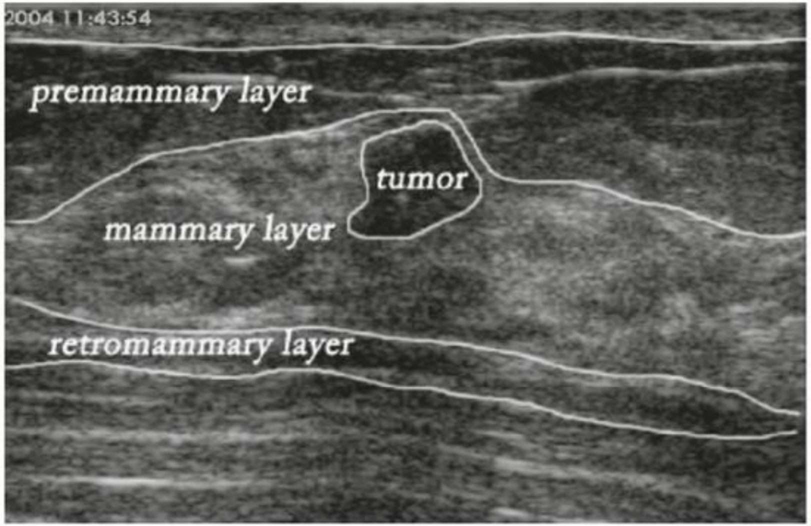
Although **mammogram** is the **gold standard** for diagnosing breast cancer, **ultrasound** is still preferred in some cases because

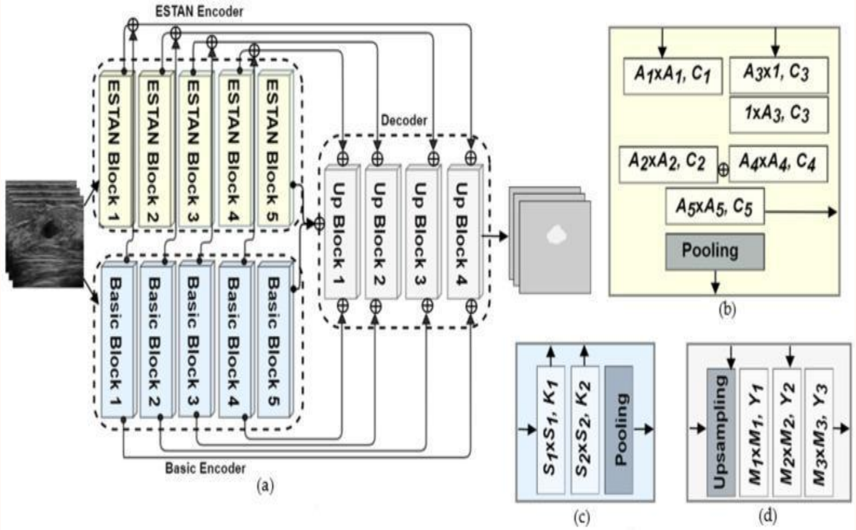
- It is cost effective
- No Ionizing Radiation (Less Risk)
- Portable & Flexible
- Preferred For Women With Dense Breast
- Ultrasound (B-mode) is a Viable Option For Developing Countries

# 02

# Previous Work

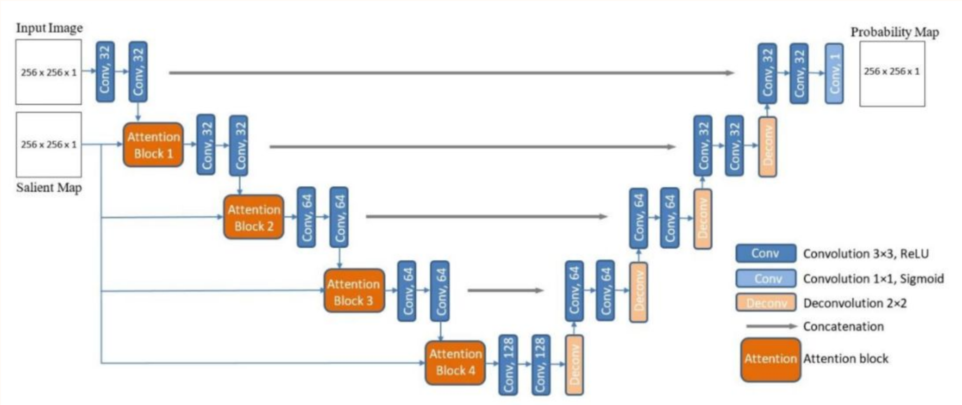
# Enhanced Small Tumor-Aware Network (ESTAN) (Shareef et al. 2022)

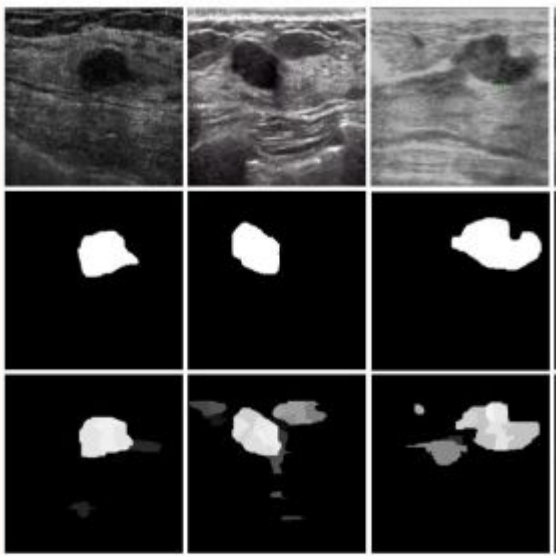



This **segmentation** approach achieved on average **81.5 dice score** on **725 ultrasound images**

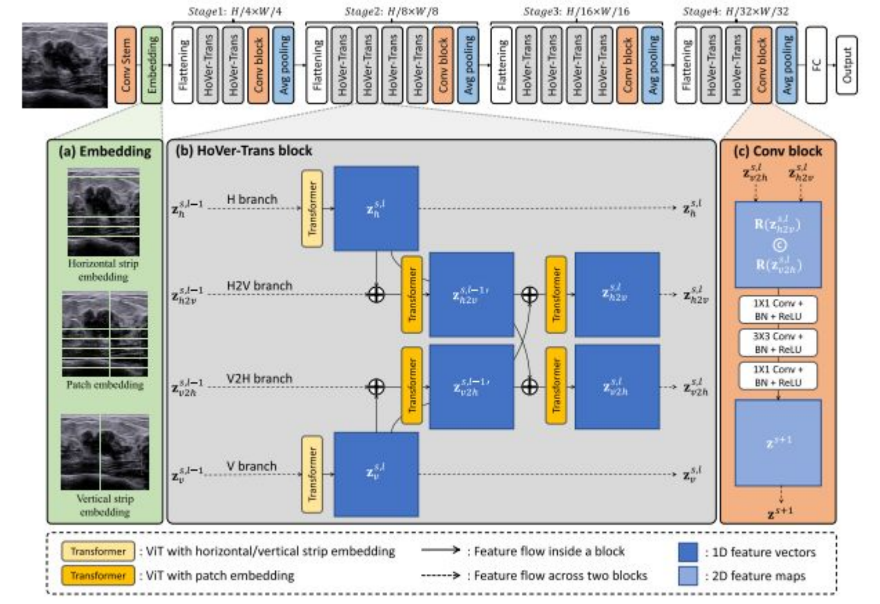
# Attention-Enriched Deep Learning Model for Breast Tumor Segmentation (Vakanski et al. 2020)

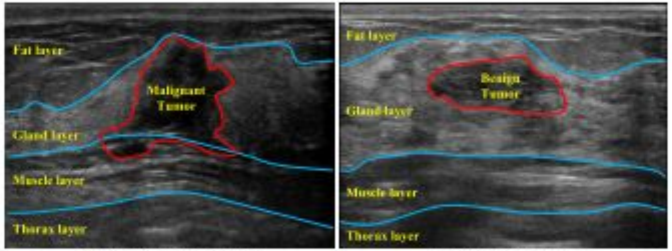


This **segmentation** approach achieved on average
**90.5 dice score** on **510 ultrasound images**

# HoVer-Trans: Anatomy-aware HoVer-Transformer for ROI-free Breast Cancer Diagnosis in Ultrasound Images (Mo. et al. 2022)



(a) Malignant tumor (a) Benign tumor

This **classification** approach achieved **92.4% AUC** on **2405 Ultrasound Images**

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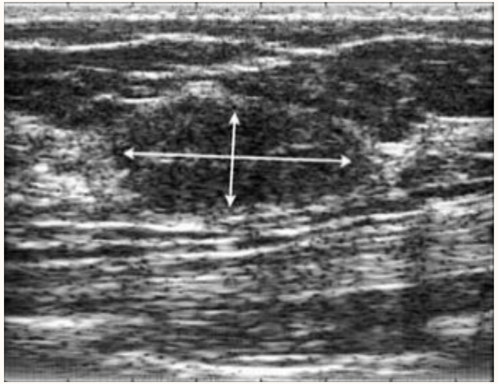
# Methods

# Datasets

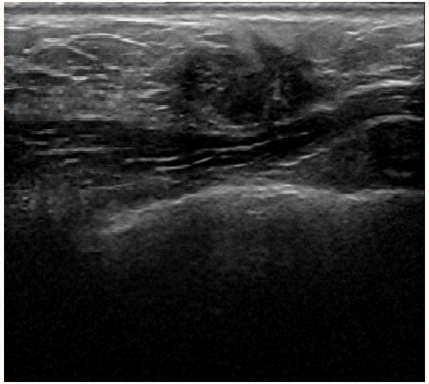
| Data | Acq Year | Patients | Transducers | Device | No. Of Samples |
|---|---|---|---|---|---|
| Baheya | 2018 | 600<br>(25-75) | 1–5 MHz<br>ML6-15-D Matrix linear probe | GE LOGIQ E9 | 780 |
| UDIAT | 2012 | 163 | 8.5 MHz<br>17L5 HD linear array probe | Siemens ACUSON Sequoia C512 | 163 |
| OASBUD | 2013-2015 | 78 | 5-14 MHz<br>L14-5/38 linear array probe | Ultrasonix SonixTouch | 200 |
| GDPH & SYSUCC | 2022 | 1202 | Multiple Linear Probes | Hitachi Ascendus<br>Mindray DC-80<br>Toshiba Aplio 500<br>Supersonic Aixplorer | 2405 |
| Own Dataset | - | - | 3 – 12 MHz<br>L3-12a Linear Array Probe | Samsung WS80A | 2771 |
| **Total** | **-** | **› 2043** | **-** | **-** | **6319** |

# Examples From Datasets

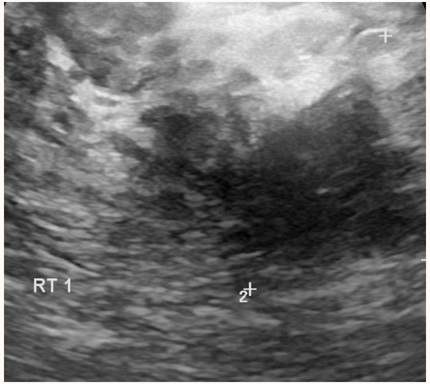
OSABUD



UDIAT



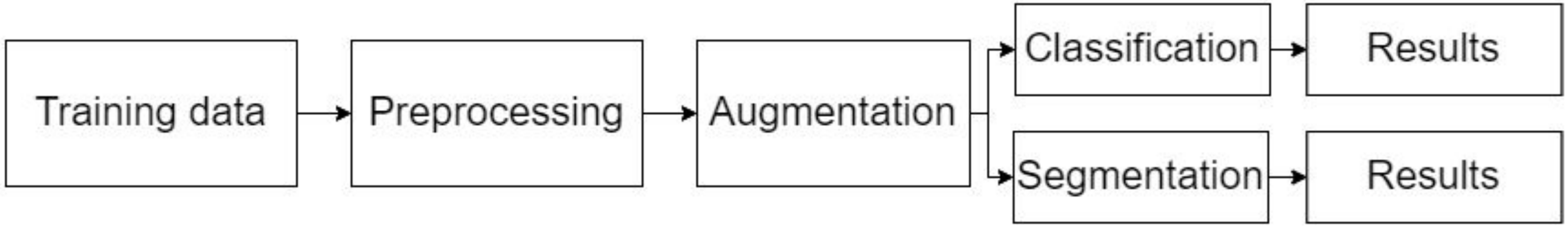
Baheya

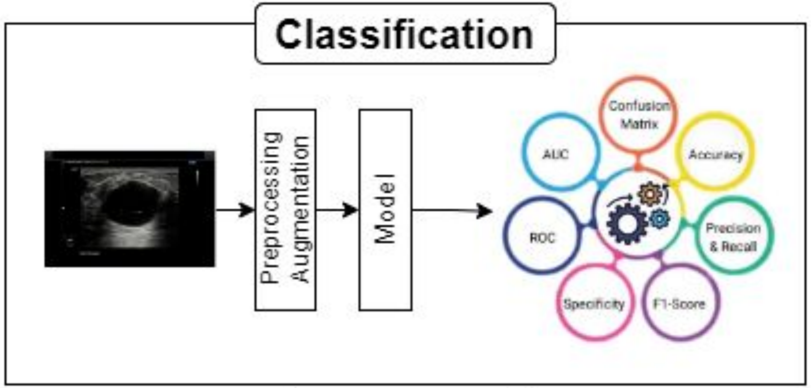


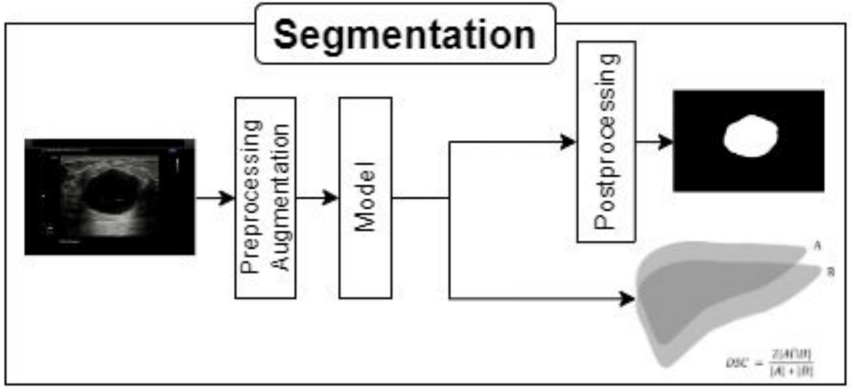

GDPH & SYSUCC

GDPH & SYSUCC

# AI Pipeline



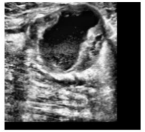



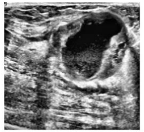

Preprocessing

- Resizing
- Black border Remove
- Bilateral Filtering
- Adaptive Histogram

Augmentation

- Blurring
- Random brightness
- Random Gamma
- Translation
- Random Cropping





# Classification Model

## Architecture

We are using the new EfficientNet architecture specifically (**Efficient-Net V2-B0**) & applied **transfer learning**

## Data Used

**2804 Samples** Were Used (**1170 Benign-1531 Malignant-103 Normal**) **Using**: BUSI, UDIAT, OASBUD, GDPH, and SYSUCC

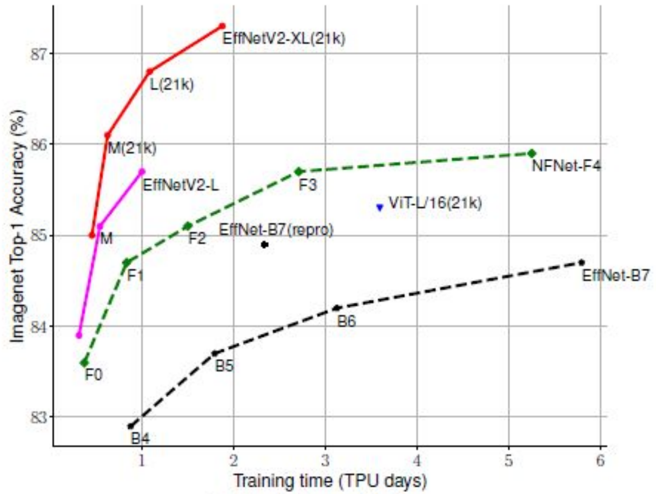
## Loss Function & Schedule

**Cross Entropy Loss** & Learning Rate Schedule Used **Decaying Cyclic Learning Rate**

## Splitting & Epochs

We Used **80% Training – 10% Validation – 10% Testing** & **Used Early Stopping (Model Trained For 14 Epochs)**

# Classification Model




(a) Training efficiency.

| | EfficientNet (2019) | ResNet-RS (2021) | DeiT/ViT (2021) | EfficientNetV2 (ours) |
|---|---|---|---|---|
| Top-1 Acc. | 84.3% | 84.0% | 83.1% | 83.9% |
| Parameters | 43M | 164M | 86M | 24M |

(b) Parameter efficiency.

# Segmentation Model

## Architecture

We are using **Attention U-Net** Architecture

## Data Used

**6319 Samples** Were Used For Segmentation **Using**: BUSI, Baheya, UDIAT, OASBUD, GDPH, SYSUCC and our own dataset

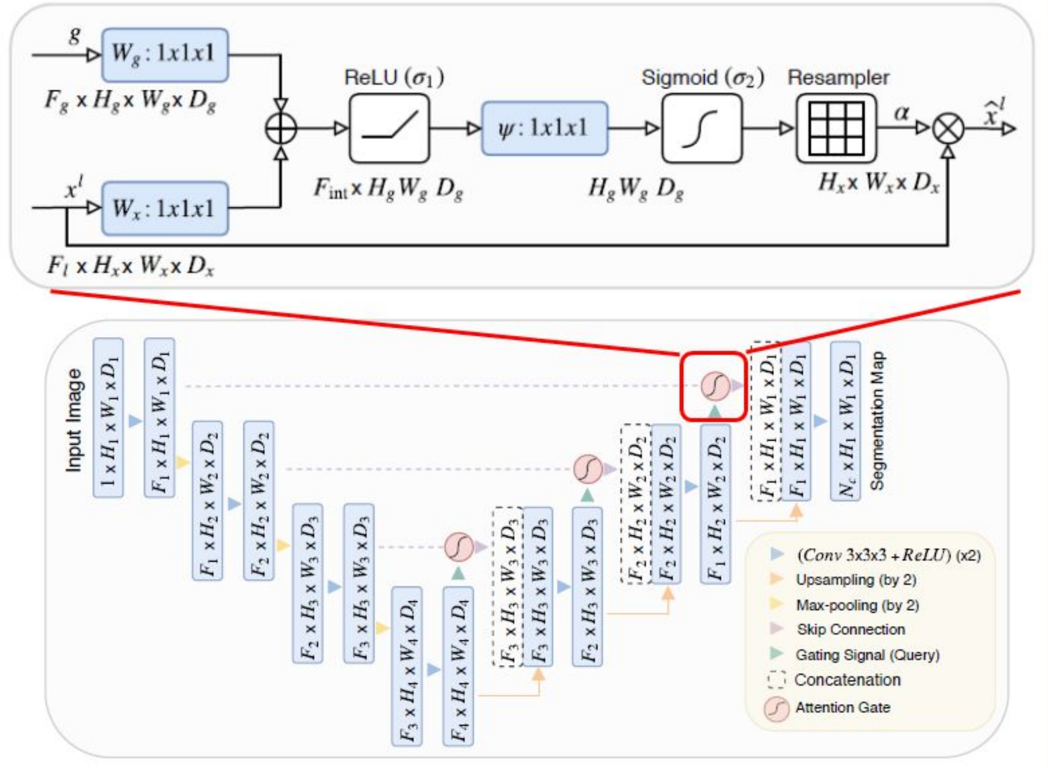
## Loss Function & Schedule

We are using a recently discovered loss function which is **Log Cosh Loss & Combo Loss** & Learning Rate Schedule Used **Cosine Annealing**

## Splitting & Epochs

We Used **80% Training – 10% Validation – 10% Testing** & **Model Trained For 75 Epochs**

# Segmentation Model

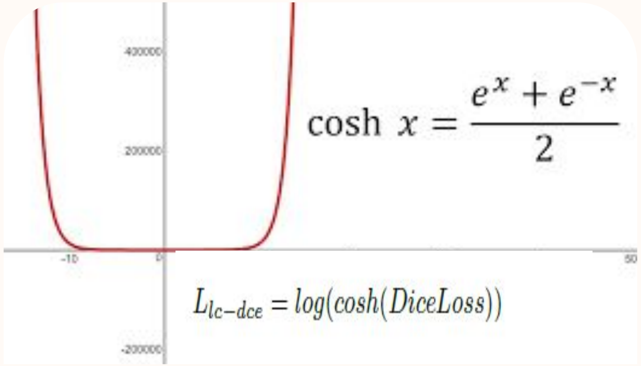


# Loss Functions

$$L_{m-bce} = -\frac{1}{N}\sum_{i} \beta(y - log(\hat{y})) + (1-\beta)(1-y)log(1-\hat{y}) \quad (17)$$

$$CL(y,\hat{y}) = \alpha L_{m-bce} - (1-\alpha)DL(y,\hat{y}) \quad (18)$$

**Combo Loss**




**Log Cosh Loss**

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# Results

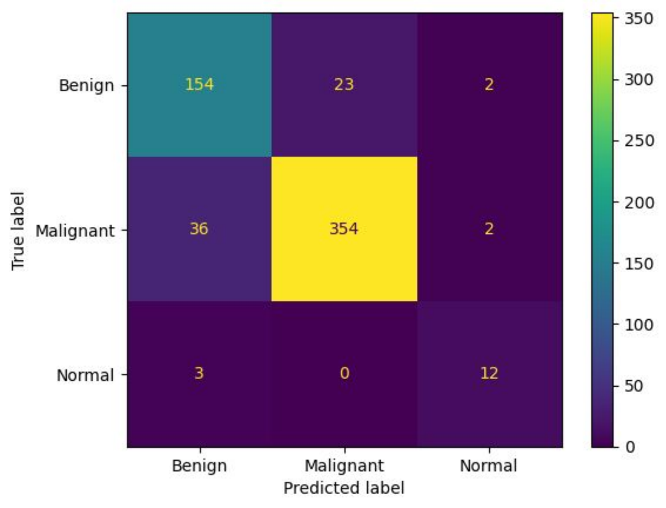
# Classification Results on All Datasets

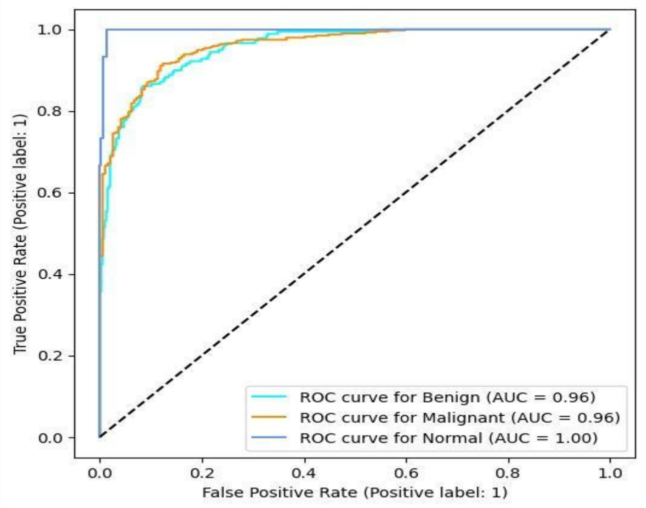
| Data | Accuracy | F1 Score | Sensitivity | Specificity | AUC |
|---|---|---|---|---|---|
| VGG16 | 76 | 0.76 | 63.6 | 82.8 | 90.1 |
| MobileNet | 83 | 0.827 | 70.6 | 88.0 | 94.75 |
| *DenseNet121* | *89* | *0.89* | *89.13* | *92.5* | *97* |
| EfficientNetB0 | 86 | 0.862 | 79.41 | 91.2 | 96.5 |
| **EfficientNetV2-B0** | **89** | **0.87** | **89.0** | **92.0** | **96** |

# EfficientNetV2-B0 Results on Each Dataset

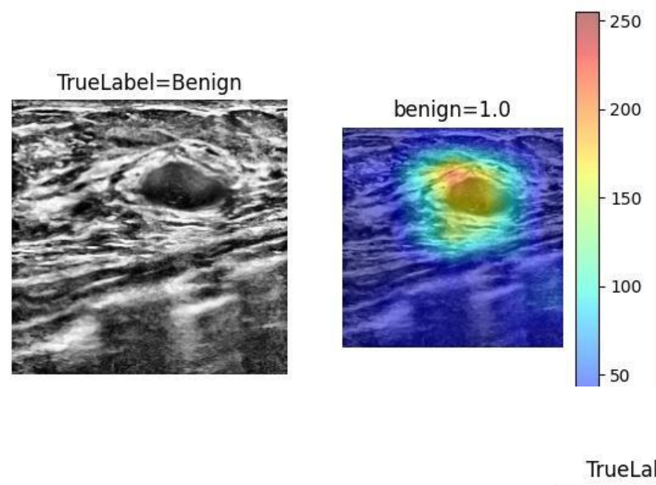
| Data | Accuracy | F1 Score | Sensitivity | Specificity | AUC |
|---|---|---|---|---|---|
| BUSI | 86 | 0.858 | 86.7 | 92.0 | 93.75 |
| UDIAT | 98 | 0.98 | 95.0 | 96.4 | 98 |
| OASBUD | 71 | 0.705 | 69.0 | 68.5 | 81.7 |
| GDPH&SYSUCC | 90 | 0.90 | 88.5 | 88.3 | 96 |

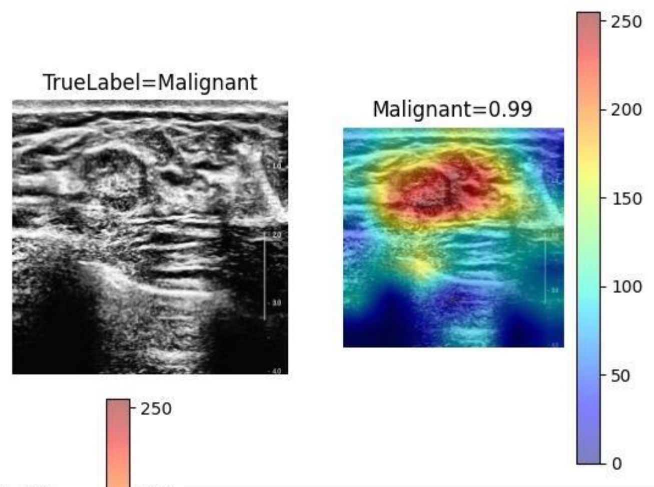
# EfficientNetV2-B0 Test Metrics

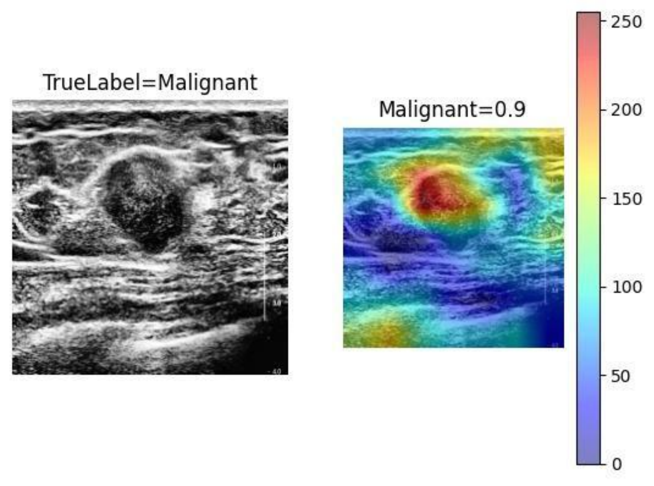


# GradCam On Test Data



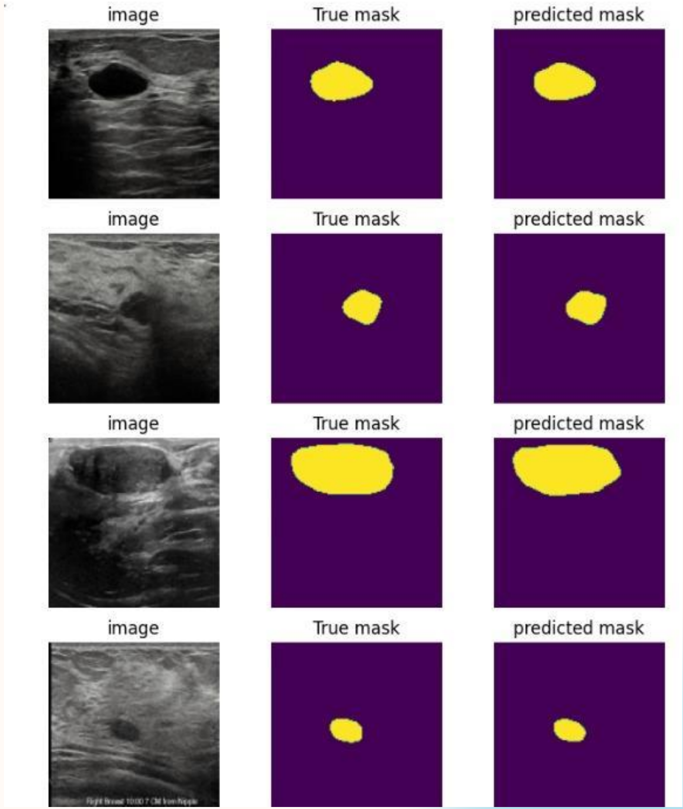



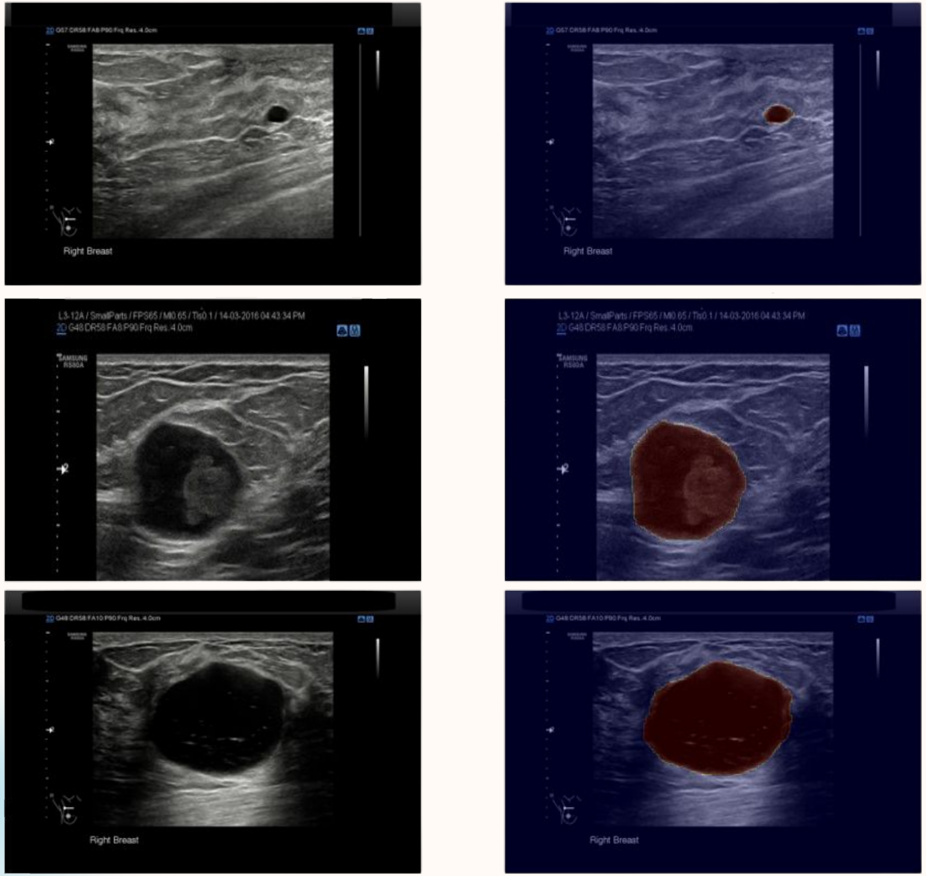



# Segmentation Results

| Model | Loss | Val Dice Score | Test Dice Score |
|---|---|---|---|
| Unet+Res Net34 Backbone | Log Cosh Dice Loss | 0.84 | 0.85 |
| Unet+Res Net50 Backbone | Combo Loss | 0.84 | 0.83 |
| Attention Unet | Combo Loss | 0.85 | 0.84 |
| **Attention Unet** | **Log Cosh Dice Loss** | **0.86** | **0.85** |

# Segmentation Output On Test Data



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# Discussion

# Contributions

- Our study focus on diverse datasets forms the cornerstone of our success in achieving high-performance results

- Achieved High Results using Efficient-Net V2 for classification of BUS images.

- Compared two loss functions for breast lesion segmentation, utilizing U-net architecture with various backbones and Attention U-net.

# Limitations

## High Variability

US Images are known to have high variability meaning benign might look like malignant , if we don’t focus on all details

## Requires Expertise

Some times physicians have **hard time deciding** whether a lesion is benign or not , that is why **follow up** is needed or **second opinion**

## Full Of Noises

US Images are full of different types of noises, the most dominant one is **speckle noise which hides important acoustic features**

# Limitations

## UI Components

From Our Experiments, we found out that **UI components** & **Black Borders** if allowed into AI Model it will **affect its decision.**

## Class Imbalance

As we discussed before, the data **distribution is highly imbalanced** so it will **affect the generalizability** of the **classification** model

# Solution Example


Image with Blackborder

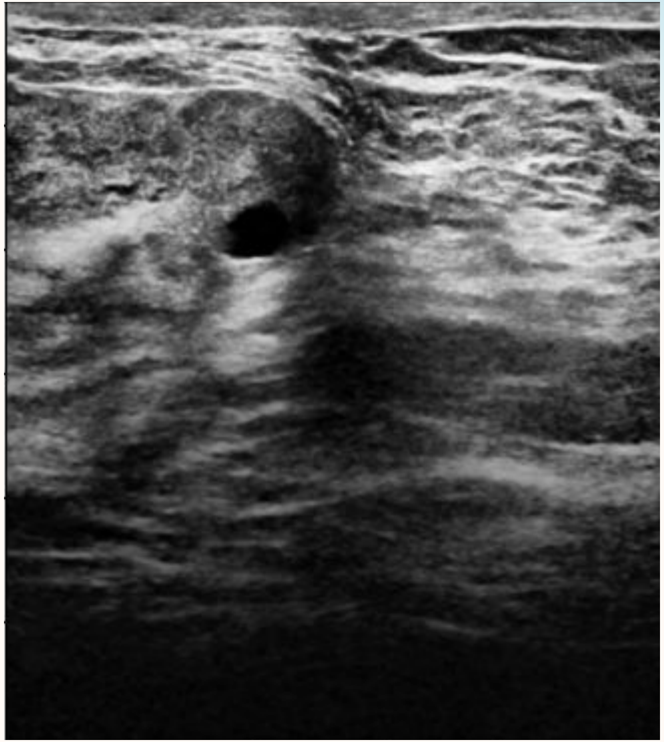

Image After Blackborder Removal

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# ACKNOWLEDGMENT

We Would Like To Express Our Gratitude to Astute Imaging For Providing The Technical & Research Support Throughout This Work

# Thank You