ECHOGUARDIAN

Empowering Radiologists, Saving Lives

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MEET THE TEAM

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AGENDA

- Epidemiology of breast cancer
- Our Product and Mission
- Regulatory Steps and Data collection
- Product Overview
- Requirements
- Dataset and Data Processing
- Evaluation Metrics
- Training & Results
- Product demo
- Case Study and Results

BREAST CANCER: EPIDEMIOLOGY

Global Impact:

- In 2022, **670,000 deaths globally** and it's the most common cancer in women globally. 0.5-1% of cases are in men.

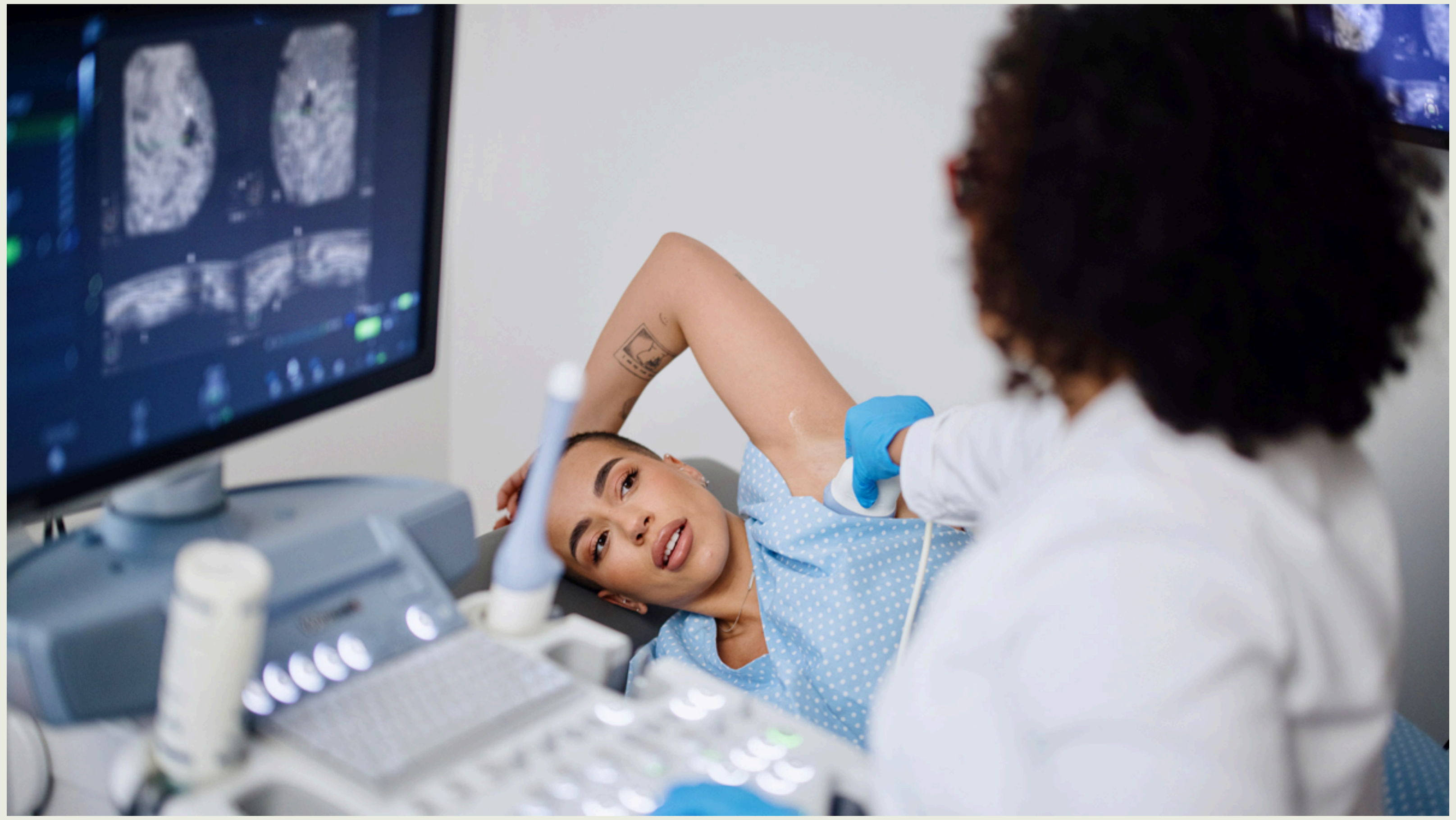
Incidence:

- In 2022, **2.3 million women** were diagnosed with breast cancer.

Early and accurate detection is crucial to improve breast cancer outcomes. Our product aids the radiologist in identifying the disease more accurately, ultimately enhancing survival rates and reducing mortality.

Source: https://www.who.int/news-room/fact-sheets/detail/breast-cancer

OUR PRODUCT AND MISSION



Our product:

- ***EchoGuardian aids radiologists in properly classifying malignant lesions in a timely and precise manner.***

Our vision:

- *Improve breast cancer detection accuracy and time by radiologists*

REGULATORY STEPS AND DATA COLLECTION

Informed Consent

Patients signed an **Informed Consent** for the use of de-identified ultrasound images.

Data collection

Ultrasound images were captured by radiologists during routine procedures and collected **without personal identifiers.**

Ethical Review and Approval

The study was approved by the **Institutional Review Board** (IRB) and adheres to ethical standards, with ongoing monitoring to ensure compliance.

These steps ensure that the data used in our study is ethically sourced, patient privacy is maintained, and the research complies with all regulatory requirements.

PRODUCT OVERVIEW

ARCHITECTURE

Segmentation Model:

- DeepLabV3+ with ResNet-34 encoder

Classification Model:

- Feed-Forward Neural Network trained on radiomic features

Our model runs **server-side in Europe** and authentication is required.

USER INTERFACE (UI)

Modern UI

The **radiologist** may **choose** between **manual or automatic segmentation**

Automatic segmentation requires the technician's confirmation

REQUIREMENTS

Hardware:

- Echograph able to export ultrasound images as PNGs
- PC with internet connection of at least 2 Mb/s in upload

Software:

- An internet browser with JavaScript enabled

Metrics:

- High sensitivity > 0.90 (classifying malignant lesions)
- High AUC > 0.85

DATASET AND DATA PROCESSING

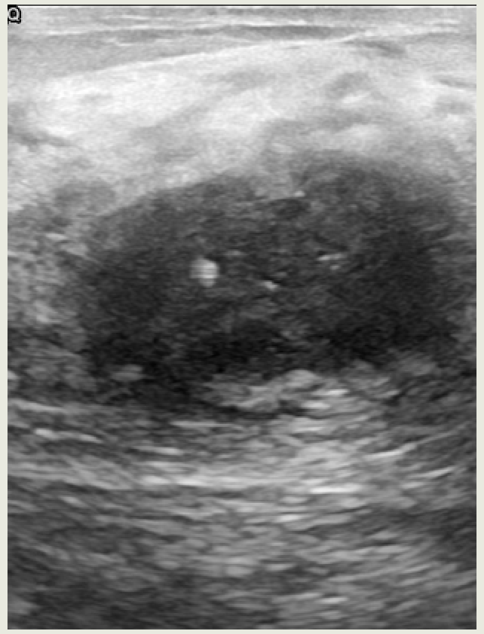
Dataset: 647 ultrasound images and their related masks of breast cancers

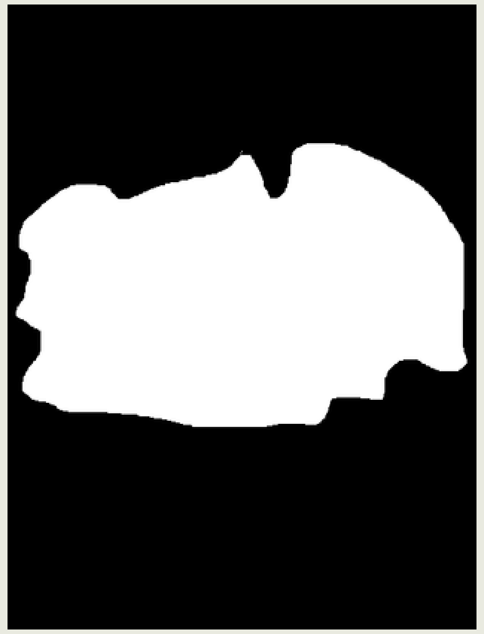
- 437 benign and 210 malignant

Dataset split: 80/10/10 %

Some images contain **multiple lesions:**

- **Classification:** the multiple lesions of a single ultrasound image were analyzed **individually**
- **Segmentation:** the masks of patients with multiple lesions were **merged** in a single mask using a **bitwise OR operation**

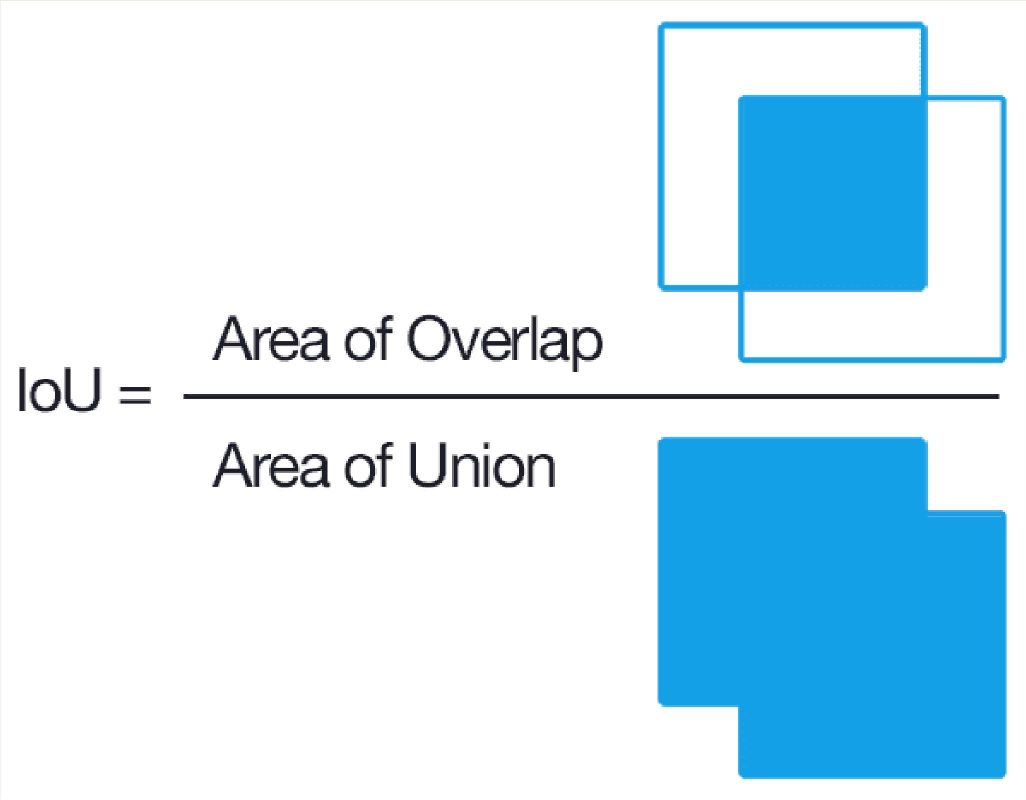




SEGMENTER'S METRICS

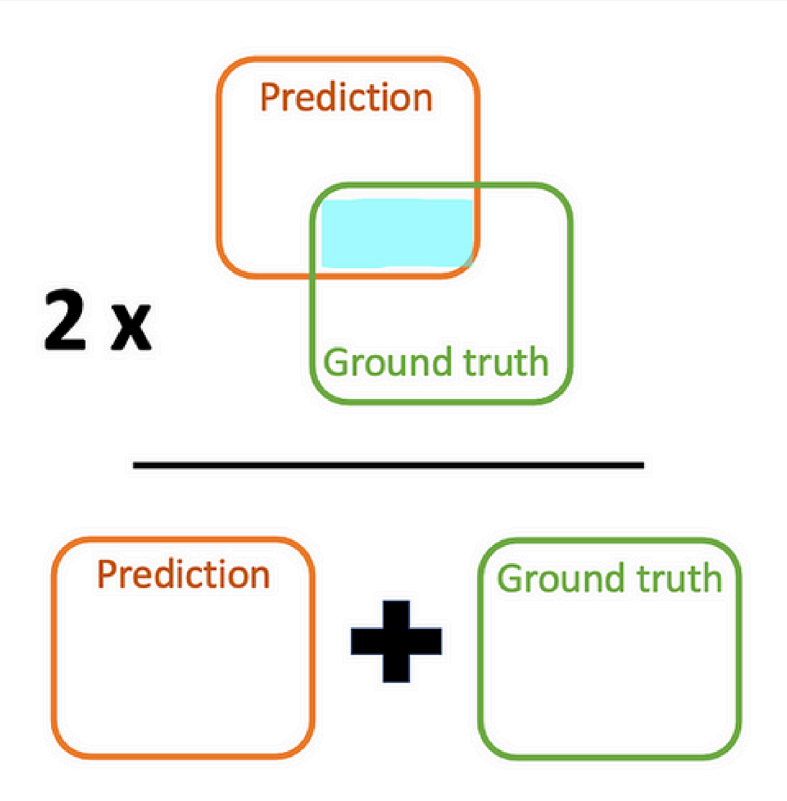
Intersection over Union (IoU)

$$\mathrm{IoU} = \frac{|A \cap B|}{|A| + |B| - |A \cap B|}$$



Dice coefficient

$$\mathrm{Dice} = \frac{2 \cdot |A \cap B|}{|A| + |B|}$$



CLASSIFIER'S METRICS

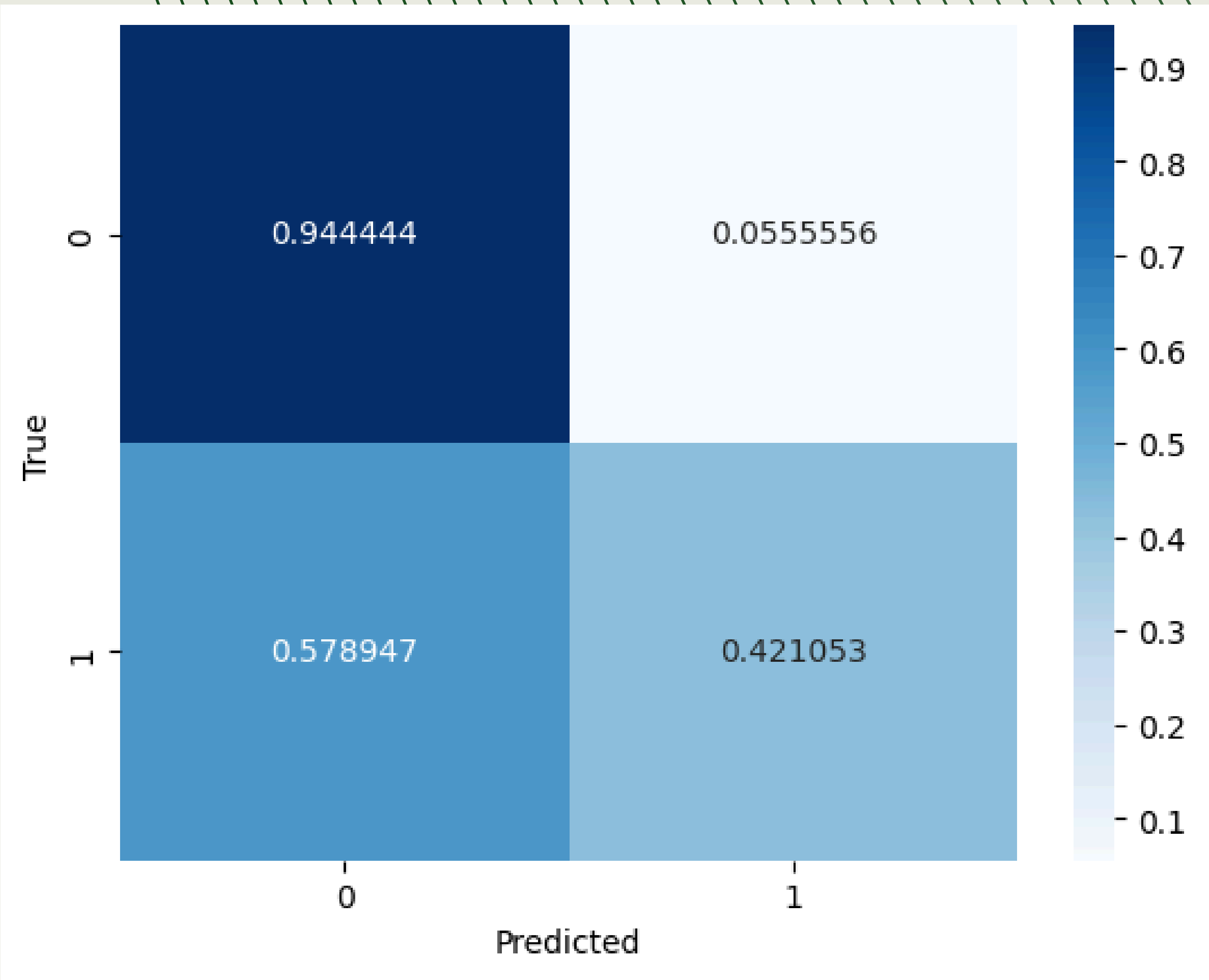
Sensitivity ⟶ $\frac{TP}{TP+FN}$

Specificity ⟶ $\frac{TN}{TN+FP}$

Accuracy ⟶ $\frac{TP+TN}{TP+TN+FP+FN}$

F1 Score ⟶ $\frac{2 \cdot TP}{2 \cdot TP+FP+FN}$

Recall ⟶ $\frac{TP}{TP+FN}$



CLASSIFIERS: TRAINING AND VALIDATION

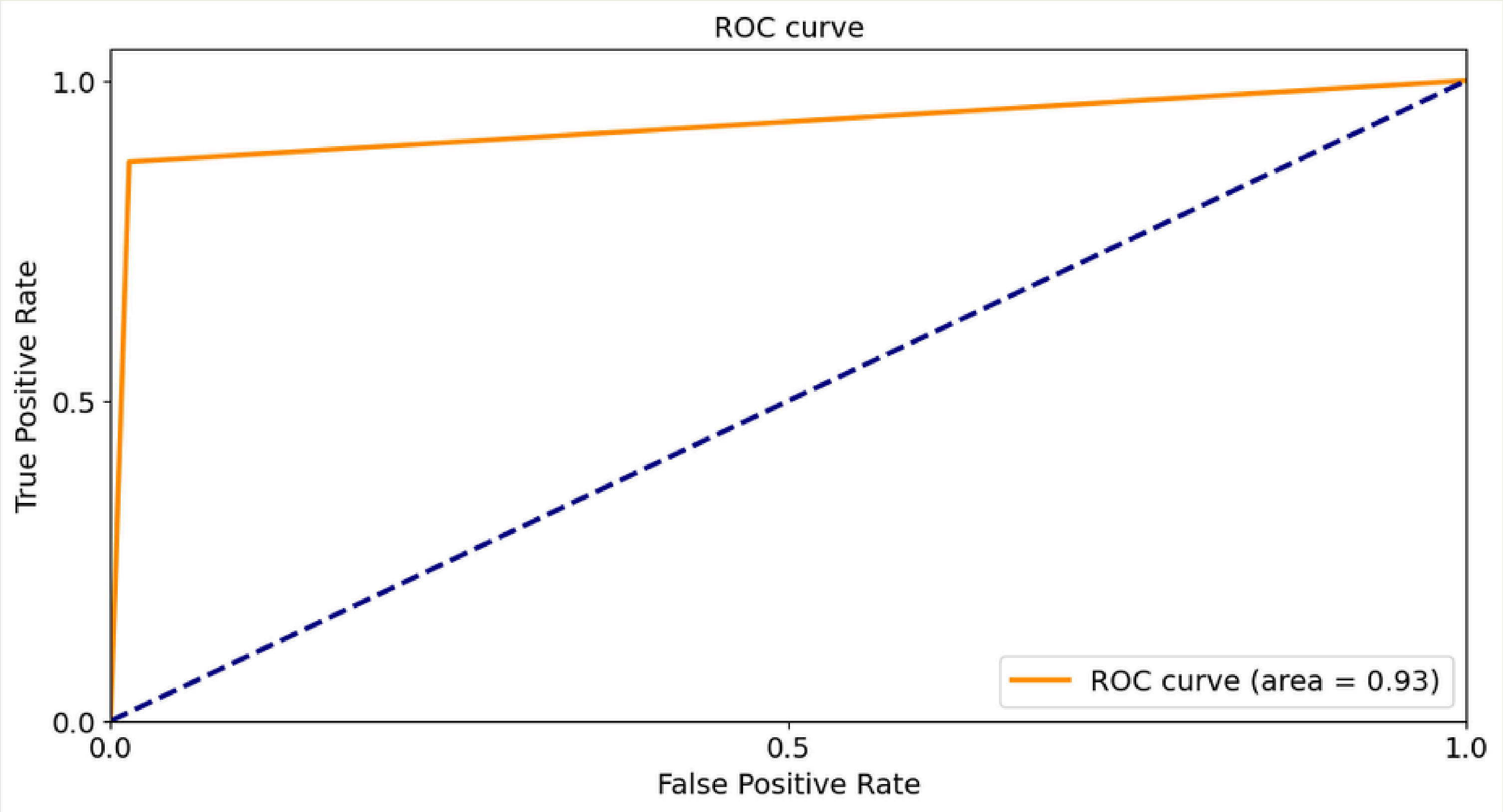
A list of ultrasound images containing annotations were excluded from training.

101 Radiomic features* were computed for each image and fed to the model.
The **sensitivity** refers to the classifier's ability of recognizing **malignant** lesions.

The following models were trained:

- Support Vector Machines (SVM)
- Random Forest
- **Feed Forward Neural Network**

Model	Sensitivity	Specificity	Accuracy
Linear SVM	0.9412	0.9756	0.9655
Random Forest	1	0.5882	0.8793
Feed Forward NN	**0.9412**	**1**	**0.9828**



*Source: Introduction to Radiomics, Society of Nuclear Medicine, Inc. (ISSN 0161-5505), Journal of Nuclear Medicine. DOI: 10.2967/jnumed.118.222893

SEGMENTATION: TRAINING AND VALIDATION

Training was performed on the **image-mask pair.**

Images underwent a series of **augmentations** to enhance generalization.

The following models were trained:

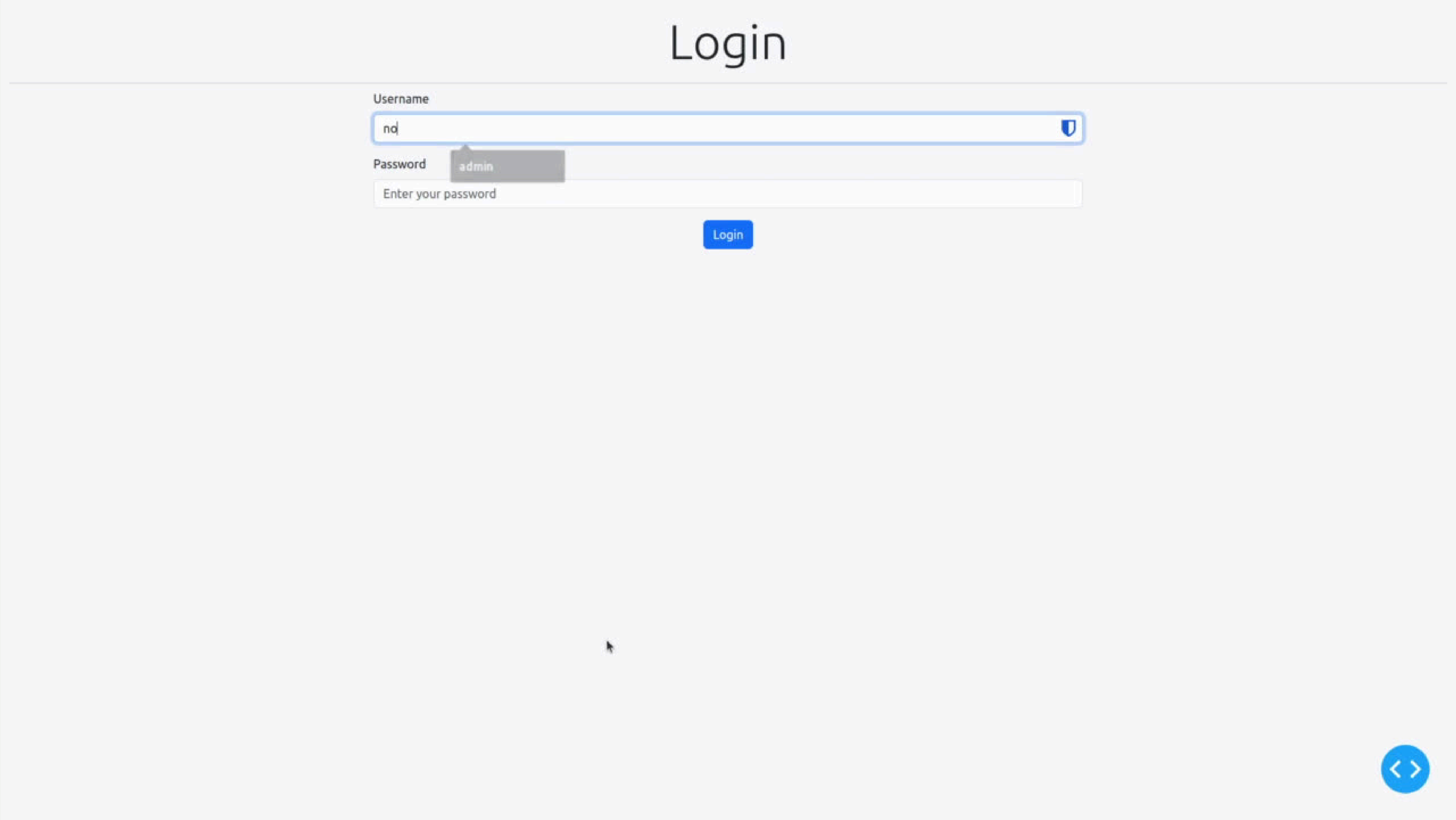
- UnetPlusPlus** with ResNet34 encoder
- **DeepLabV3Plus* with ResNet34 encoder**
- DeepLabV3Plus with ResNet50 encoder
- DeepLabV3Plus with xception65 encoder

Model	IoU	Dice
UnetPlusPlus w/ ResNet34	0.562	0.719
DeepLabV3Plus w/ ResNet34	**0.704**	**0.826**
DeepLabV3Plus w/ ResNet50	0.683	0.811
DeepLabV3Plus w/ xception65	0.583	0.737

***Source**: Chen, L.-C., Zhu, Y., Papandreou, G., Schroff, F., & Adam, H. (2018). Encoder-Decoder with Atrous Separable Convolution for Semantic Image Segmentation. arXiv preprint arXiv:1802.02611

****Source**: Zhou, Z., Siddiquee, M. M. R., Tajbakhsh, N., & Liang, J. (2018). UNet++: A Nested U-Net Architecture for Medical Image Segmentation. arXiv preprint arXiv:1807.10165.

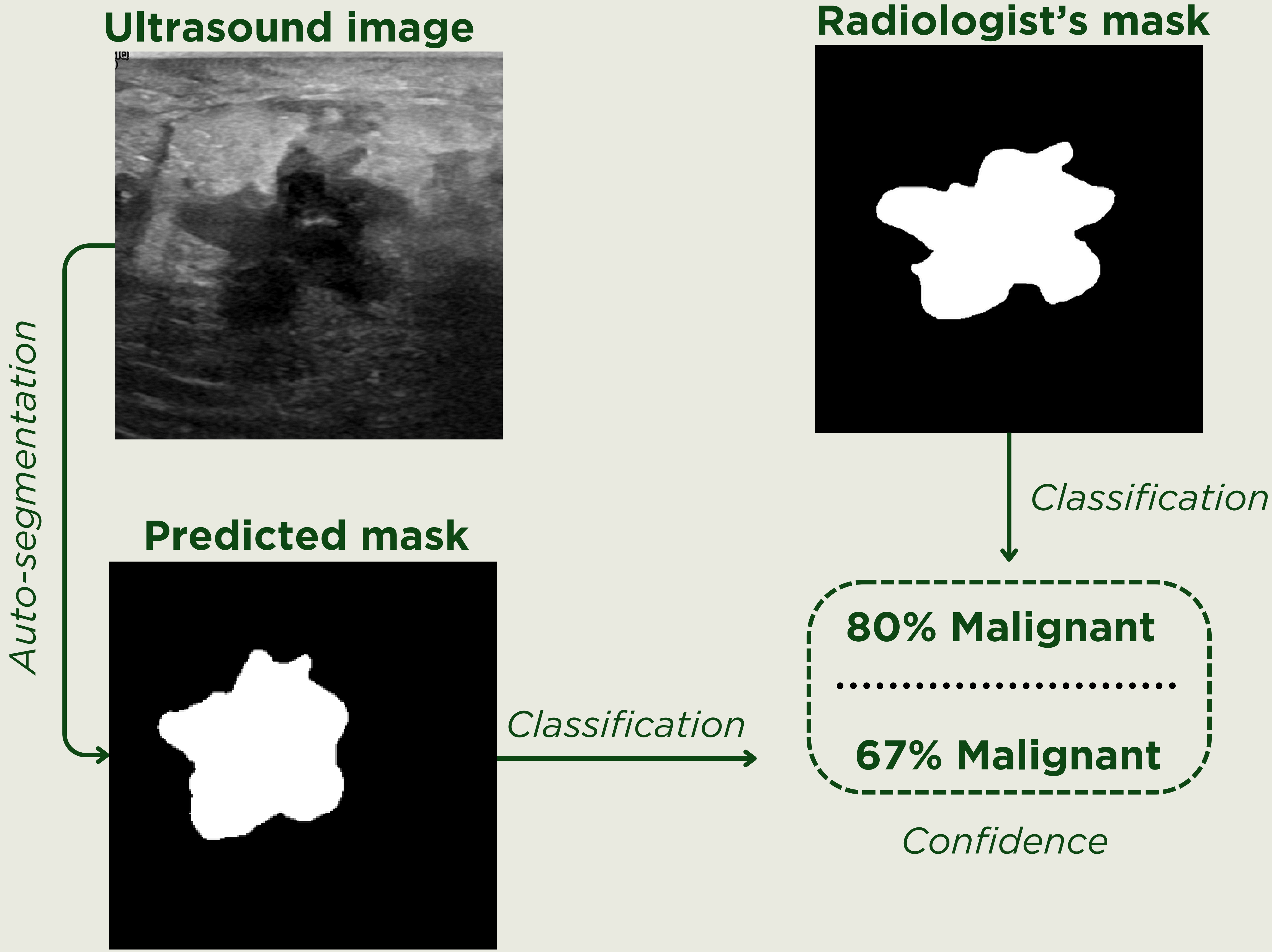
USER INTERFACE AND WORKFLOW



CASE STUDY AND RESULTS

Example Case Study:

- Initial ultrasound image
- Segmentation result
- Classification outcome



Thank you.

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