



BrainStation

Machine-Learning APPROACHES FOR ULTRASOUND- BASED BREAST CANCER DETECTION

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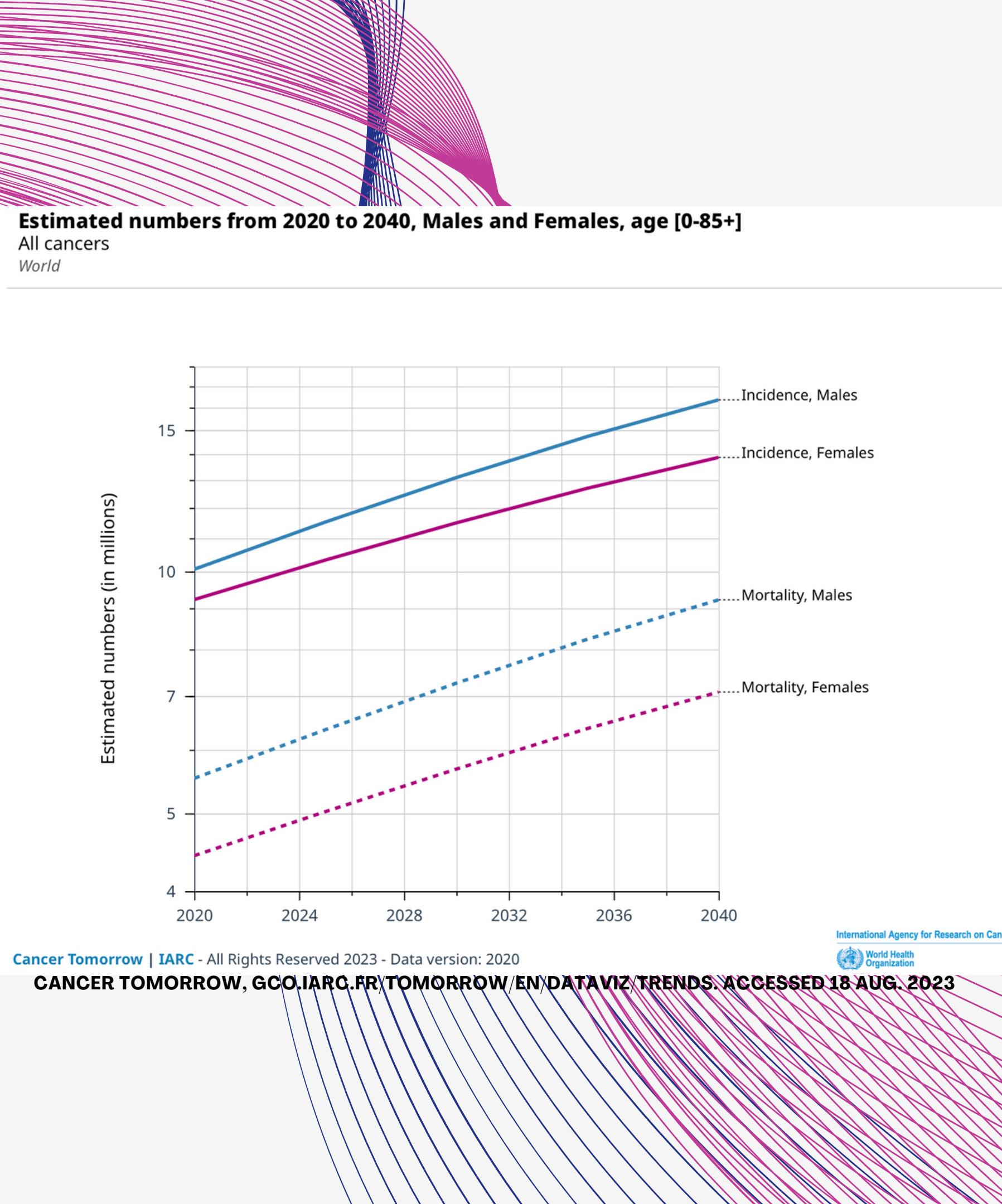
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CANCER TOMORROW

- In 2020, there were 19,292,789 cancer cases.
- In 2040, the projected number of cancer cases is 30,226,151.
- The number of cancer cases might increase by around 10,933,362 (56.7%) between 2020 and 2040.

Project STATEMENT

Breast cancer is a significant global health concern, with early detection and accurate staging being critical for effective treatment and improved patient outcomes. The proposed project aims to leverage the power of machine learning and ultrasound imaging to differentiate between benign and malignant breast tumors, assisting healthcare practitioners in accurate diagnosis and staging of breast cancer.

Proposed OBJECTIVES

- Breast cancer as a global health concern.
- Importance of early detection and accurate staging.
- Role of machine learning and ultrasound imaging

Primary Objective

- Develop a robust machine learning model.
- Utilize ultrasound images of breast tumors.
- Accurately differentiate between benign and malignant tumors.

Key Goals

- Enhance diagnostic accuracy: Minimize false positives and false negatives.
- Improve patient outcomes: Enable timely and precise treatment decisions.
- Empower healthcare practitioners: Provide a reliable tool for diagnosis and staging.

Benefits

- Patients: Earlier detection, tailored treatments, better survival rates.
- Healthcare Practitioners: Enhanced diagnostic confidence, reduced workload.
- Healthcare System: Cost-effective, efficient resource allocation.

Proposed STEPS

01 Data Collection and Curation

02 Data Preprocessing and Feature Extraction

03 Model Selection and Training

04 Benign-Malignant Classification

05 Staging Prediction

06 User Interface Development

07 Model Evaluation and Validation

08 Ethical Considerations and Bias Mitigation

09 Project Conclusion and Future Directions

THE DATA



DATA ACQUISITION AND ORIGIN

- **Dataset source:**
Kaggle platform
- **Dataset name:**
"Breast Ultrasound Images Dataset"
- **Purpose:**
Focus on breast cancer detection using ultrasound scans
- **Goal:**
Enhance breast cancer diagnosis accuracy through machine learning



DATASET COMPOSITION AND STRATIFICATION

- **Dataset structure:**
Wide range of medical images capturing benign and malignant tumors
- **Categorization:**
Two classes - benign and malignant
- **Model training:**
Distinguishing between non-cancerous and cancerous conditions
- **Validation set:**
Dedicated set for testing and evaluating model's performance
- **Stratified division:**
Assesses model's generalization and accuracy optimization



ACCESS AND UTILIZATION

- **Access:**
Dataset link provided for deeper exploration and research
- **Link:**
[\[Dataset Link\]](#)
- **Potential:**
Ultrasound images can contribute to breast cancer diagnosis
- **Integration:**
Machine learning algorithms for insights and early detection
- **Impact:**
Potential to save lives through accurate diagnosis

EDA



RESIZING

Adjusting the dimensions or proportions of an image.



AUGMENTING

Applying various transformations or modifications to data,



DENOISING

Removed unwanted or random noise



BALANCING

Class of images is equally represented, promoting fairness

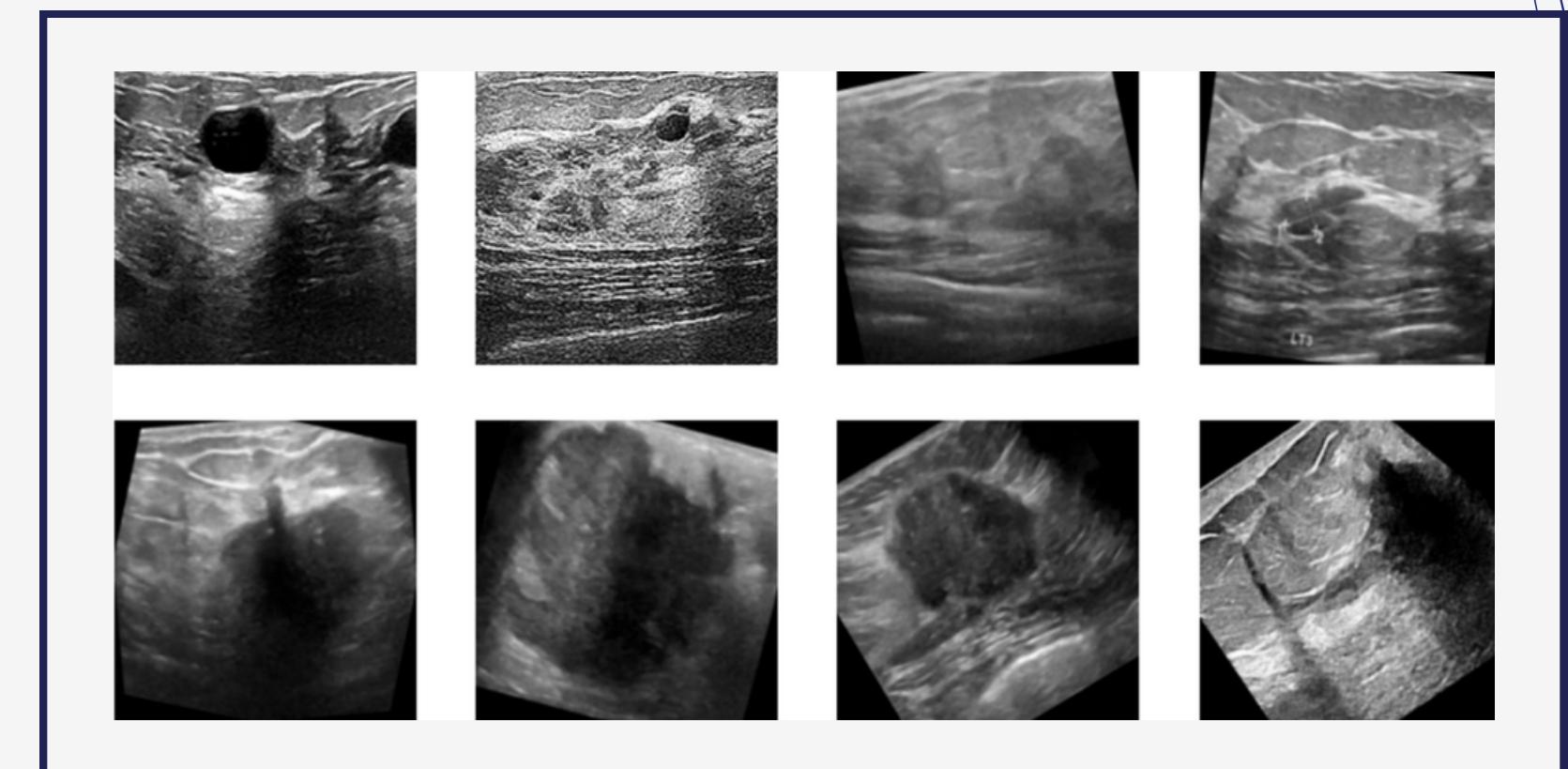


RESIZE_IMAGE

FLOW

DENOISE_WAVELET

BALANCE_CLASSES



Convolutional Neural Network

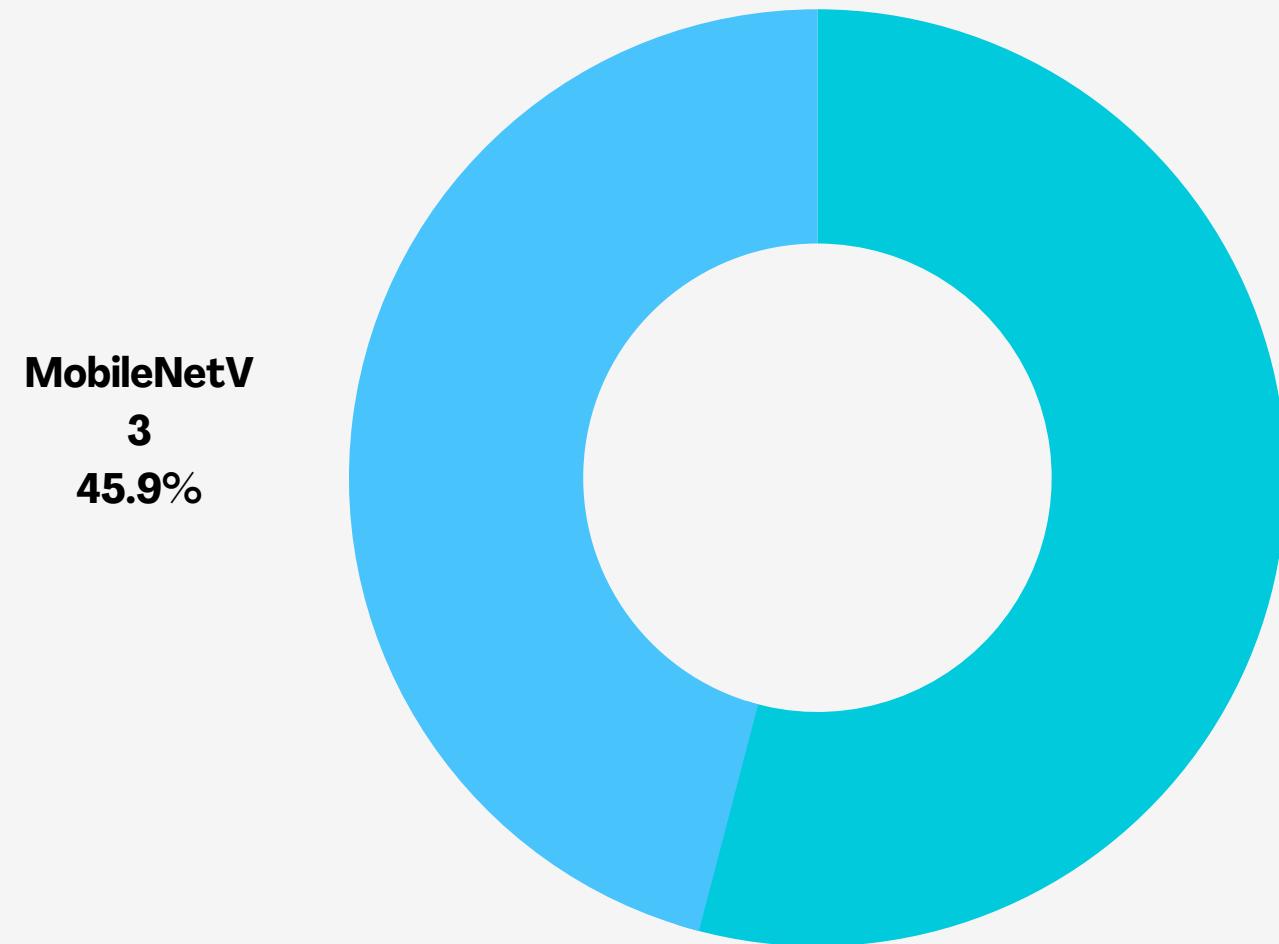
CNNs are deep learning models designed for visual data analysis, using specialized layers like convolution and pooling to automatically extract features. They are crucial for tasks such as image classification, object detection, and facial recognition, impacting fields like autonomous driving, medical imaging, and biometrics.

MobileNetV3

MobileNetV3 is a mobile-friendly neural network designed for efficient and accurate deep learning on smartphones and similar devices. It uses advanced techniques to reduce computational demands while maintaining competitive performance, making it suitable for tasks like image classification and object detection in resource-constrained environments.

MODELS

MODEL	Accuracy	Validation Accuracy	Loss	Validation Loss
CNN	97.45%	98.60%	9.96%	8.73%
MobileNetV3	82.78%	82.20%	39.98%	46.63%



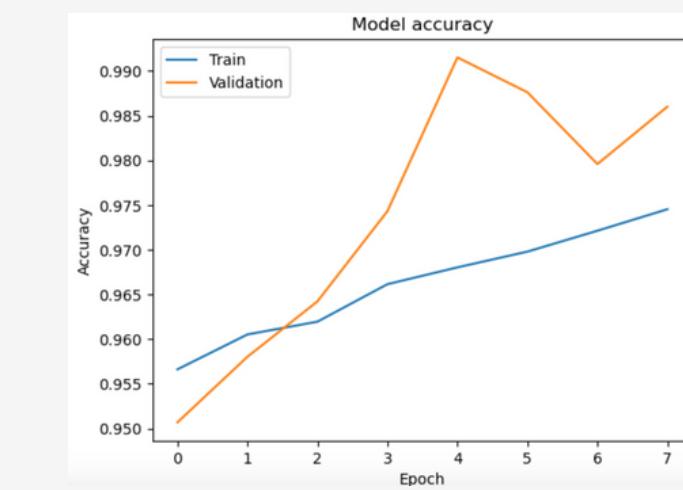
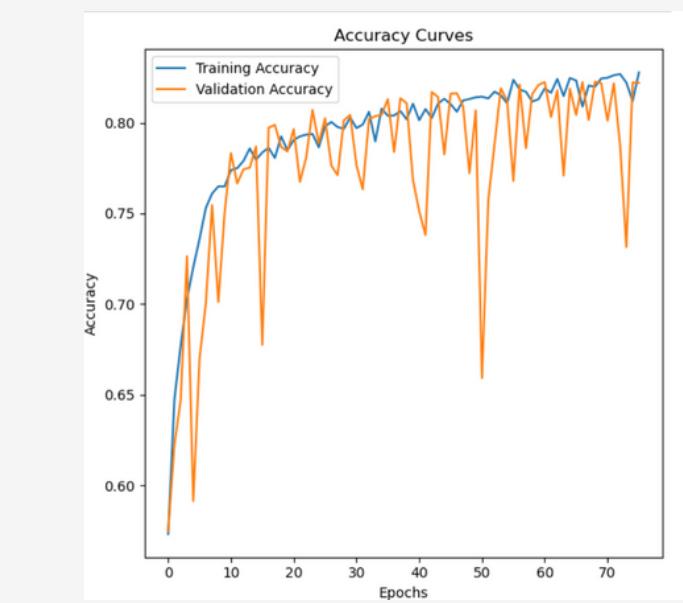
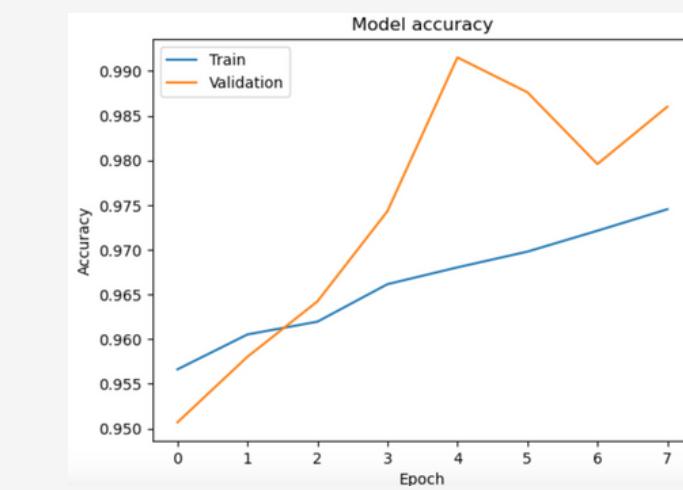
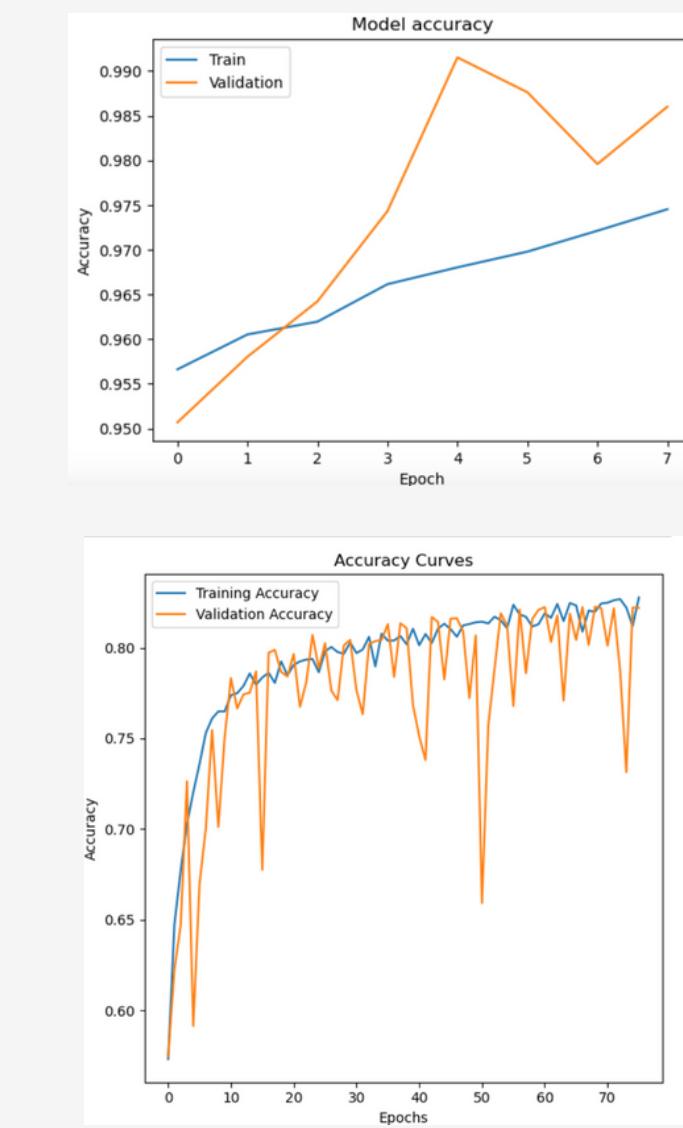
**CNN
54.1
%**

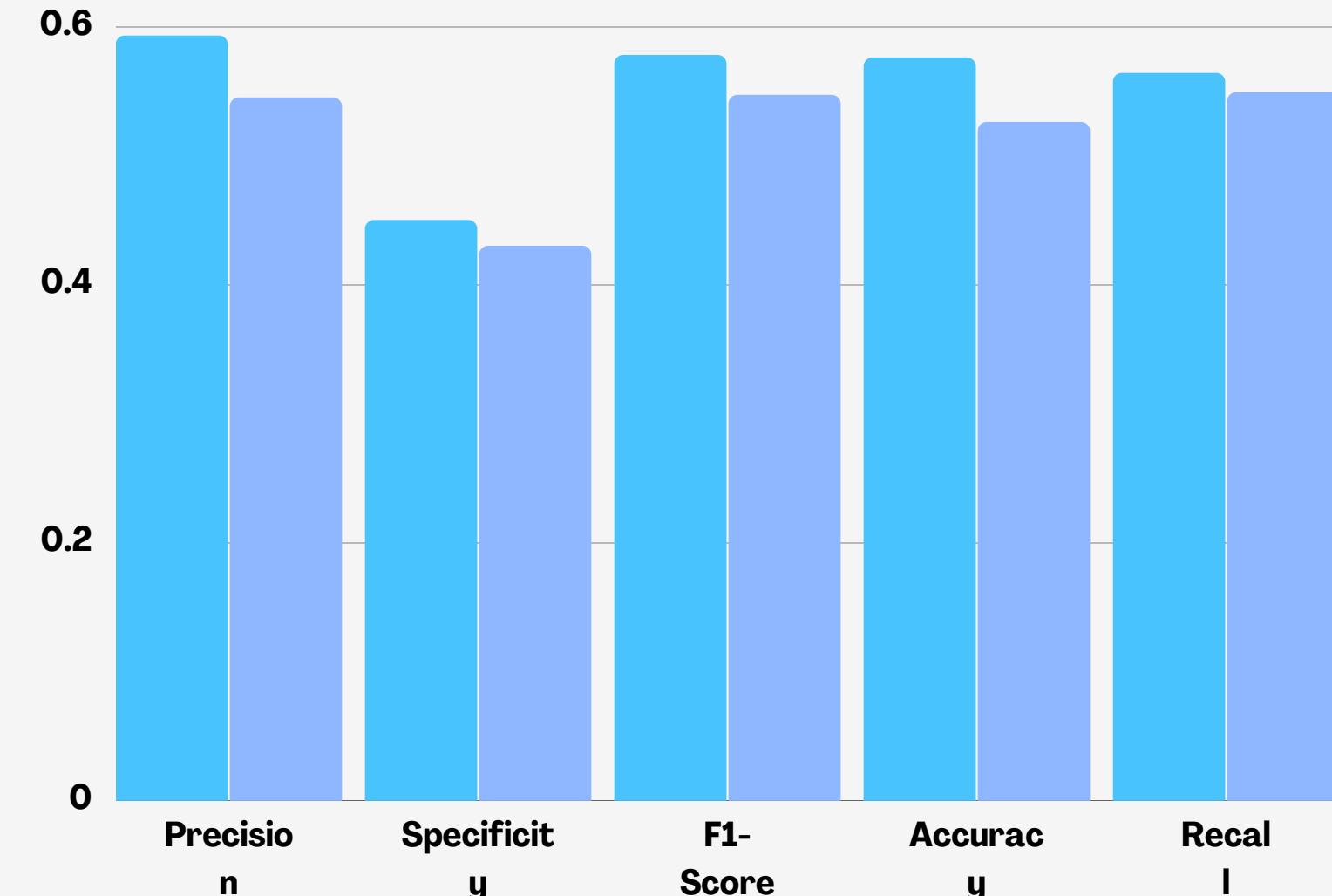
**MobileNetV
3
45.9%**

ACCURACY COMPARISON

MOBILENETV3

Based on higher accuracy and lower loss values, the "CNN" model outperforms the "MobileNetV3" model in this evaluation.





Confusion MATRIX

Which **Model** will have the better performance ?

1. If we want a model with better **precision, specificity, F1-score**, and **overall accuracy**, **MobileNetV3** is the better choice.
2. If **maximizing recall** is more critical for your application, **CNN** has a slightly higher recall rate.

Making PREDICTIONS

- Based on the provided metrics, **MobileNetV3** appears to be the better predictor model for this classification task. It achieves higher precision, specificity, F1-score, accuracy, and recall compared to the custom CNN model

```
def predict_image_class(image_path):
    image_file = pathlib.Path(image_path)

    # Load and preprocess the test image
    test_image = Image.open(image_file)
    test_image = test_image.resize((200, 100))
    test_image = test_image.convert('L')
    test_image = np.array(test_image) / 255.0
    test_image = np.expand_dims(test_image, axis=0)

    # Make predictions using the CNN model
    result = CNN_model.predict(test_image)

    # Interpret the prediction using the class mapping
    predicted_class_index = np.argmax(result, axis=1)
    predicted_class_name = [k for k, v in class_mapping.items() if v == predicted_class_index[0]]

    return predicted_class_name[0]
]

]: # Define path
image_path_1 = "/Users/alirazi/BreastCancerUltrasound/data/ultrasound_breast_classification/main/test/0/135.jpg"

# Predicting the class
predicted_class_1 = predict_image_class(image_path_1)
print("Predicted Class for Image 1:", predicted_class_1)
```

CNN

```
In [ ]: import tensorflow as tf
import numpy as np

# Load the image from a file
image_path = '/Users/alirazi/BreastCancerUltrasound/data/ultrasound_breast_classification'
pred_img = tf.image.decode_image(tf.io.read_file(image_path))

# Resize the image
pred_img_resized = tf.image.resize(pred_img, (224, 224))

# Run the prediction
prediction = MV_model.predict(tf.reshape(pred_img_resized, (1, 224, 224, 3)))
print("Target class percentage probabilities: benign(0), malignant(1)")
np.round(prediction, 4) * 100
imgplot = plt.imshow(res)
```

In []:

In []:

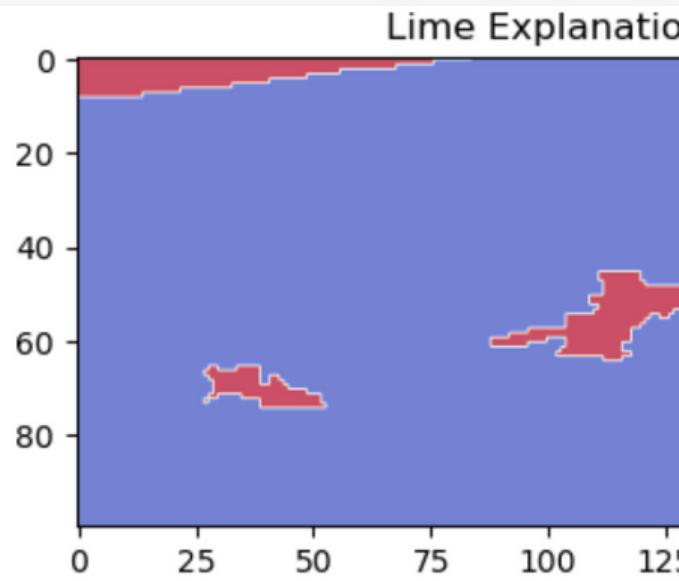
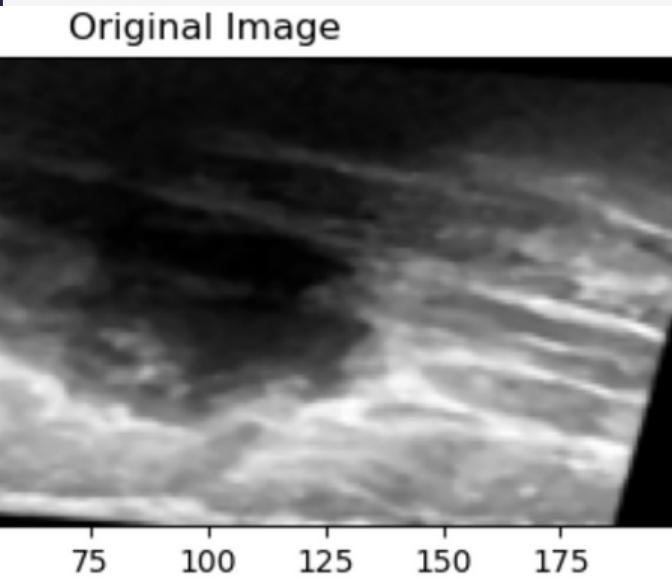
In []:

In []:

MOBILENETV3

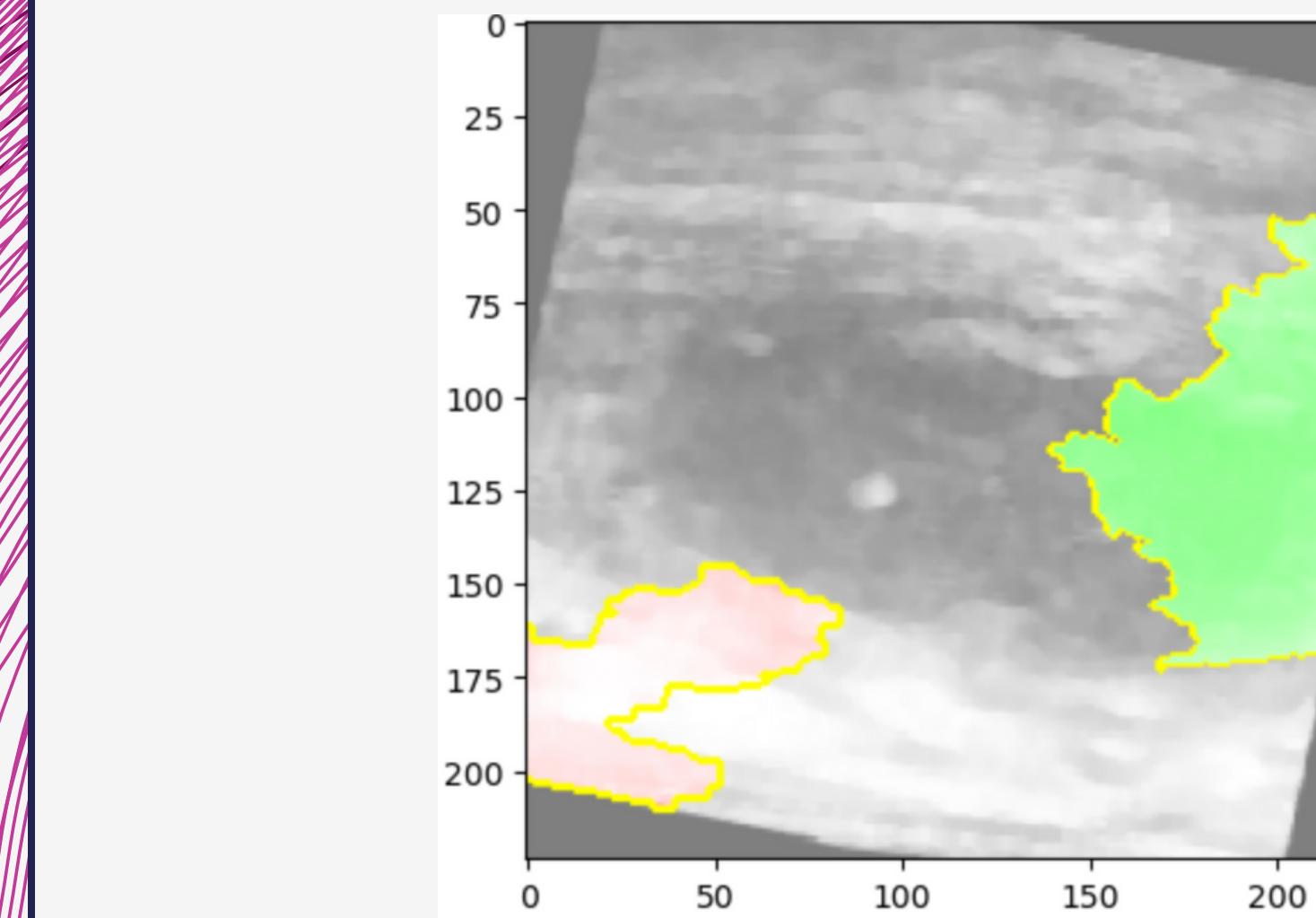
CNN

- Warmer Colors (e.g., Red): These regions are the most important for the model's prediction that the condition is benign. They contribute positively to the predicted class. In the context of a medical ultrasound image, warmer colors may highlight areas that are indicative of benign characteristics or features.
- Cooler Colors (e.g., Blue): These regions are less important or may even negatively contribute to the prediction of benignity. In a medical ultrasound image, cooler colors may indicate areas that are not relevant to the benign condition or may even be misleading for the model.



MobileNetV3

Both the green and red regions are located close to the tumor and correspond to the model's prediction of malignancy, it suggests that the model is correctly identifying features associated with malignancy in those areas.



CONCLUSION

By leveraging machine learning and ultrasound imaging, our project aims to revolutionize breast cancer diagnosis, ensuring accurate differentiation between benign and malignant tumors, and ultimately saving lives

RESOURCE

- 1.“Breast Cancer Medical Animation by Geometric Medical.” YouTube, 7 Sept. 2020, www.youtube.com/watch?v=3DE6V_xHpVY. Slide 1.
- 2.Cancer Tomorrow, gco.iarc.fr/tomorrow/en/dataviz/trends. Accessed 18 Aug. 2023.
- 3.Kalafi, E. Y., Nor, N. A. M., Taib, N. A., Ganggayah, M. D., Town, C., & Dhillon, S. K. (2019). Machine learning and deep learning approaches in breast cancer survival prediction using clinical data. *Folia biologica*, 65(5/6), 212-220.
- 4.Wu, G. G., Zhou, L. Q., Xu, J. W., Wang, J. Y., Wei, Q., Deng, Y. B., ... & Dietrich, C. F. (2019). Artificial intelligence in breast ultrasound. *World Journal of Radiology*, 11(2), 19.
- 5.Shareef, B., Xian, M., & Vakanski, A. (2020, April). Stan: Small tumor-aware network for breast ultrasound image segmentation. In 2020 IEEE 17th International Symposium on Biomedical Imaging (ISBI) (pp. 1-5). IEEE.
6. Baek, J., O'Connell, A. M., & Parker, K. J. (2022). Improving breast cancer diagnosis by incorporating raw ultrasound parameters into machine learning. *Machine Learning: Science and Technology*, 3(4), 045013.



SCAN ME

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