

# Breast Cancer Detection Using Deep Learning:

## Model Development and Validation Using Kaggle's RSNA Dataset

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# Graphical Executive Summary

## AI-Powered Breast Density Classification: A Deep Learning Approach

### The Clinical Challenge:

Why Automate Breast Density Assessment?



#### What is Breast Density?

Proportion of fibrous and glandular tissue compared to fatty tissue, visible on mammogram.

Not related to size or firmness.



#### of Women Have Dense Breasts

Dense tissue (milk glands, ducts, supportive tissue) is a significant portion of the screening population.

### The Dual Problem of High Breast Density



1) Independent risk factor for breast cancer.



2) Can mask tumors on mammograms, reducing screening sensitivity.



#### Human Assessment is Subjective

Radiologist's assessment varies, needing a consistent, automated tool for early detection.

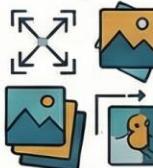
### The Pipeline:

From Mammogram to AI-Powered Classification



#### Input Data: The RSNA Dataset

Trained on RSNA Breast Imaging Dataset, using full-field digital mammography images (DICOMs to PNGs).



#### Preprocessing: Image Enhancement

Patients with implants excluded. Patient-level split for training/validation to prevent data leakage.



#### Data Prep: Cleaning and Splitting

Patients with implants excluded. Patient-level split for training/validation to prevent data leakage.



#### Preprocessing: Image Enhancement

Images resized to 224x224, normalized, and augmented (flops, rotations, contrast changes) to prevent overfitting.

#### The Model: Vision Transformer (DeiT)

Pre-trained Data-efficient Image Transformer (DeiT) with ~86M parameters used instead of traditional CNN. Classifies into four density categories (A, B, C, D).

#### Training & Optimization

Trained for 50 epochs using AdamW optimizer and CrossEntropyLoss to learn density class patterns.

### Performance & Results:

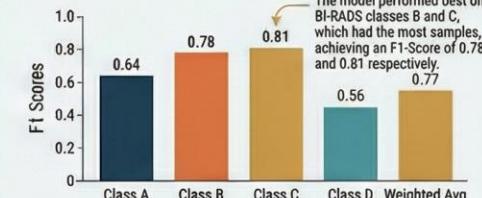
How Well Did the Model Perform?



#### Test Accuracy

Correctly classified breast density category on the hold-out test dataset with significant accuracy.

#### Highest Performance on Densely-Populated Classes



#### Performance Challenges with Minority Classes

Struggled most with Class D (densest, least common category), indicating impact of class imbalance.

Density Class	Precision	Recall	F1-Score
Class A: 0.63	0.65	0.64	Class B: 0.81
Class B: 0.76	0.79	0.78	Class C: 0.81
Class D: 0.75	0.43	0.56	Weighted Avg: 0.77   0.77   0.77

### Conclusion & Future Directions



#### A Robust & Objective AI Tool

Successfully created a pipeline using Vision Transformers to support radiologist workflow and reduce inter-reader variability.



#### Current Limitations

Key challenges: class imbalance in dataset and potential loss of fine-grained details from resizing images (224x224).



#### What's Next?

Future work includes validation on external multi-center data, adding explainability (e.g., Grad-CAM), and comparing performance against standard CNN models.



# Background & Clinical Importance

## The Leading Cause of Cancer Death in Women Worldwide

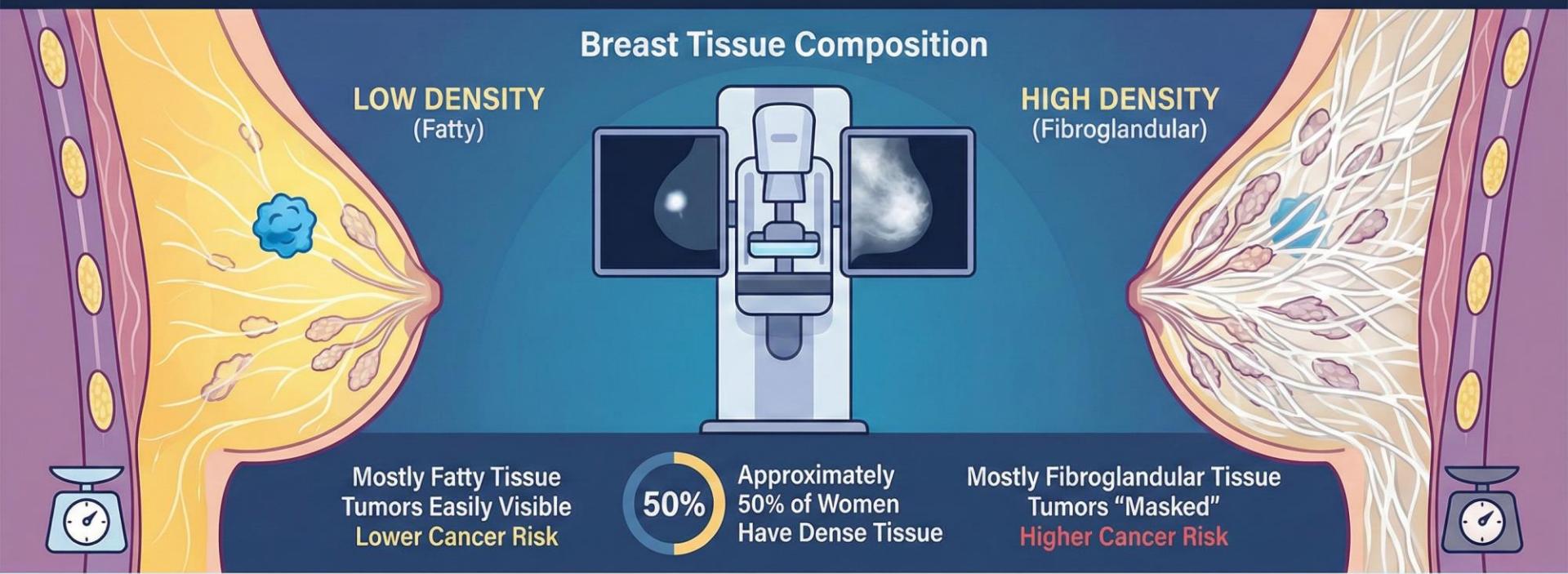
“Breast cancer has emerged as the leading malignancy threatening women’s health worldwide.”

In 2020, an estimated  
**685,000**  
deaths were attributed to  
breast cancer globally.

→ Early detection is the most effective way to reduce mortality. The 5-year survival rate for Stage 1 breast cancer is **nearly 100%**, but drops to **25%** for Stage 4.

# Background & Clinical Importance

## Understanding Breast Density: Tissue Composition & Clinical Implications



### Assessment & Factors



Assessed by  
**MAMMOGRAM ONLY**



NOT related to  
**SIZE or FIRMNESS**

### Tissue Components



Composed of:

- Milk Glands
- Ducts
- Supportive Tissue

### Clinical Importance



Crucial for  
**SCREENING &  
RISK ASSESSMENT**



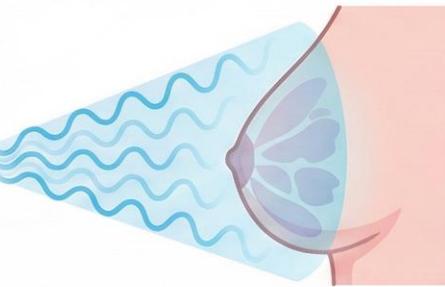


# Background & Clinical Importance

## MAMMOGRAPHY:

### Key Facts for Early Detection

#### WHAT IT IS



**Specialized Medical Imaging Technique.**  
Uses low-energy X-rays to examine breast tissue.



#### PRIMARY GOAL

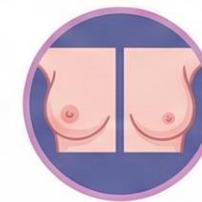
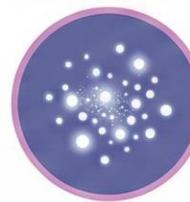


MASSES

MICROCALCIFICATIONS

ASYMMETRIES

DISTORTIONS



Identifies characteristic abnormalities in breast tissue.

#### PRIMARY GOAL



**Early Detection of Breast Cancer.**  
Aims to diagnose before symptoms appear.

#### ACCURACY & IMPORTANCE



**85-90%  
ACCURATE**

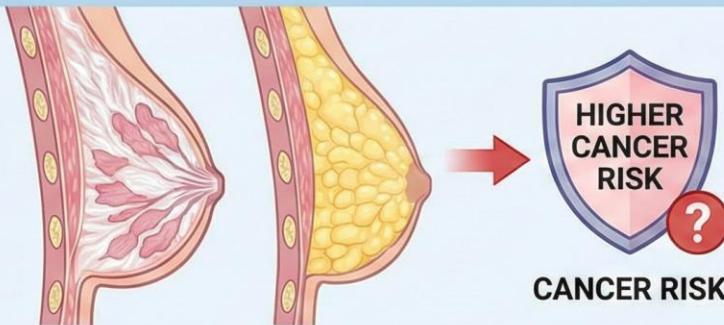


Crucial for screening. Significantly improves treatment outcomes through early diagnosis.



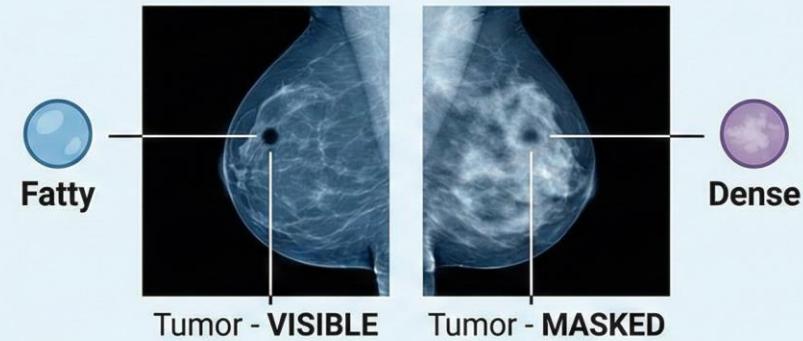
# Background & Clinical Importance

## 1. INDEPENDENT RISK FACTOR



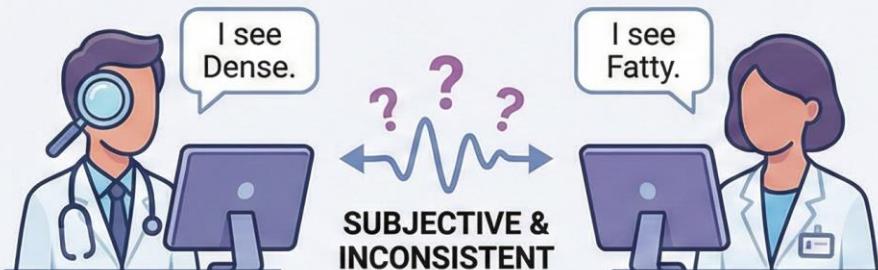
Dense breast tissue is linked to an increased likelihood of developing cancer.

## 2. DECREASED MAMMOGRAPHY SENSITIVITY



High density can hide lesions, lowering detection rates.

## 3. RADIOLOGIST ASSESSMENT VARIABILITY



Human interpretation varies, leading to inconsistent classification.

## 4. DEEP LEARNING SOLUTION



AI algorithms improve consistency and aid in early identification.



# Background & Clinical Importance

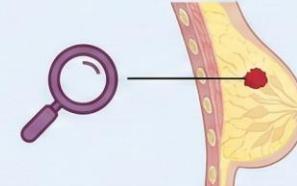
## AUTOMATING BREAST DENSITY CLASSIFICATION: A DEEP LEARNING APPROACH (ViTs)

### THE CHALLENGE: BREAST DENSITY & RISK



#### FATTY TISSUE (Low Density)

- Clear Visibility
- Lower Masking Risk



#### DENSE TISSUE (High Density)

- Independent Cancer Risk Factor
- Tumors Hard to Detect

### PROJECT GOAL: FROM CNNs TO VISION TRANSFORMERS (ViTs)



#### TRADITIONAL CNNs

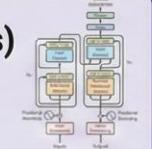
~~Manual Assessment~~

Limited by Local Features



#### VISION TRANSFORMERS (ViTs)

- Captures Global Context
- Enhanced Pattern Recognition



### CLINICAL VALUE: CONSISTENT, OBJECTIVE, ACTIONABLE



AUTOMATED ViT ASSESSMENT



CONSISTENT,  
OBJECTIVE METRIC



SUPPLEMENTAL SCREENING  
(Ultrasound/MRI)

Identify High-Risk Patients for Follow-up



IMPROVED PATIENT OUTCOMES

Early Detection & Personalized Care

# Dataset Description (RSNA)

## RSNA Breast Density Dataset: From Source to AI-Ready Data



Source: RSNA Breast Cancer Detection Competition

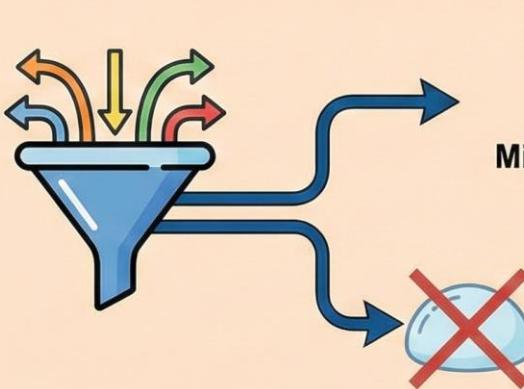


Target Variable: Breast Density Categories (BI-RADS)

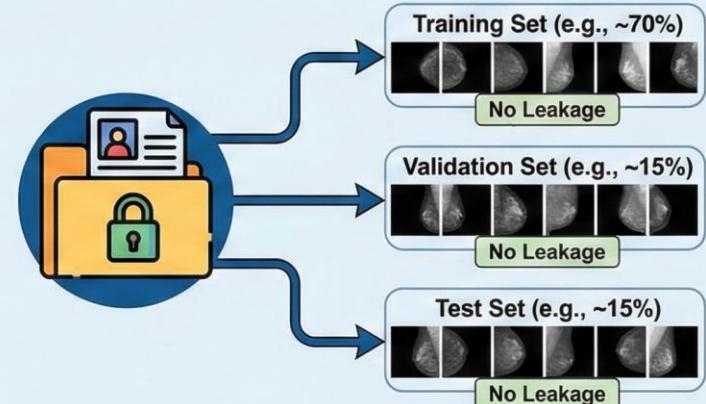
A	B	C	D
Almost Entirely Fatty	Scattered Fibroglandular	Heterogeneously Dense	Extremely Dense

Label Encoded: 0 1 2 3

### Cleaning & Filtering Process

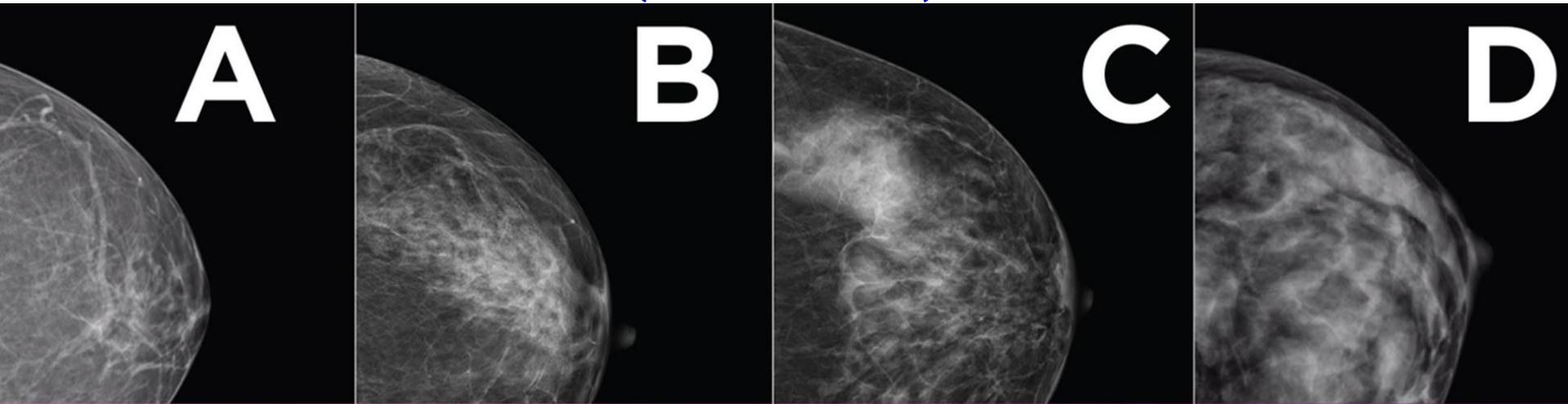


### Data Splitting Strategy: Stratified by Patient ID



# Dataset Description (RSNA)

## Breast Imaging Reporting and Data System (BI-RADS)



### Almost Entirely Fatty

There is almost no dense tissue which makes abnormalities easy to detect.

### Scattered Fibroglandular Densities

Scattered areas of density but majority of tissue is fatty.

### Heterogeneously Dense

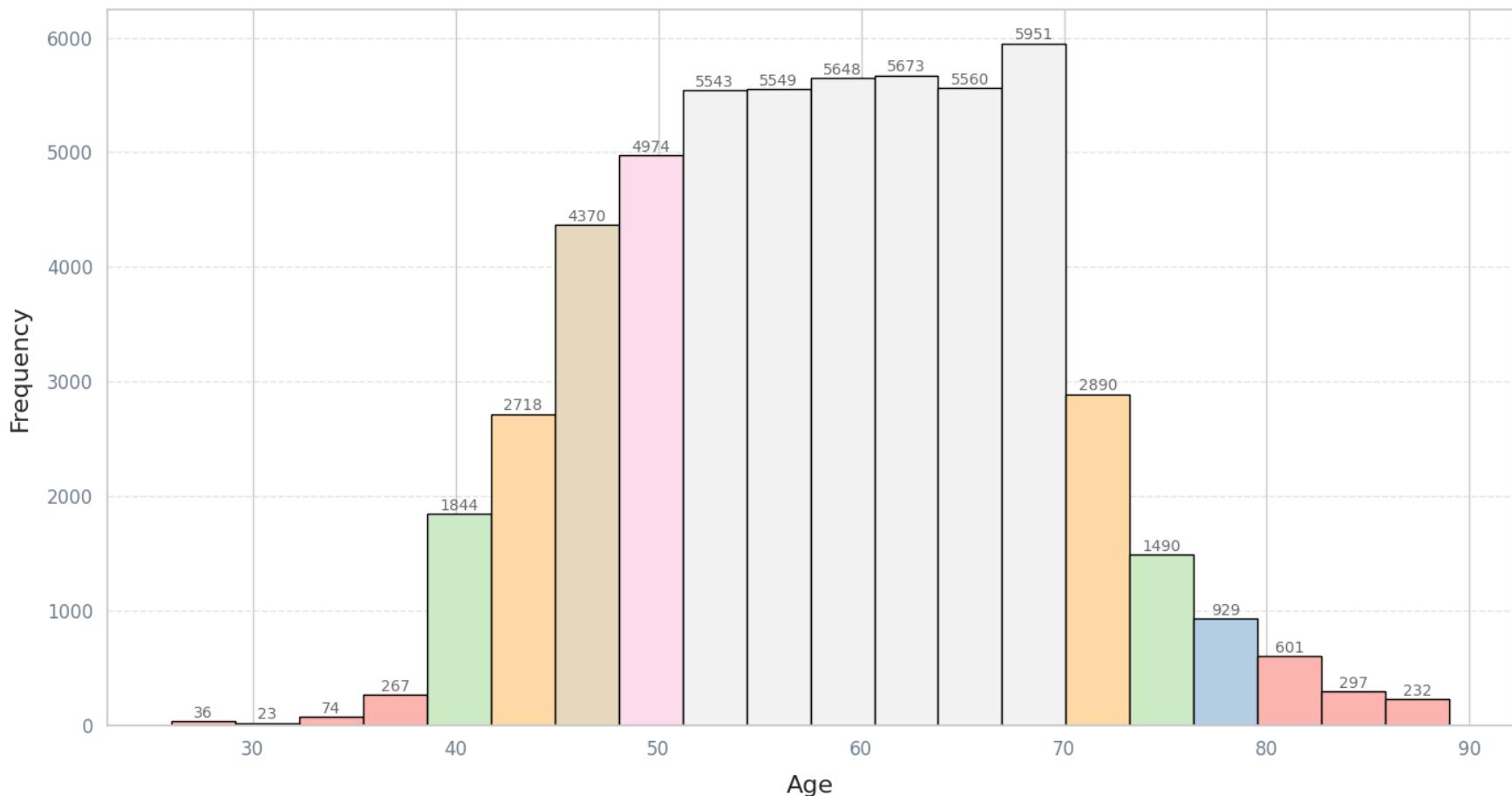
More than half the breast is dense tissue.

### Extremely Dense

Nearly all of the tissue is dense.

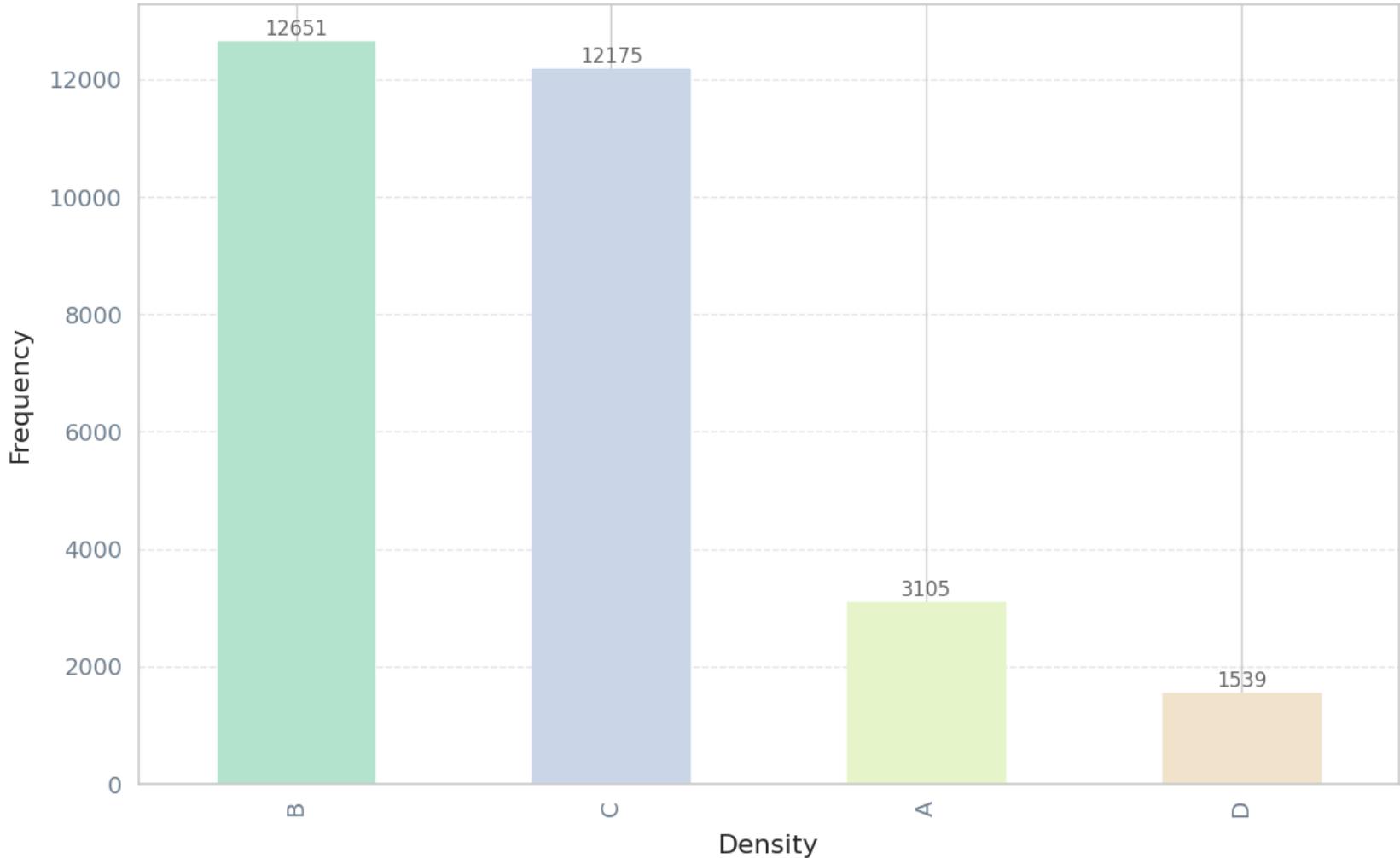
# Dataset Description (RSNA)

Age Distribution in Dataset



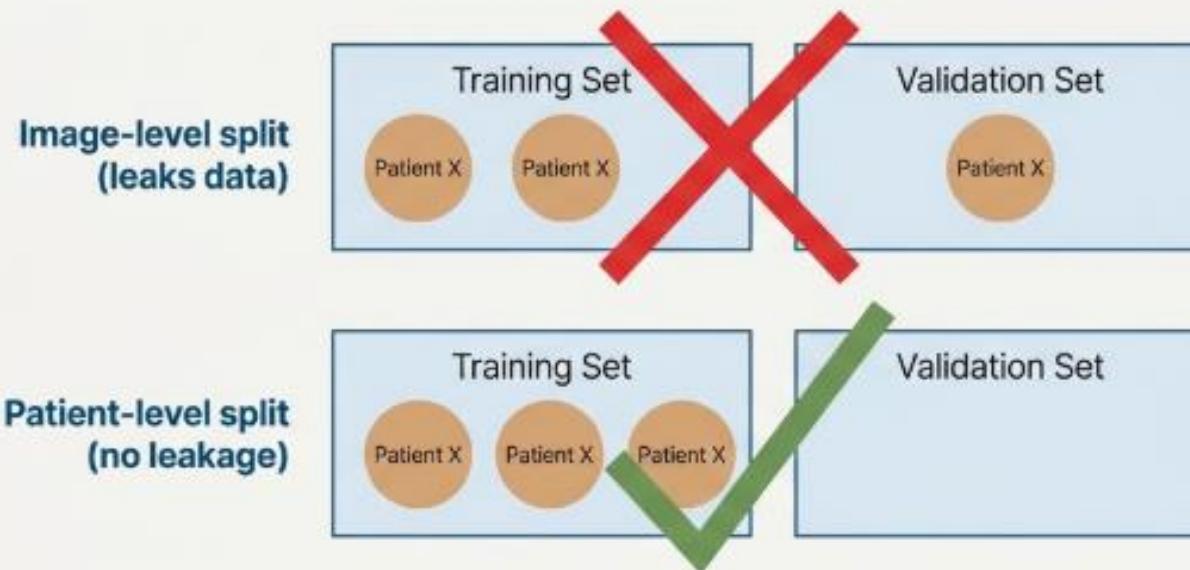
# Dataset Description (RSNA)

## Distribution of Density in Dataset



# Dataset Description (RSNA)

## A Patient-Level Stratified Split to Ensure Model Integrity

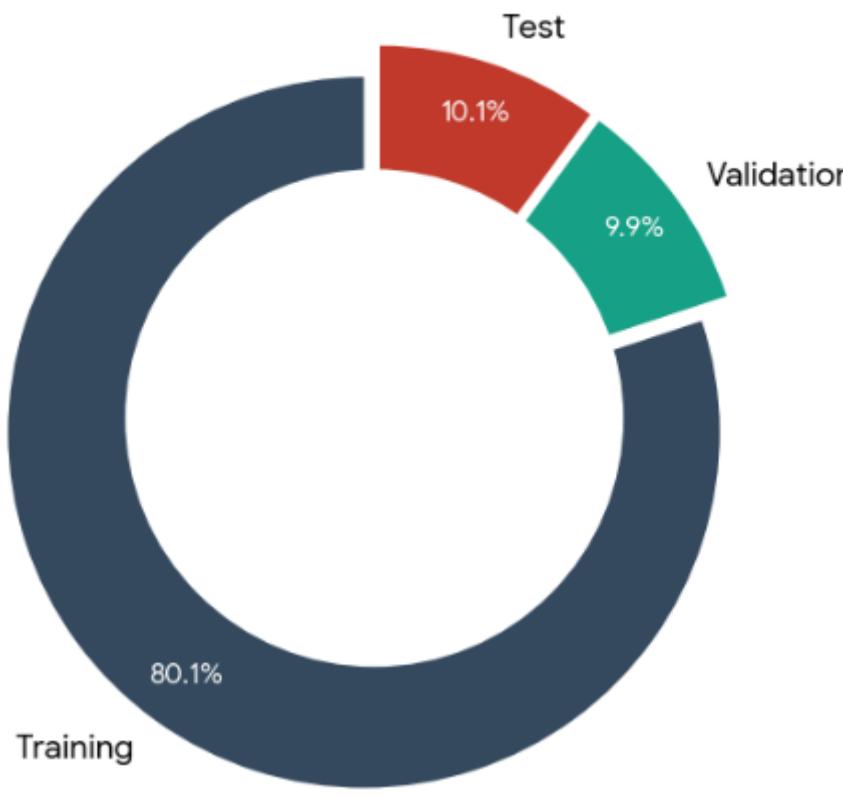


To prevent the model from learning patient-specific features, all images from a single patient were strictly confined to one set (Training, Validation, or Test).

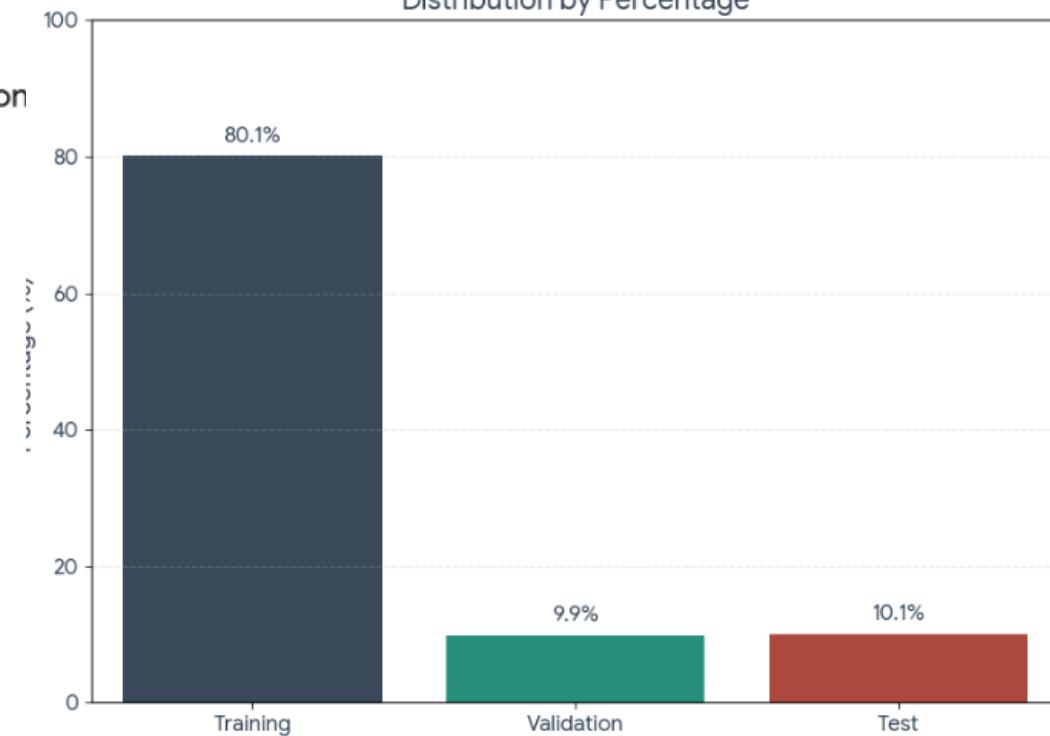
# Dataset Description (RSNA)

## Dataset Split Distribution

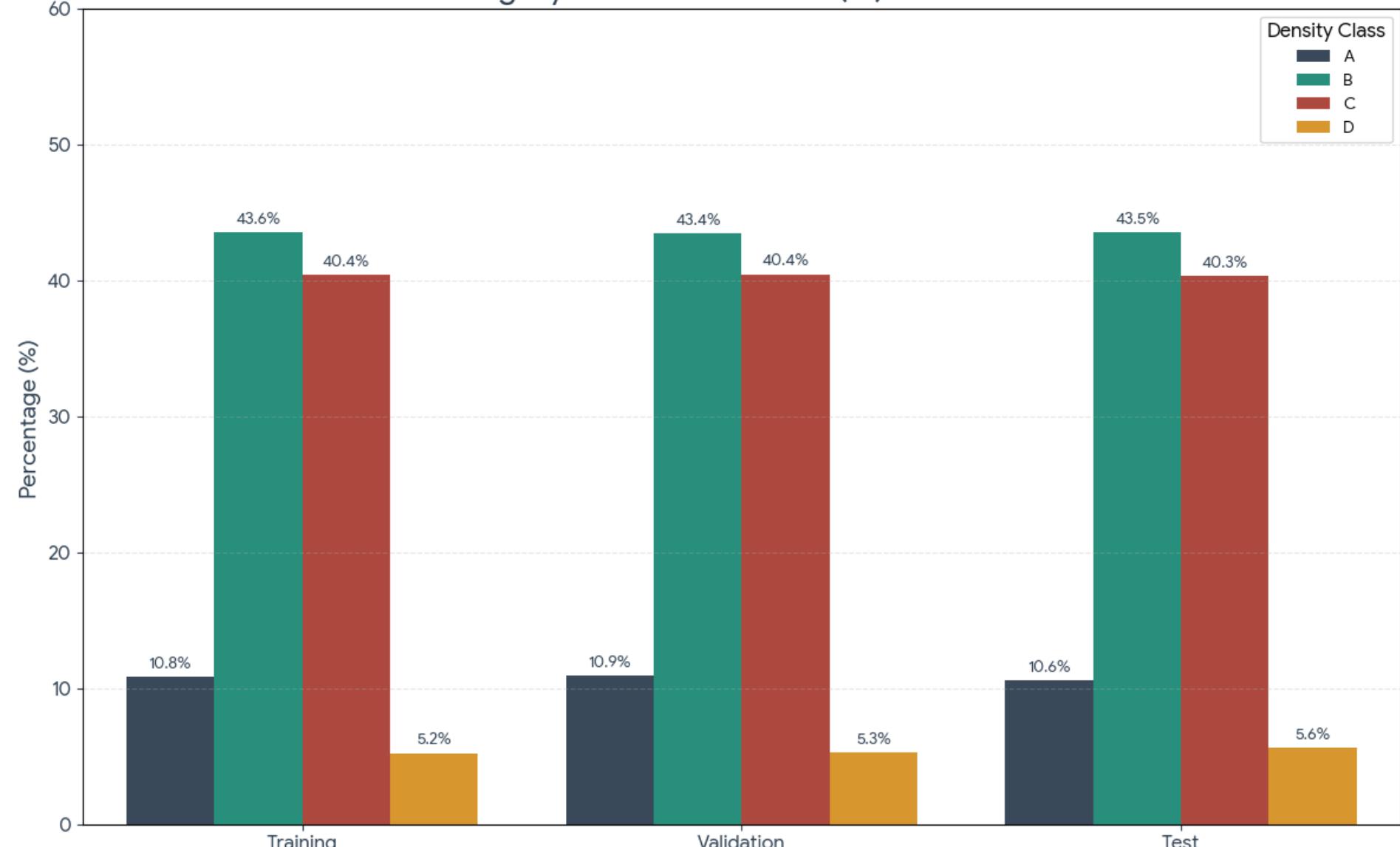
Ratio (Donut)



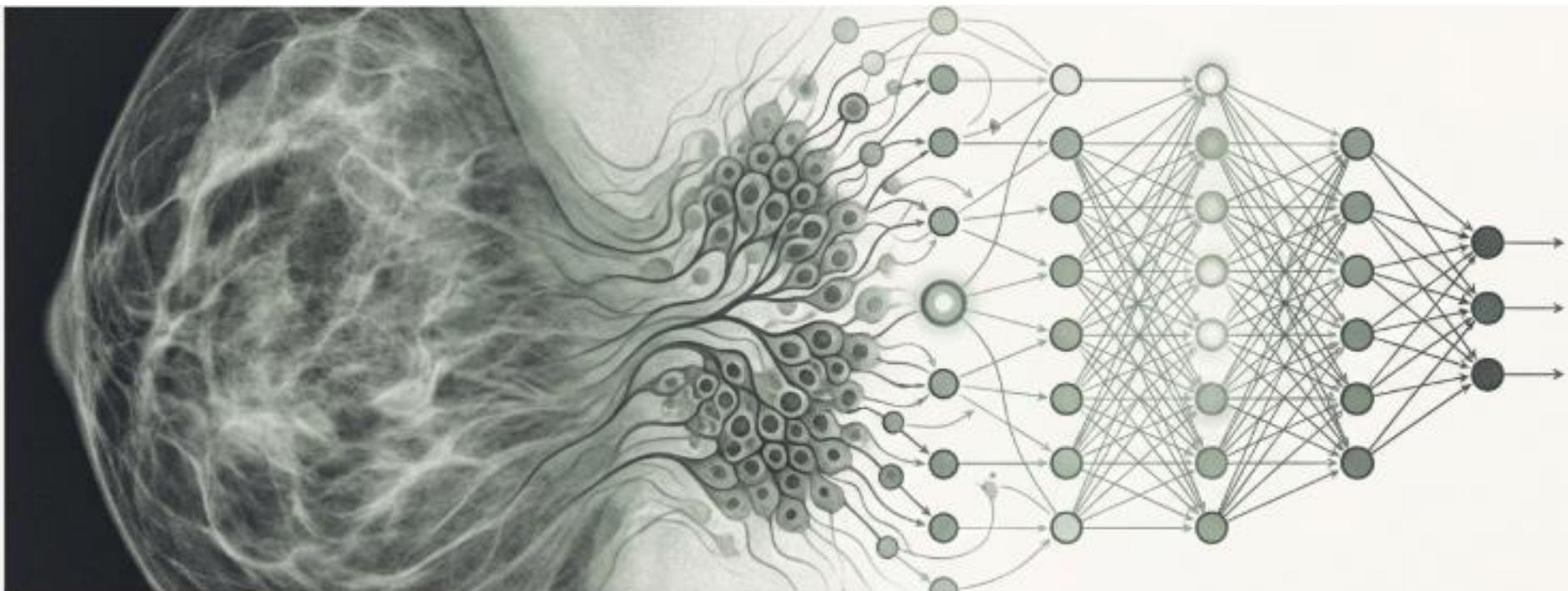
Distribution by Percentage



## Category-wise Distribution (%) in Each Set

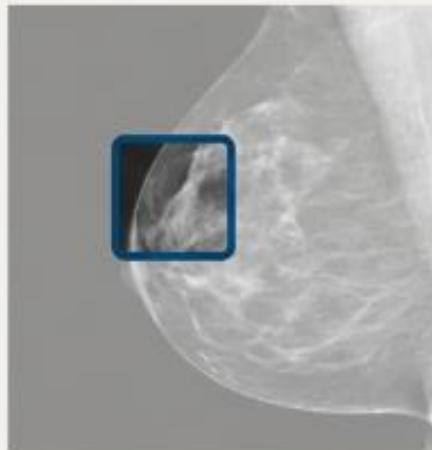


# Model Architecture

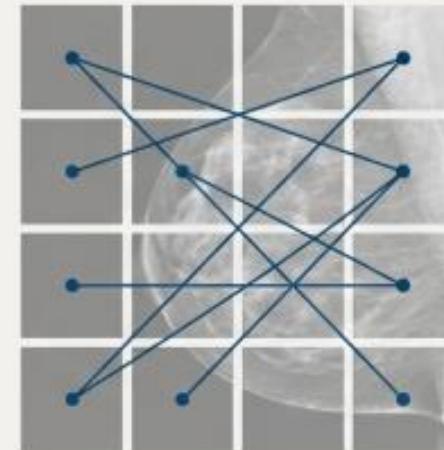


# Model Architecture

**CNN: Focus on Local Features**



**ViT: Understands Global Relationships**



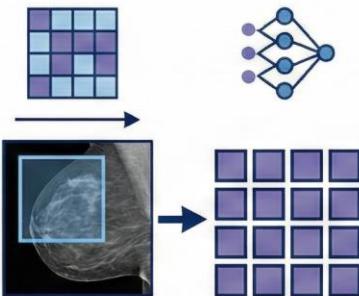
Unlike CNNs, Vision Transformers process an image's patches in parallel, allowing the model to weigh the importance of all regions simultaneously to understand the overall tissue structure.

# Model Architecture

## MODEL ARCHITECTURE: Data-efficient Image Transformer (DeiT) for Breast Density

### 1. DeiT FOUNDATION

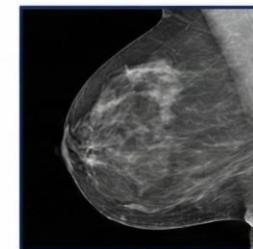
Small-Dataset Optimized Vision Transformer



CNNs  
(Convolutions)      ViT/DeiT  
(Patches & Attention)

Effectively trains on smaller datasets than original ViT.

### 2. MECHANISM: PATCHES TO TRANSFORMERS



16x16 PATCHES

LINEAR EMBEDDING + POSITION EMBEDDINGS

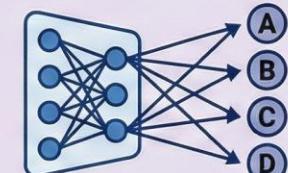
TRANSFORMER ENCODER  
(Multi-Head Attention & MLP)

Splits image into fixed patches, embeds them with position, then processes via standard Transformer encoder, unlike CNNs.

### 3. PROJECT CUSTOMIZATION

**BASE MODEL:**  
`deit_base_patch16_224`  
(Pretrained)

**CUSTOM HEAD**  
(Replaces Original Classification)

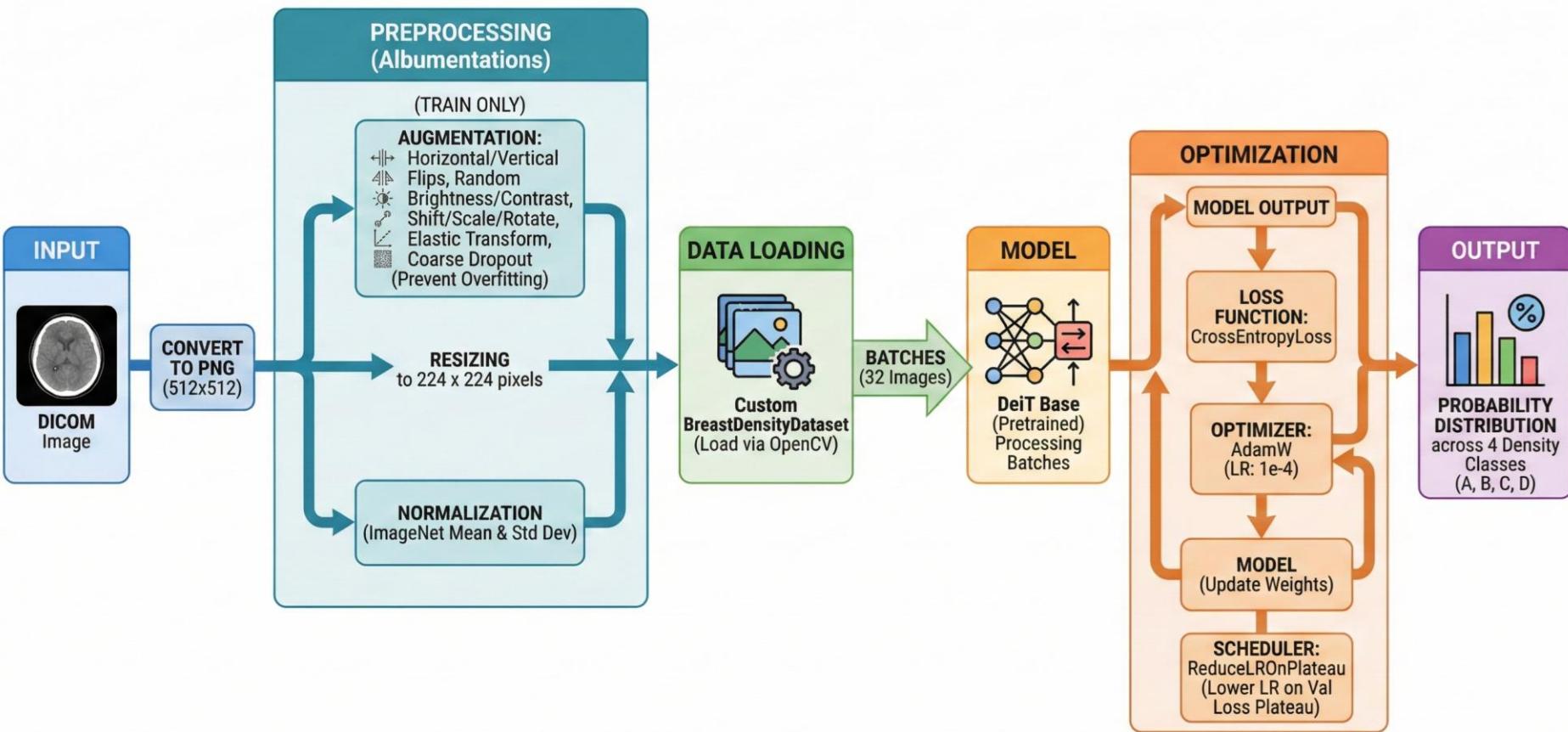


`nn.Linear Layer`  
(4 Classes: Density A, B, C, D)

**TOTAL PARAMETERS:**   
**~86 MILLION**  
Trainable Weights

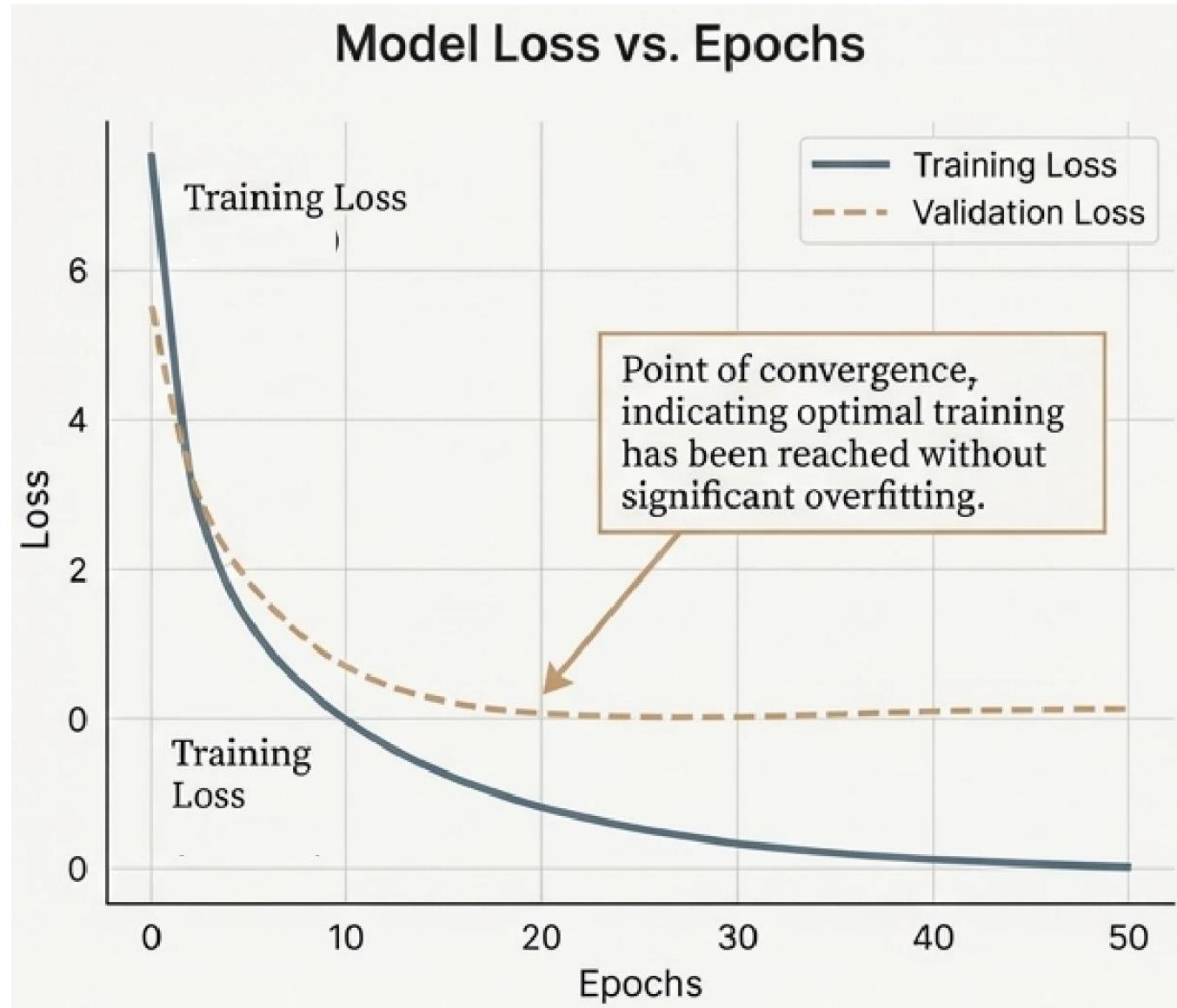


# Deep Learning Pipeline Flowchart



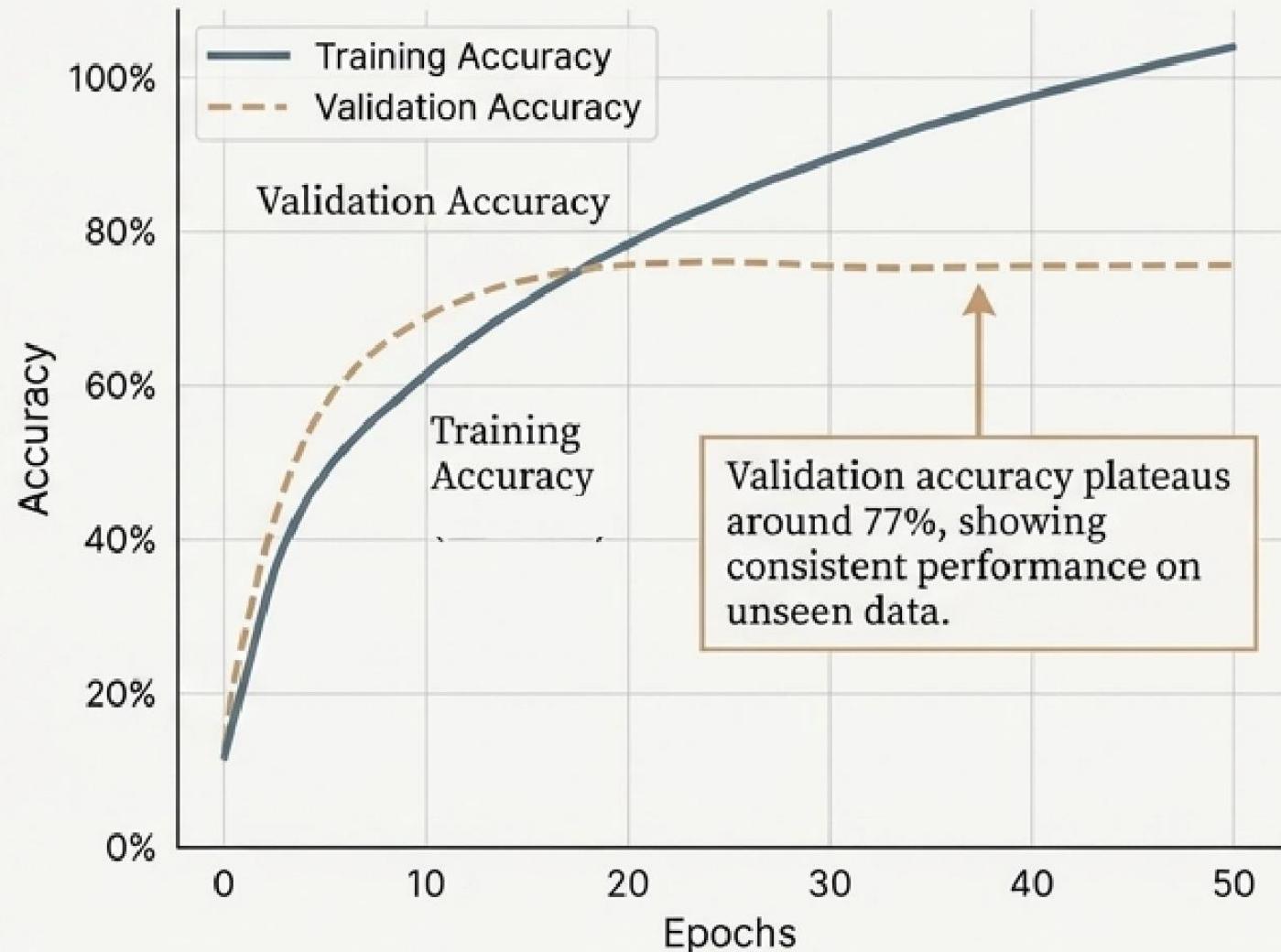


# Results



# Results

## Model Accuracy vs. Epochs



# Results

Density Class	Precision	Recall	F1-Score	Support
Class A	0.63	0.65	0.64	301
Class B	0.76	0.79	0.78	1,198
Class C	0.81	0.81	0.81	1,116
Class D	0.75	0.45	0.56	145
Accuracy			<b>0.77</b>	<b>2,760</b>
Macro Avg	0.74	0.68	0.70	2,760
Weighted Avg	0.77	0.77	0.77	2,760

**Support** refers to the **number of actual occurrences** of each class in the validation dataset

$$\text{Macro Avg} = \frac{\text{Score}(A) + \text{Score}(B) + \text{Score}(C) + \text{Score}(D)}{4}$$

$$\text{Weighted Avg} = \frac{(\text{Score}_A \times 301) + (\text{Score}_B \times 1198) + (\text{Score}_C \times 1116) + (\text{Score}_D \times 145)}{2760}$$



# Results

**The Model Achieves 77% Weighted Average Accuracy on the Validation Set**

Density Class	Precision	Recall	F1-Score	Support (N)
Class A	0.63	0.65	0.64	301
Class B	0.76	0.79	0.78	1,198
Class C	0.81	0.81	0.81	1,116
Class D	0.75	0.45	0.56	145
<b>Weighted Avg</b>	<b>0.77</b>	<b>0.77</b>	<b>0.77</b>	<b>2,760</b>

## Key Insight

Excellent performance is observed on the most common classes (B and C). Class C. The lower recall (0.45) for Class D is a key area for improvement, likely due to the low number of samples (145) and its inherent visual similarity to Class C.



# Results

Density Class	Precision	Recall	F1-Score	Support
Class A	0.63	0.65	0.64	301
Class B	0.76	0.79	0.78	1,198
Class C	0.81	0.81	0.81	1,116
Class D	0.75	0.45	0.56	145
<b>Weighted Avg</b>	<b>0.77</b>	<b>0.77</b>	<b>0.77</b>	<b>2,760</b>

## High Performance

Excellent F1-scores for the most common classes, B and C, demonstrating robustness where it matters most.

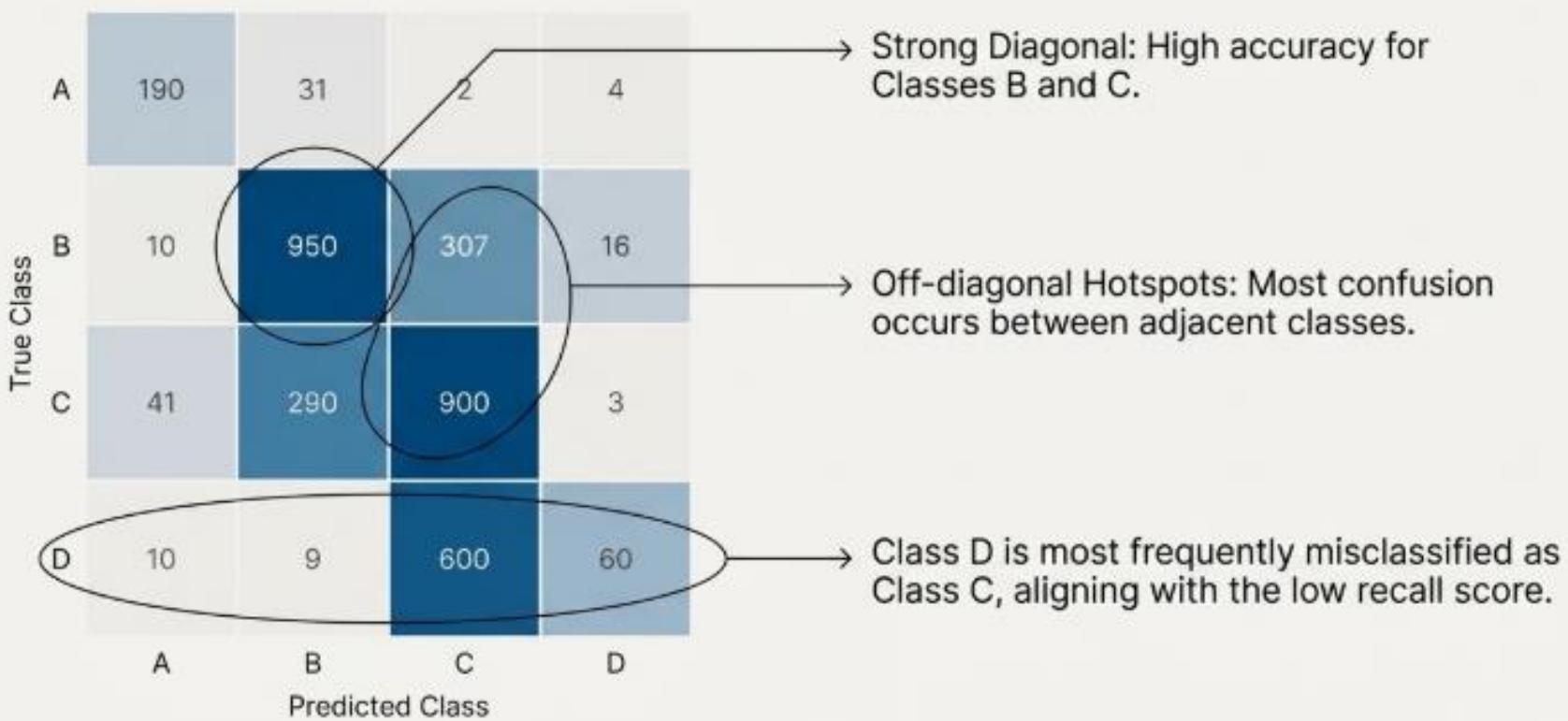
## Imbalance Challenge

Lower recall (0.45) for Class D highlights the challenge of predicting the least frequent class, a known issue in imbalanced datasets.



# Results

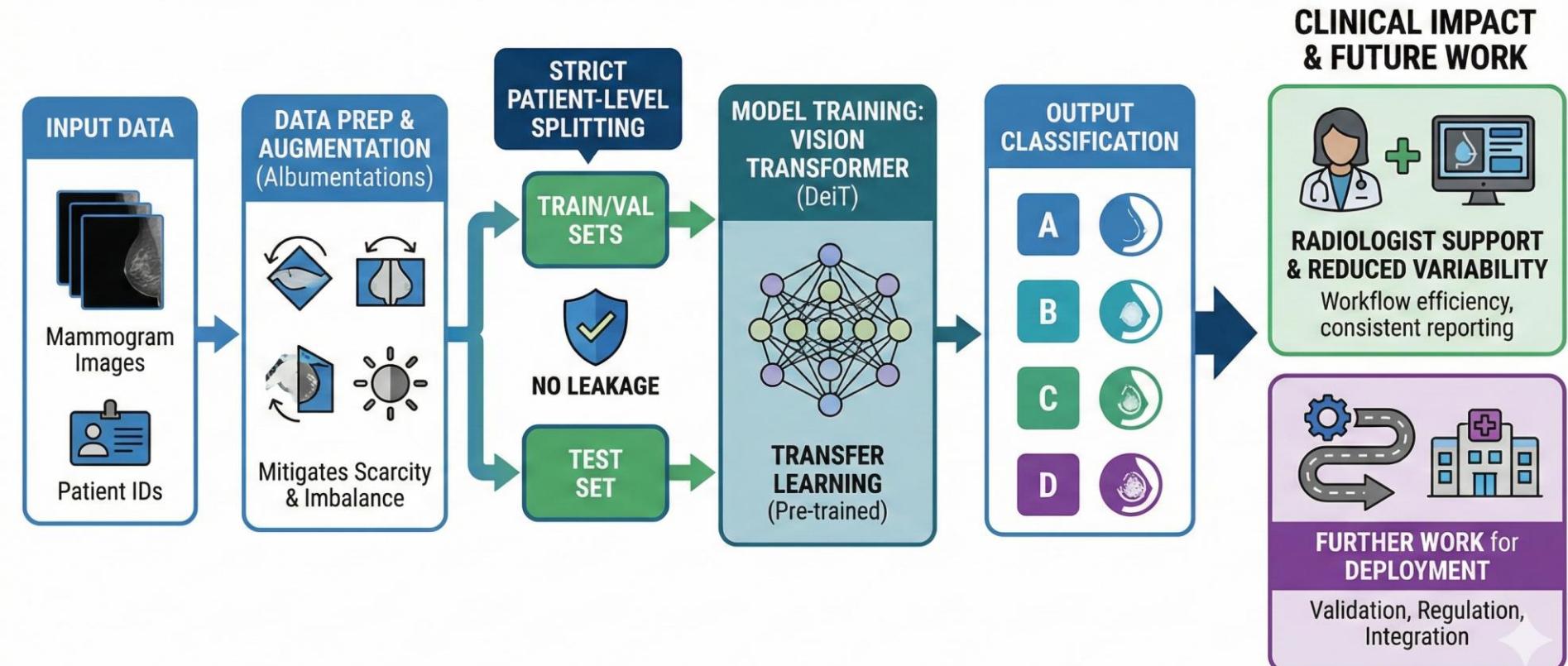
## The Confusion Matrix Reveals Misclassification Patterns





# Conclusion

## ROBUST BREAST DENSITY CLASSIFICATION PIPELINE with VISION TRANSFORMERS

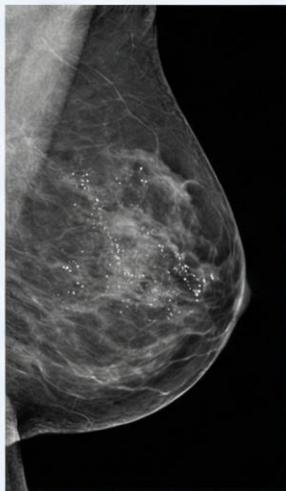




# Limitations & Future Work

## PROJECT LIMITATIONS & FUTURE WORK FOR BREAST DENSITY CLASSIFICATION

### LIMITATION 1: RESOLUTION LOSS



FINE DETAILS LOST

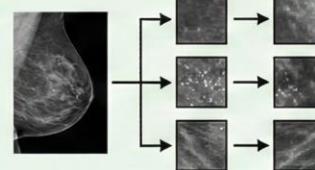


Resized  
(224x224 Input)

Original  
(High-Res Details)

Images resized to  
224x224 for DeiT.  
Microcalcifications  
may be lost.

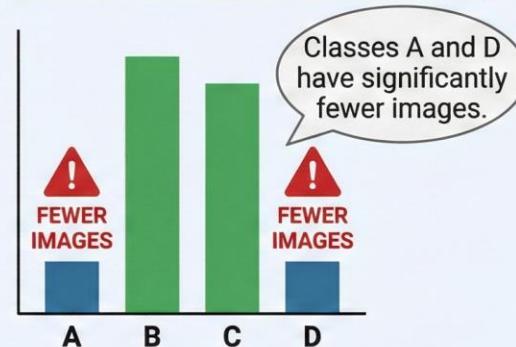
#### FUTURE WORK



HIGH-RESOLUTION /  
PATCH-BASED PROCESSING

✓ Preserve fine details,  
improve accuracy.

### LIMITATION 2: CLASS IMBALANCE



Classes A and D  
have significantly  
fewer images.

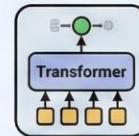
#### FUTURE WORK



Implement Weighted Random  
Sampling or Class-Weighted  
Loss functions.

✓ Balance dataset for  
better learning.

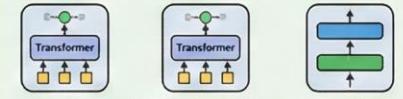
### LIMITATION 3: MODEL COMPARISON



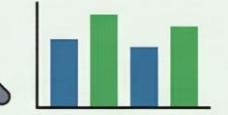
DeiT  
(Sole Focus)



#### FUTURE WORK



DeiT      EfficientNet      ResNet



#### PERFORMANCE BENCHMARK

Compare against CNN baselines  
(EfficientNet, ResNet).

✓ Validate Transformer  
superiority for this task.



# References

- RSNA Breast Imaging Dataset.
- Touvron, H., et al. "Training data-efficient image transformers & distillation through attention." (2020).