

# 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.

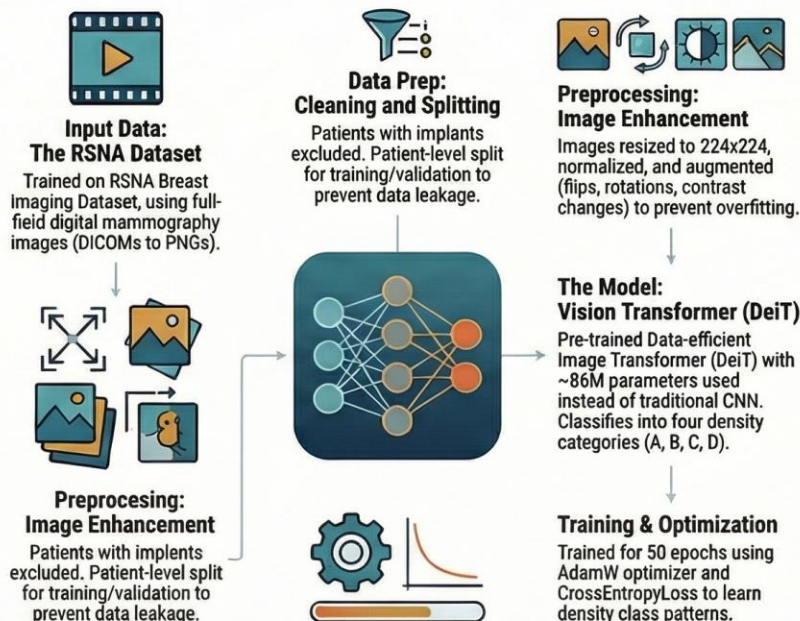


#### Human Assessment is Subjective

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

### The Pipeline:

From Mammogram to AI-Powered Classification



### Performance & Results:

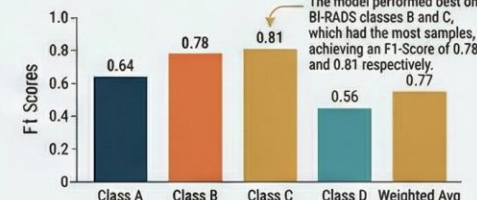
How Well Did the Model Perform?



#### 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	0.81   0.81
Class B: 0.76	0.79   0.78	Class C: 0.81	0.81   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.

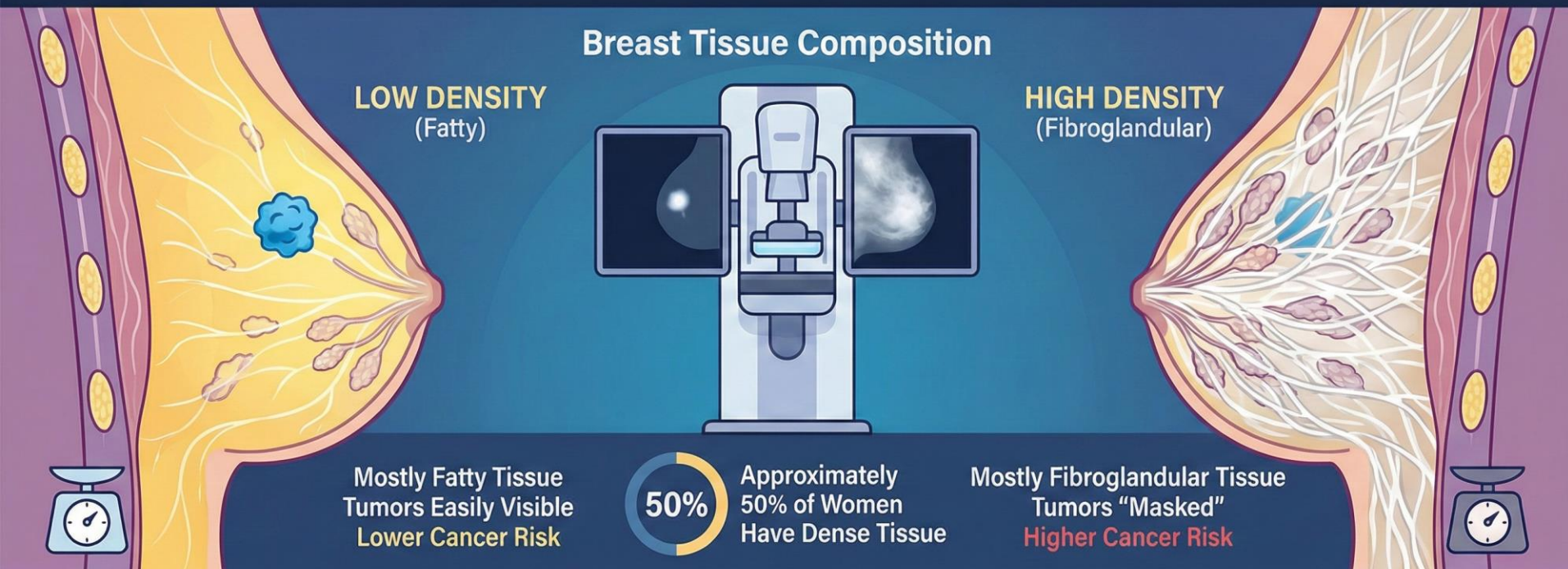


→ **Early detection** is the most effective way to reduce mortality. The 5-year survival rate for Stage 1 breast cancer is **nearly 100%**, but drops to **25%** for Stage 4.



# 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



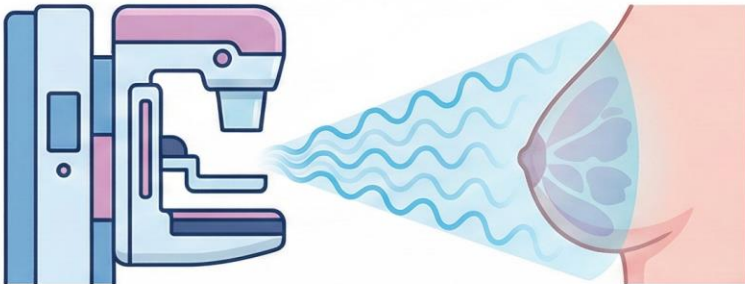
Crucial for  
SCREENING &  
RISK ASSESSMENT



# 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

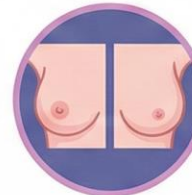
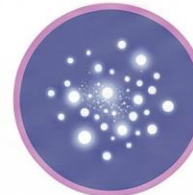


MASSES

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**

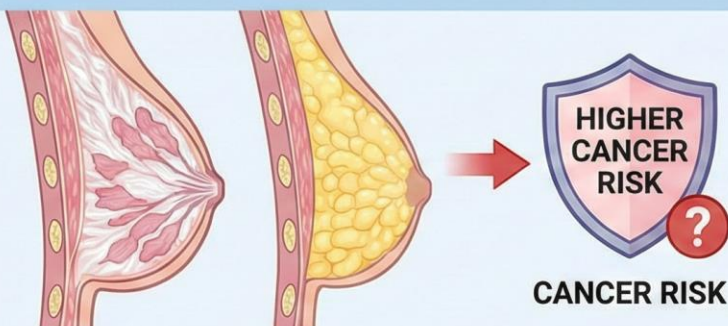


Crucial for screening. Significantly improves treatment outcomes through early diagnosis.



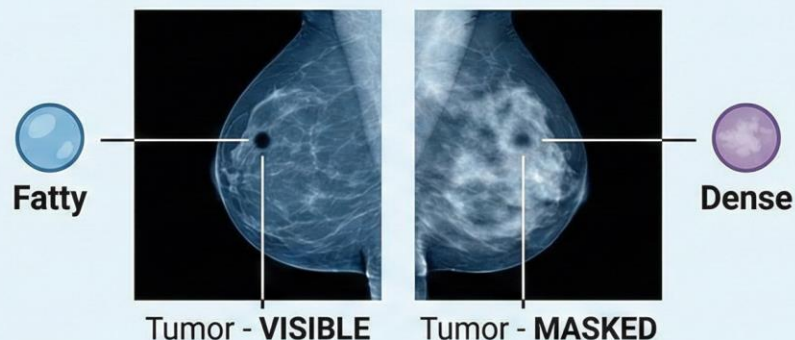
# Background & Clinical Importance

## 1. INDEPENDENT RISK FACTOR



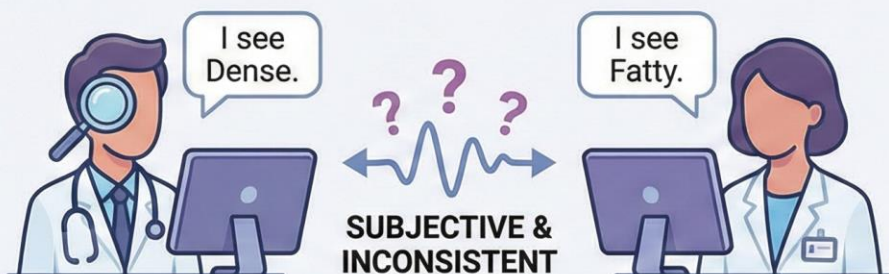
Dense breast tissue is linked to an increased likelihood of developing cancer.

## 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

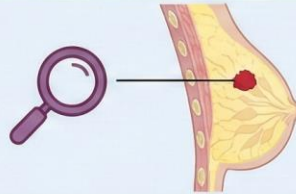
## AUTOMATING BREAST DENSITY CLASSIFICATION: A DEEP LEARNING APPROACH (ViTs)

### THE CHALLENGE: BREAST DENSITY & RISK



#### FATTY TISSUE (Low Density)

- Clear Visibility
- Lower Masking Risk



MASKING EFFECT:  
Hides Cancers

#### 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



Missing Values Removed



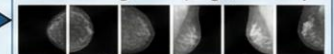
Patients with Implants Excluded (implant == 1)



### Data Splitting Strategy: Stratified by Patient ID

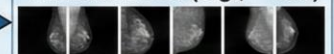


Training Set (e.g., ~70%)



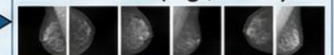
No Leakage

Validation Set (e.g., ~15%)



No Leakage

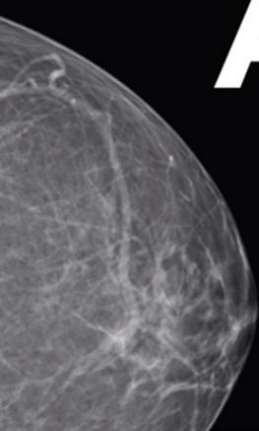
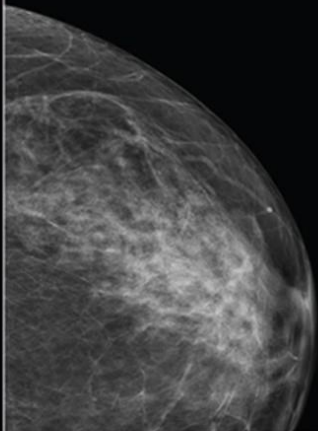
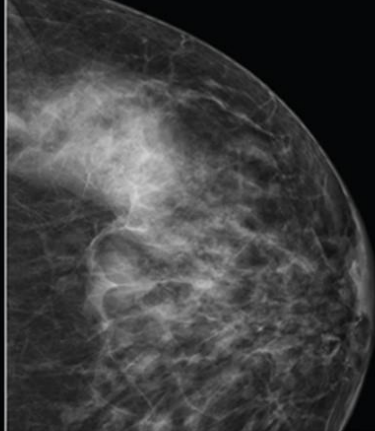
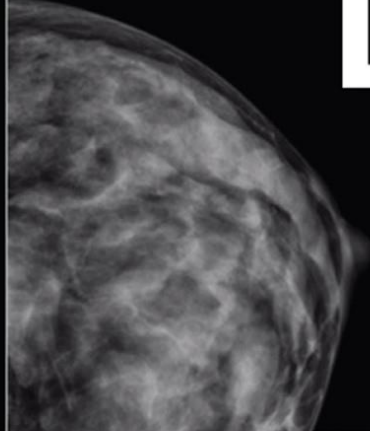
Test Set (e.g., ~15%)



No Leakage

# Dataset Description (RSNA)

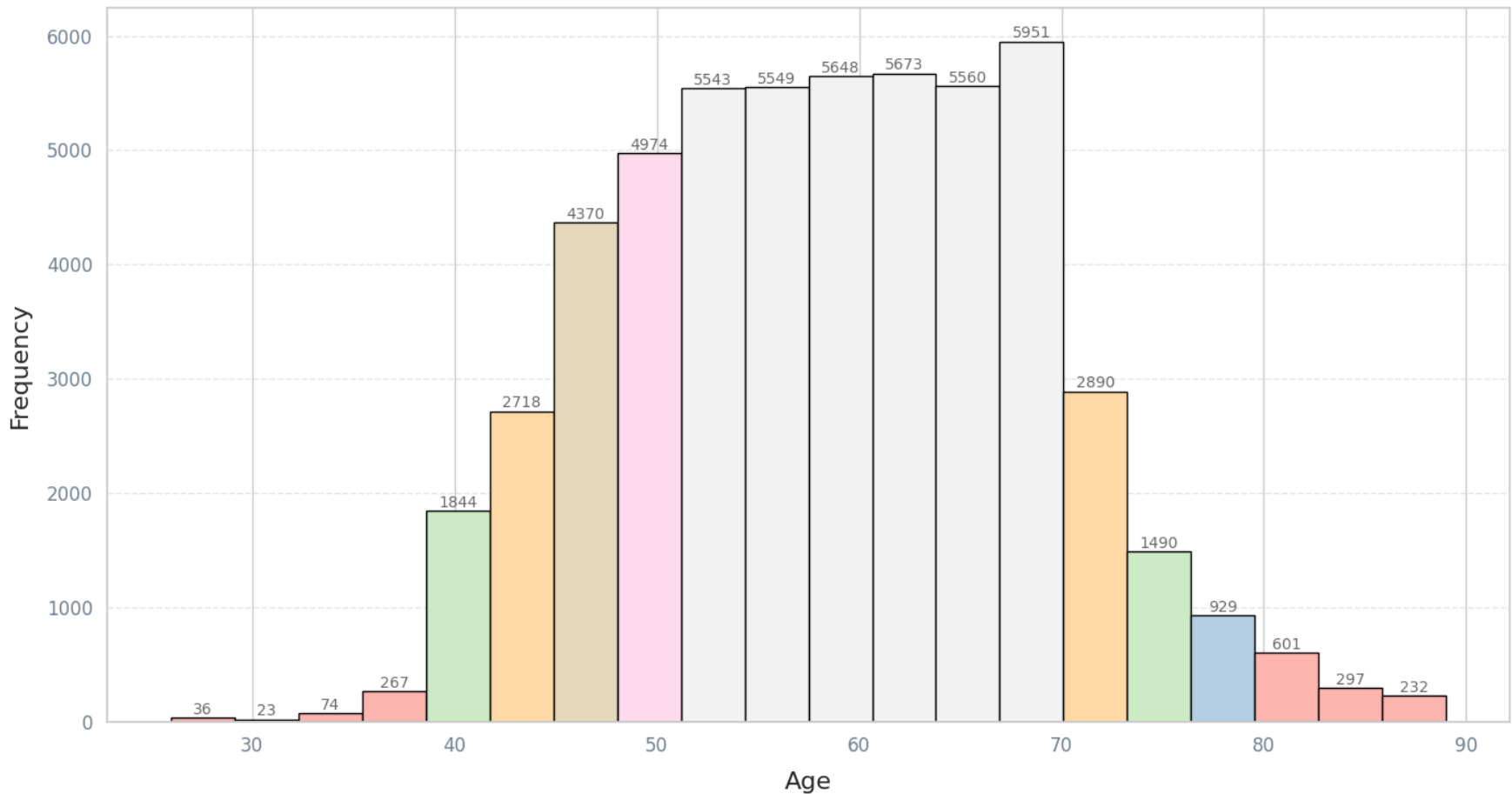
## Breast Imaging Reporting and Data System (BI-RADS)

 <b>A</b>	 <b>B</b>	 <b>C</b>	 <b>D</b>
<p><b>Almost Entirely Fatty</b></p> <p>There is almost no dense tissue which makes abnormalities easy to detect.</p>	<p><b>Scattered Fibroglandular Densities</b></p> <p>Scattered areas of density but majority of tissue is fatty.</p>	<p><b>Heterogeneously Dense</b></p> <p>More than half the breast is dense tissue.</p>	<p><b>Extremely Dense</b></p> <p>Nearly all of the tissue is dense.</p>



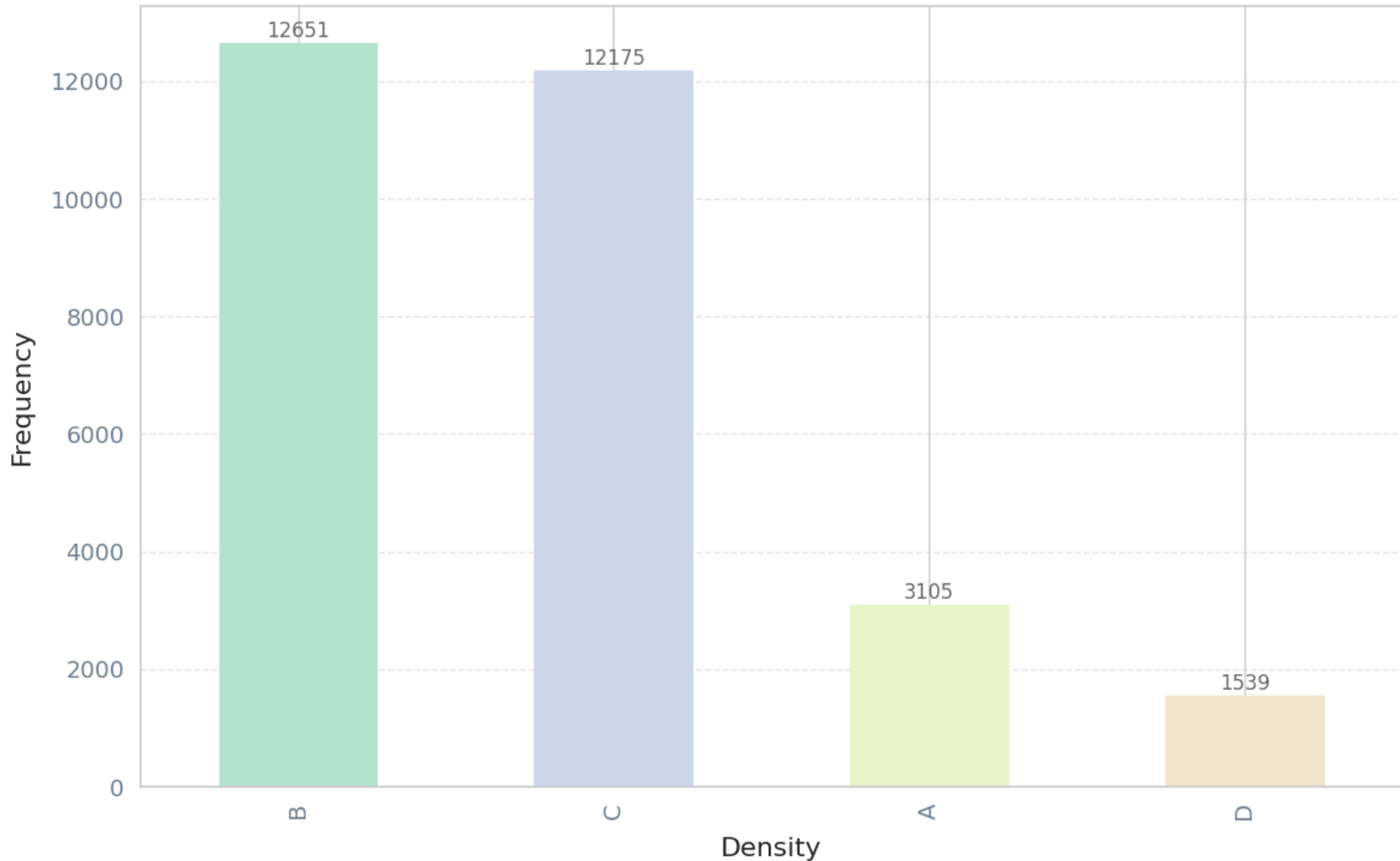
# Dataset Description (RSNA)

**Age Distribution in Dataset**



# Dataset Description (RSNA)

## Distribution of Density in Dataset





# Dataset Description (RSNA)

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

Image-level split  
(leaks data)



Patient-level split  
(no leakage)

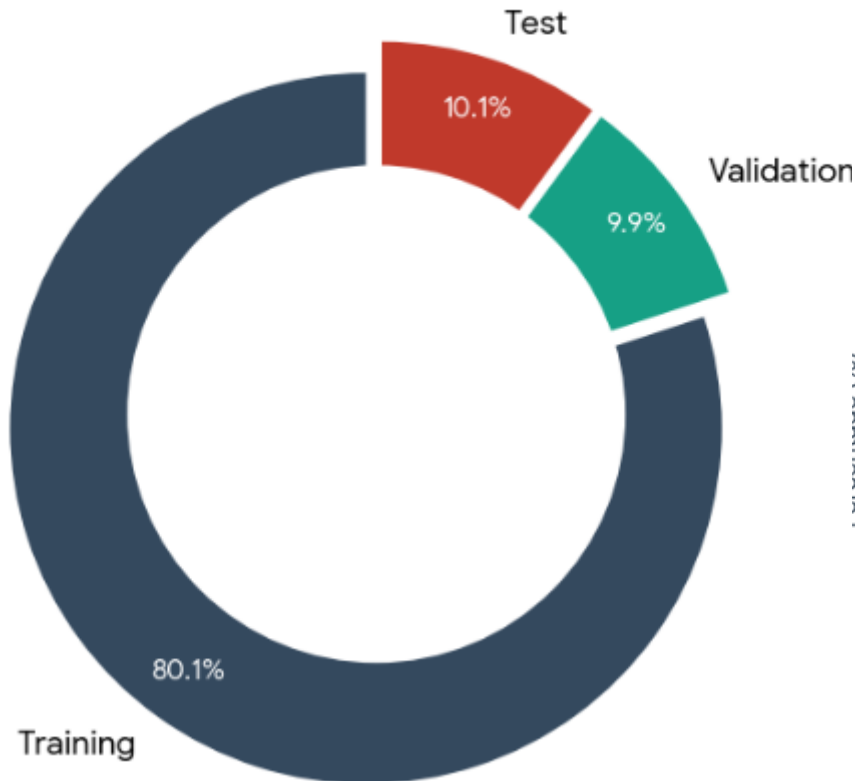


To prevent the model from learning patient-specific features, all images from a single patient were strictly confined to one set (Training, Validation, or Test).

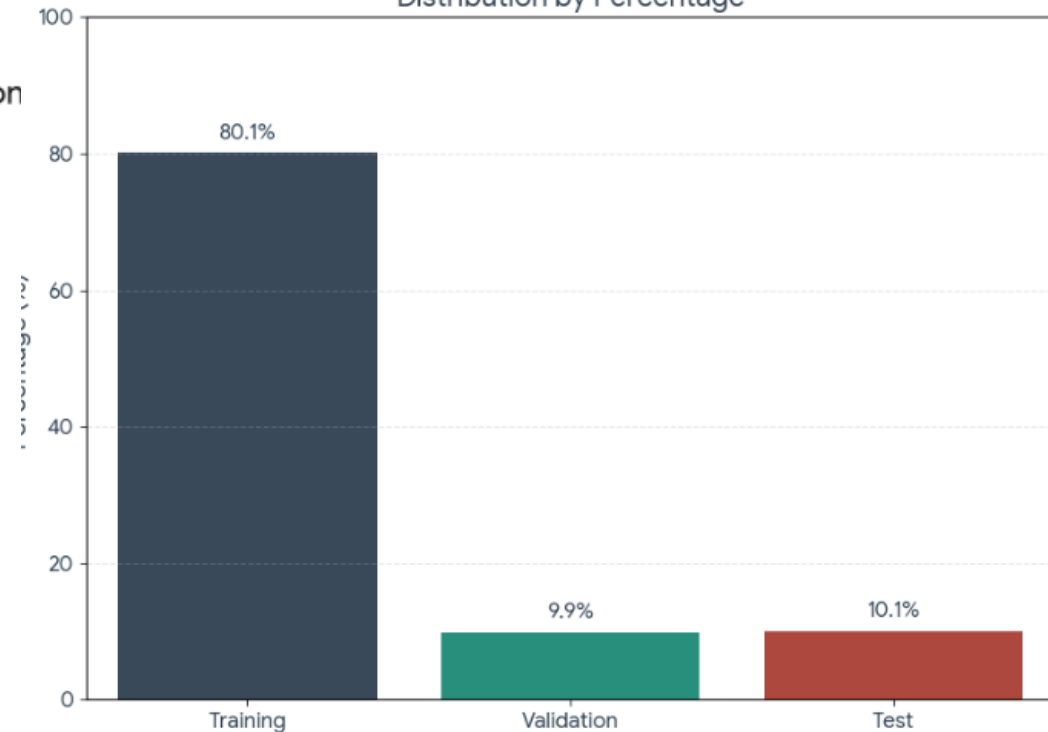
# Dataset Description (RSNA)

## Dataset Split Distribution

Ratio (Donut)

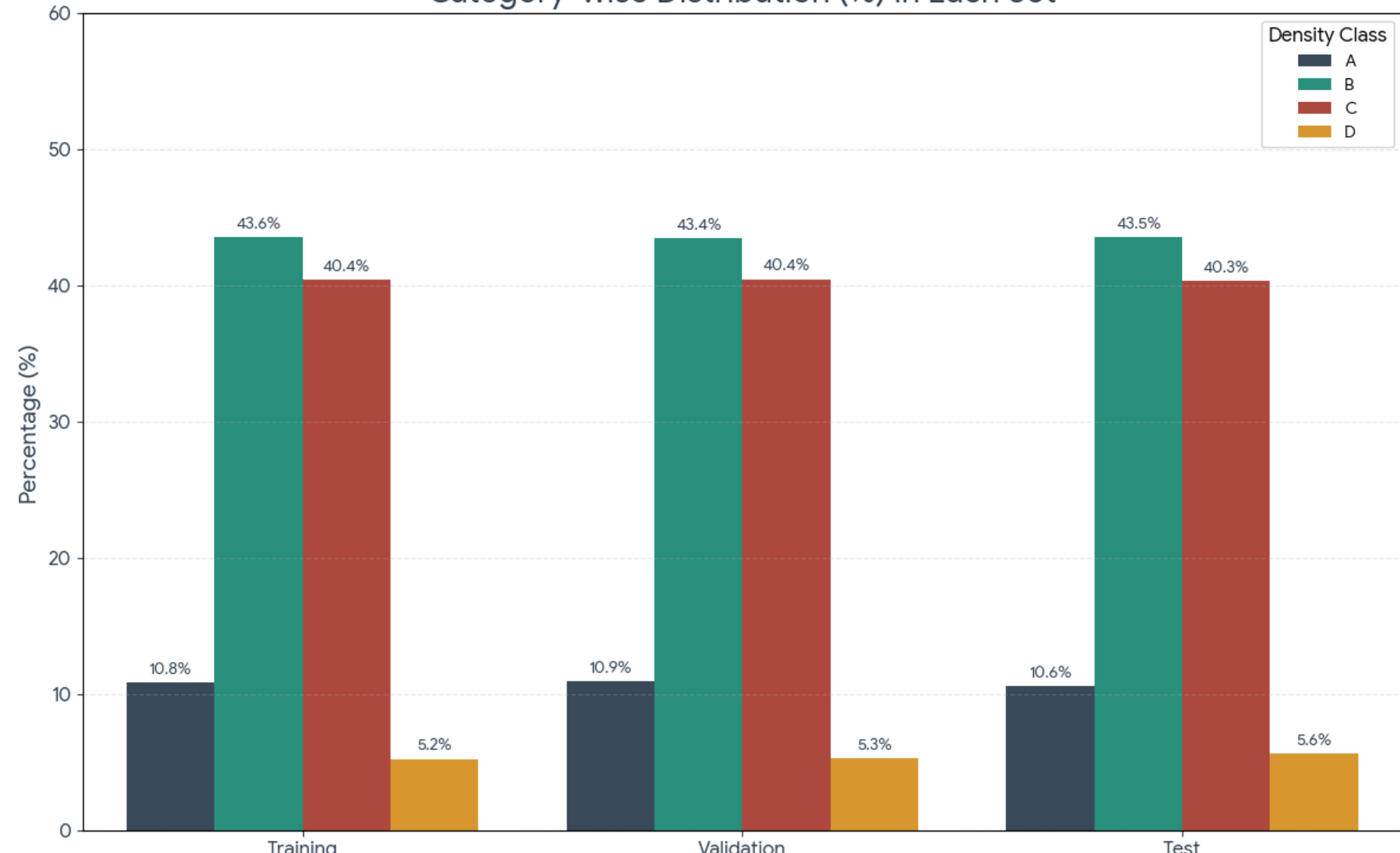


Distribution by Percentage

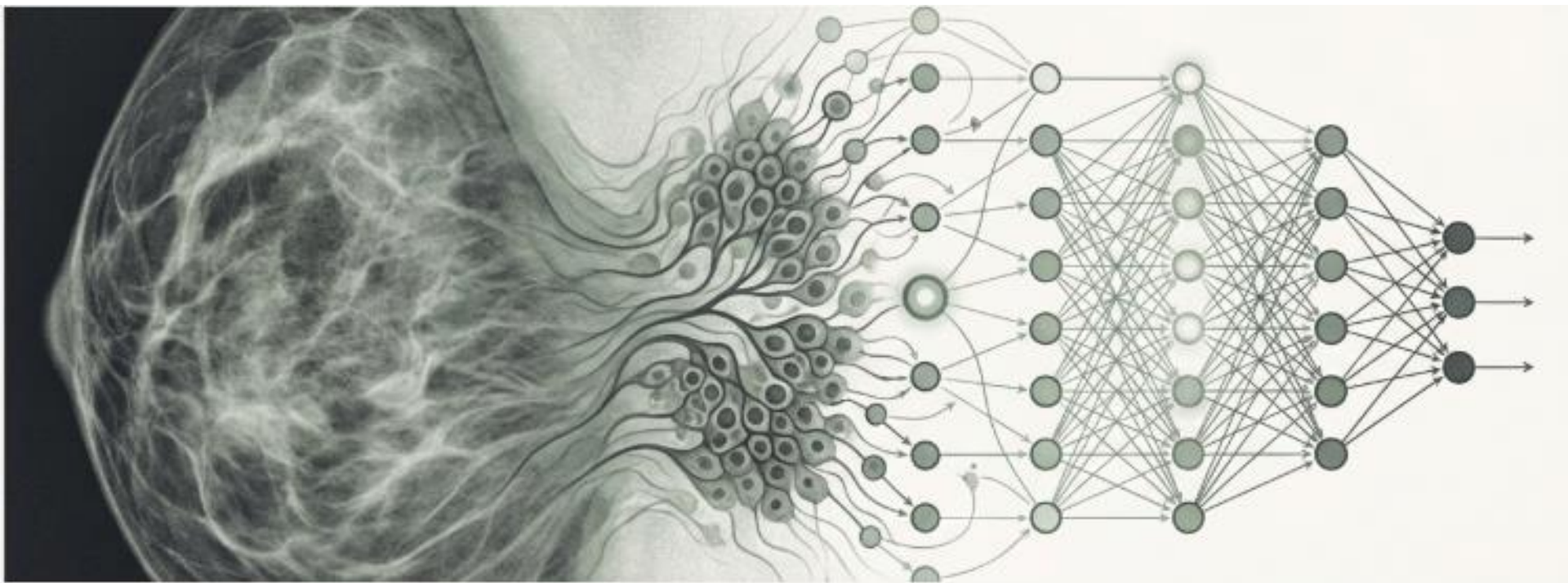




Category-wise Distribution (%) in Each Set

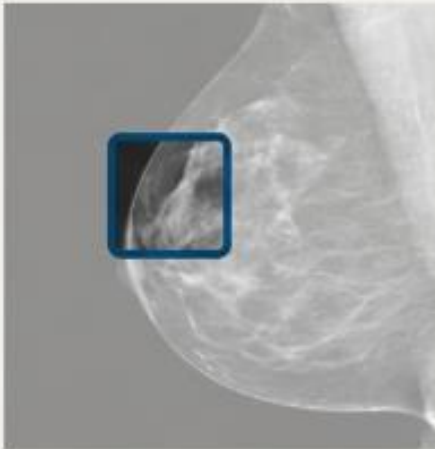


# Model Architecture

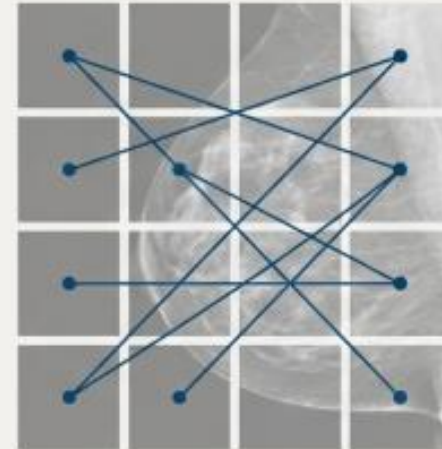


# Model Architecture

**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.

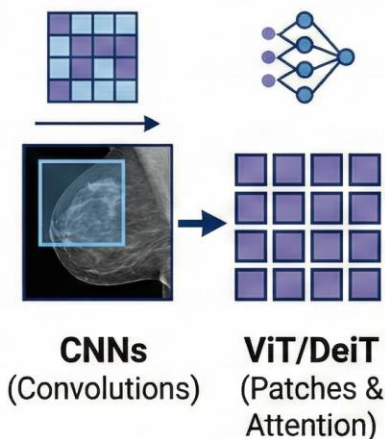


# Model Architecture

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

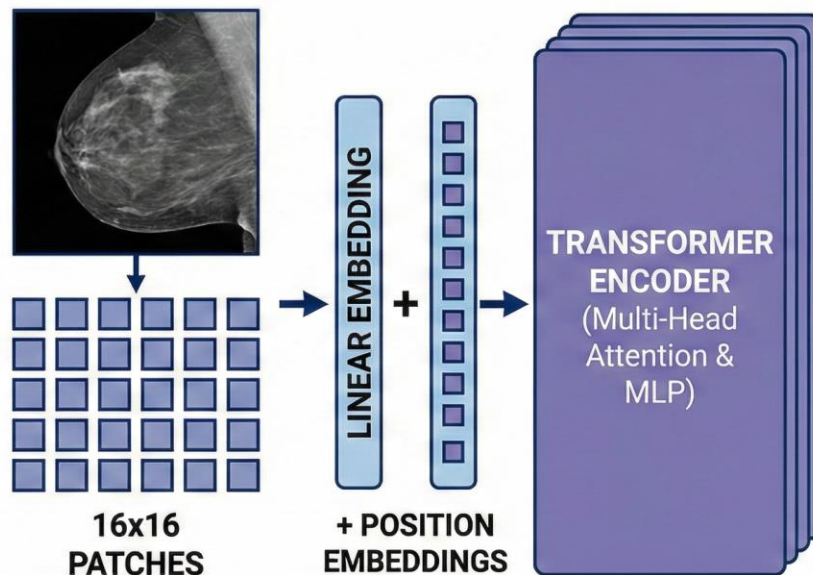
### 1. DeiT FOUNDATION

Small-Dataset Optimized  
Vision Transformer



Effectively trains on  
smaller datasets than  
original ViT.

### 2. MECHANISM: PATCHES TO TRANSFORMERS

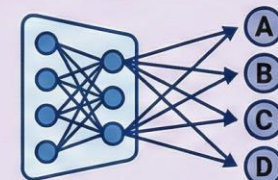


Splits image into fixed patches, embeds them  
with position, then processes via standard  
Transformer encoder, unlike CNNs.

### 3. PROJECT CUSTOMIZATION

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

**CUSTOM HEAD**  
(Replaces Original Classification)



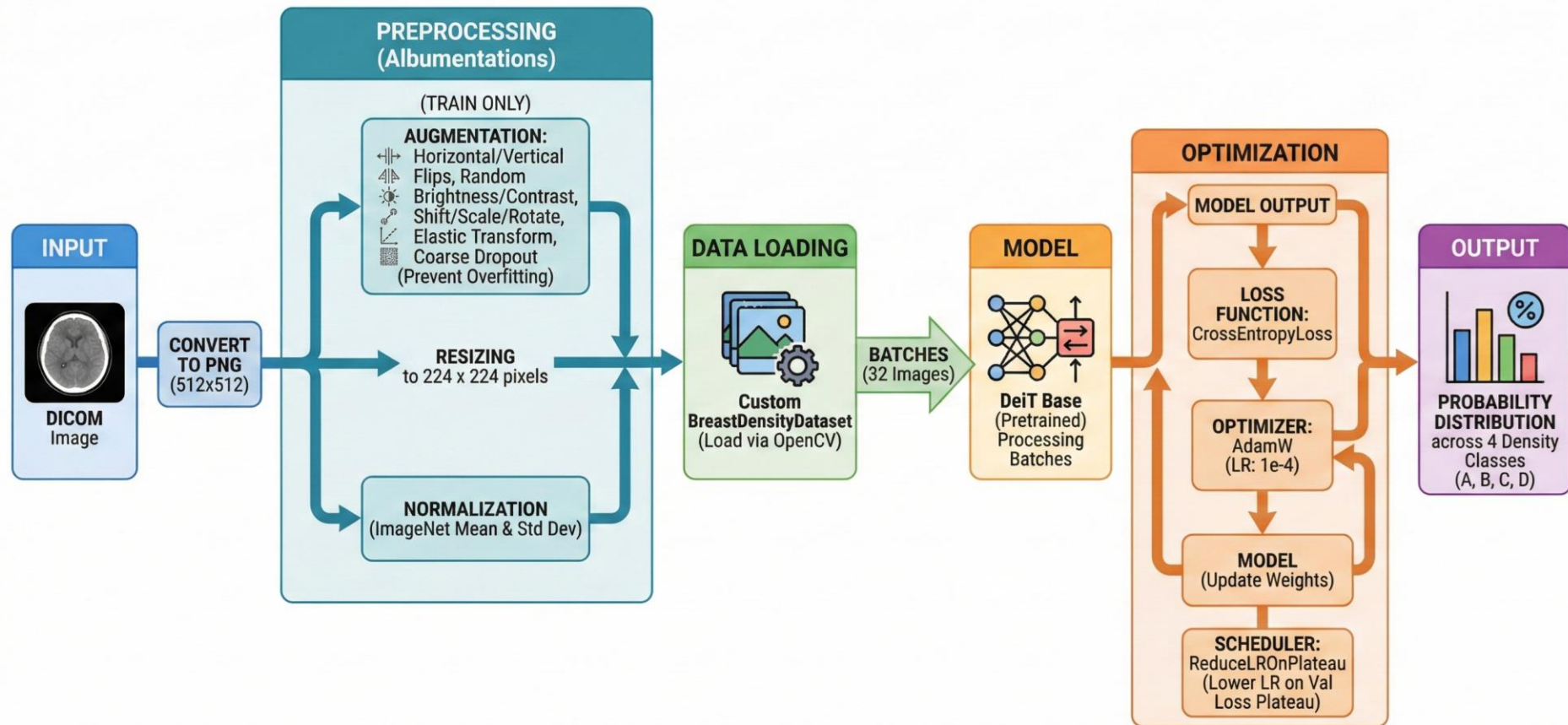
**nn.Linear Layer**  
(4 Classes: Density A, B, C, D)

**TOTAL PARAMETERS:**

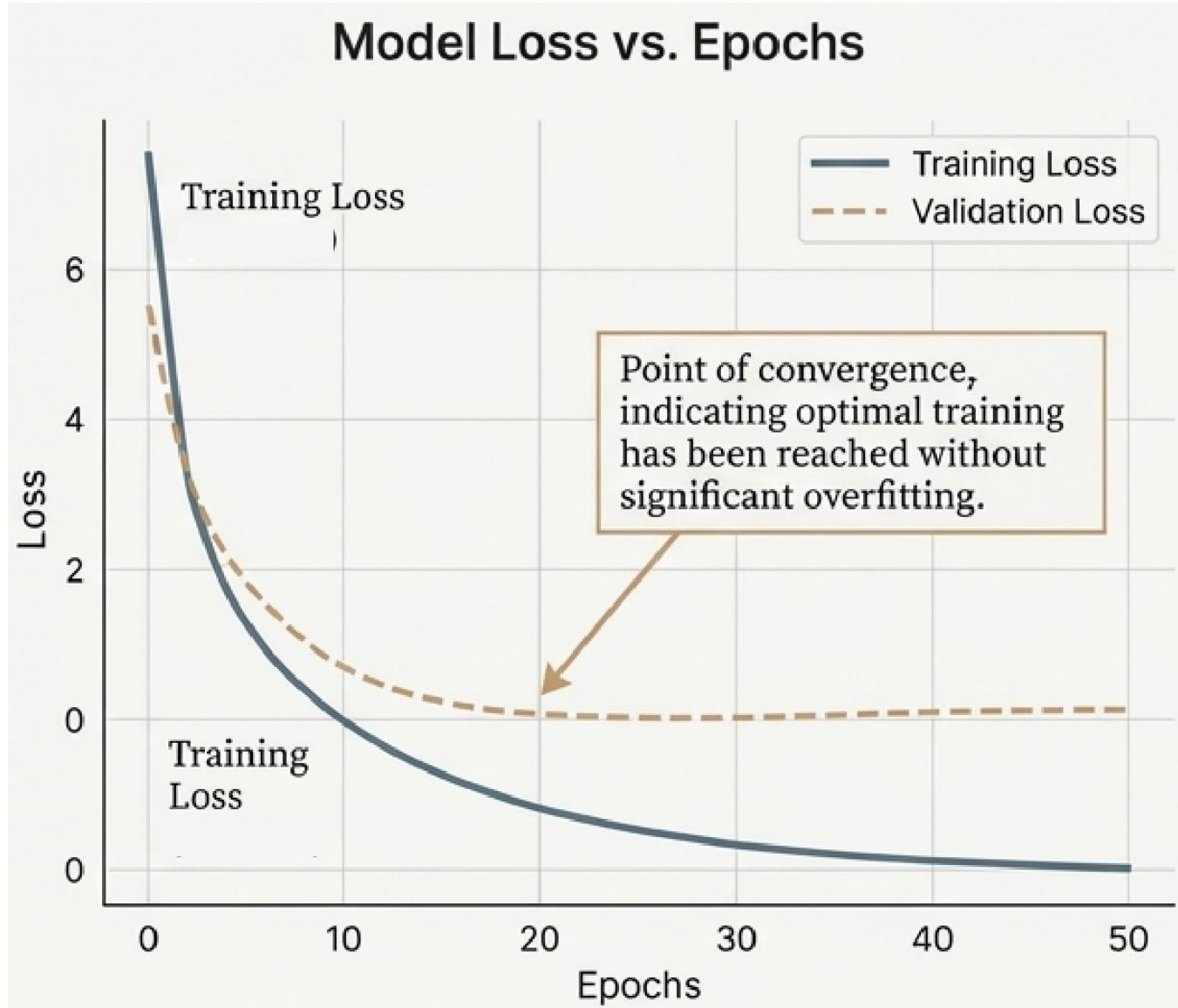
**~86 MILLION**

Trainable Weights

# Deep Learning Pipeline Flowchart



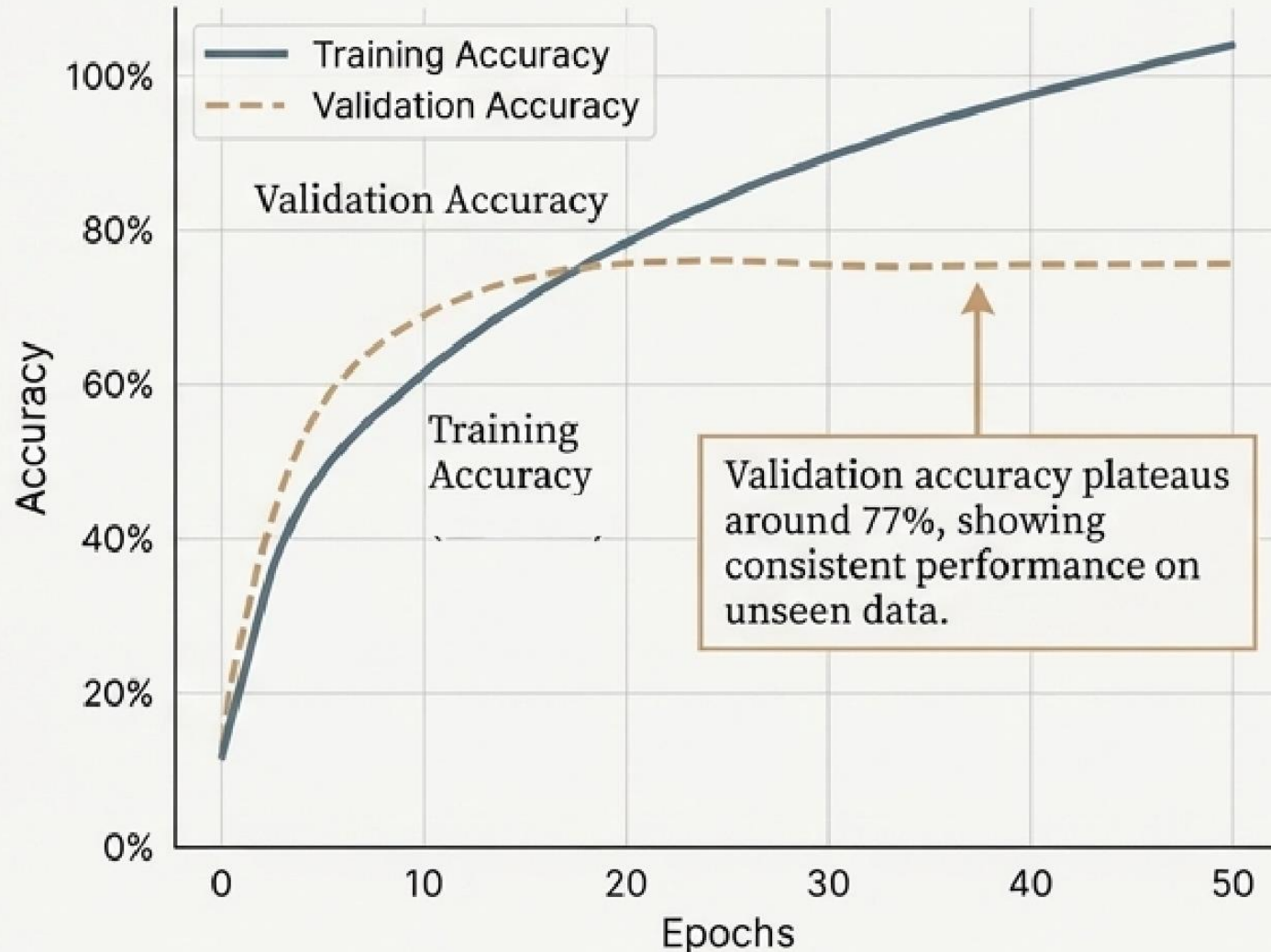
# Results





# 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
Weighted Avg	0.77	0.77	0.77	2,760

### Key Insight

Excellent performance is observed on the most common classes (B and 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
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Class C	0.81	0.81	0.81	1,116
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<b>Weighted Avg</b>	<b>0.77</b>	<b>0.77</b>	<b>0.77</b>	<b>2,760</b>

## High Performance

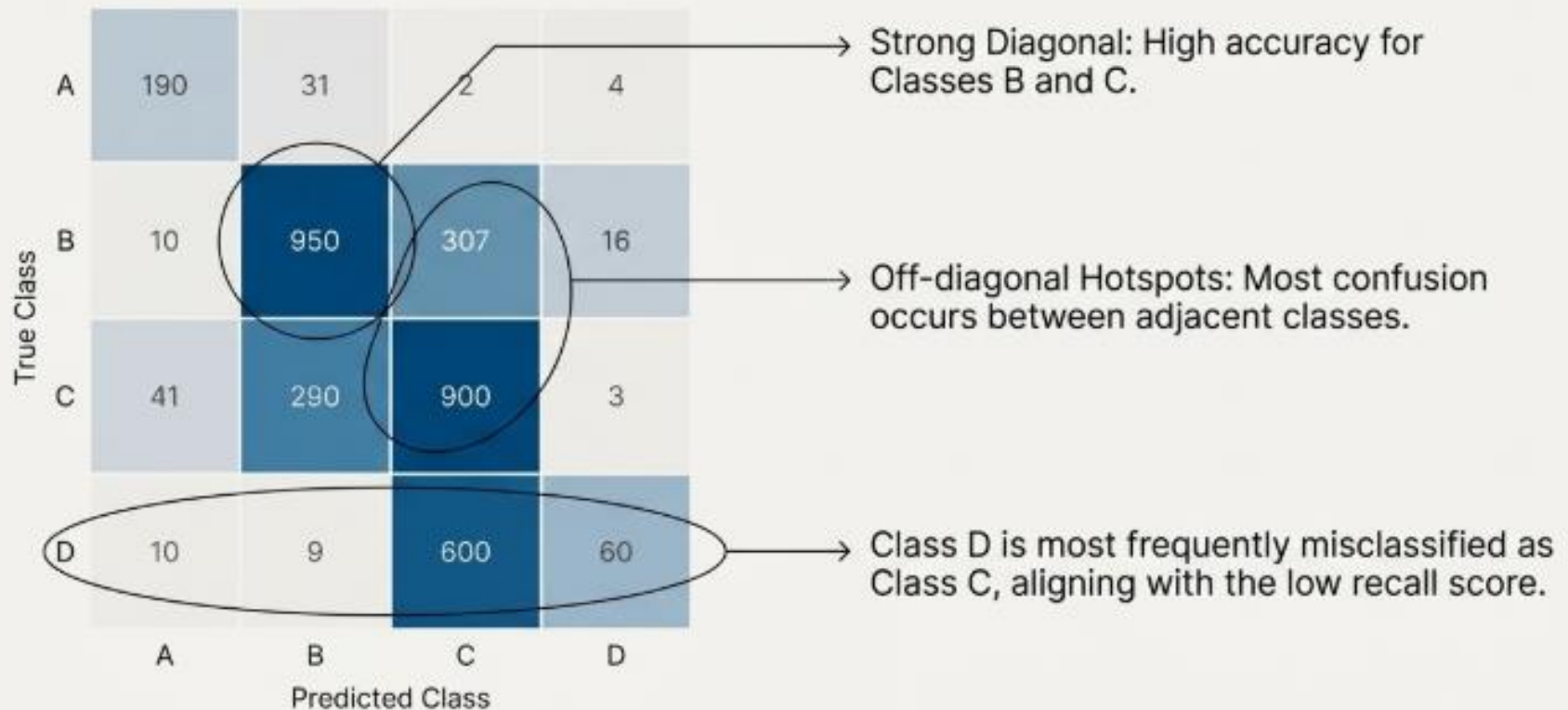
Excellent F1-scores for the most common classes, B and C, demonstrating robustness where it matters most.

## Imbalance Challenge

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

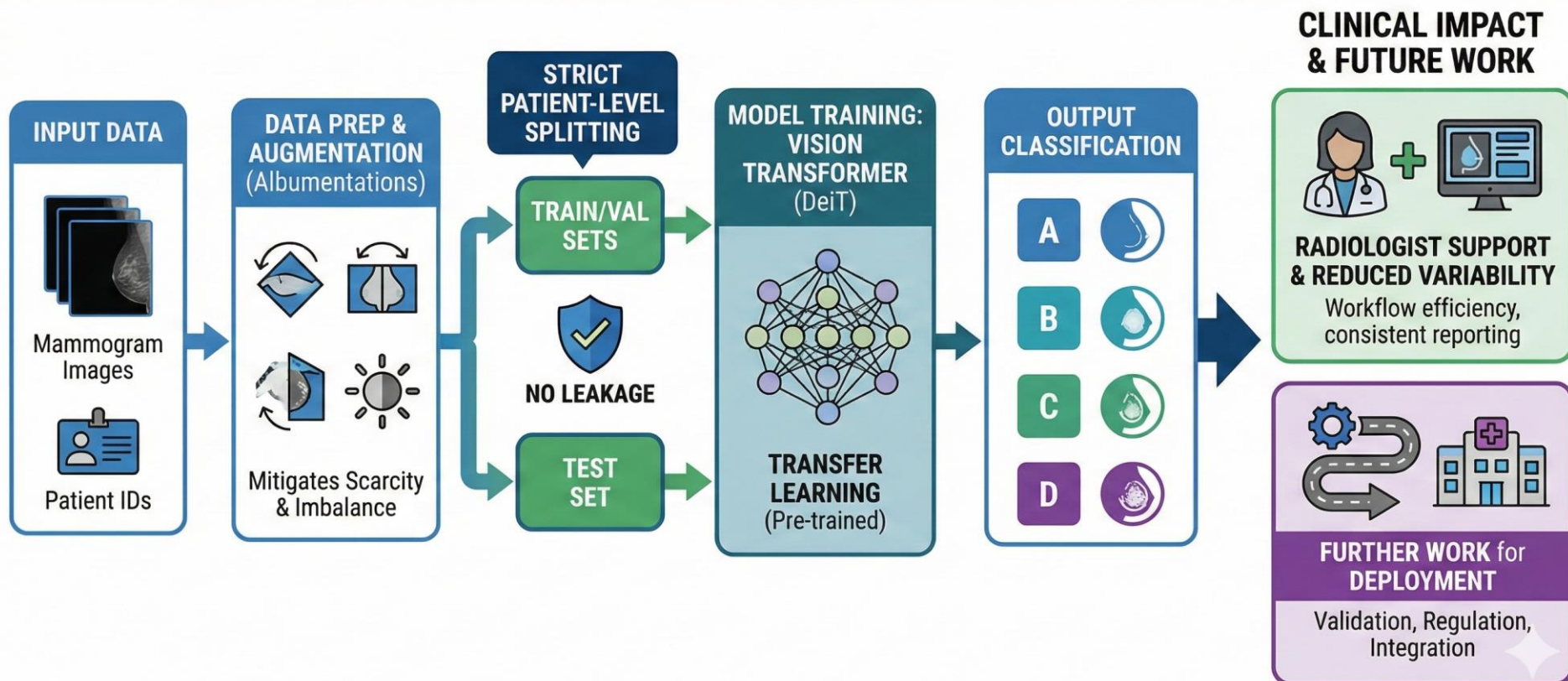
# Results

## The Confusion Matrix Reveals Misclassification Patterns



# Conclusion

## ROBUST BREAST DENSITY CLASSIFICATION PIPELINE with VISION TRANSFORMERS

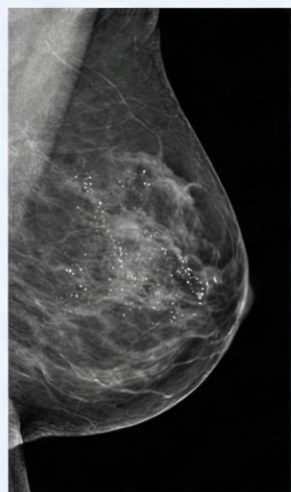




# Limitations & Future Work

## PROJECT LIMITATIONS & FUTURE WORK FOR BREAST DENSITY CLASSIFICATION

### LIMITATION 1: RESOLUTION LOSS



**Original**  
(High-Res Details)

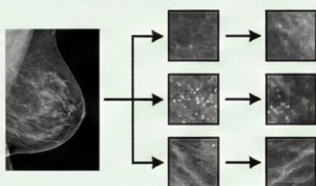
Images resized to 224x224 for DeiT. Microcalcifications may be lost.



**FINE DETAILS LOST**

**Resized**  
(224x224 Input)

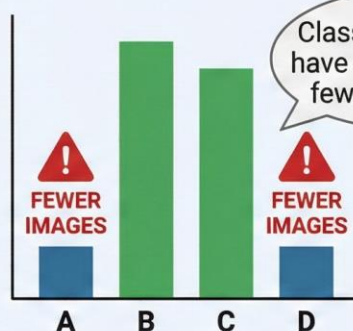
#### FUTURE WORK



**HIGH-RESOLUTION /  
PATCH-BASED PROCESSING**

✓ Preserve fine details,  
improve accuracy.

### LIMITATION 2: CLASS IMBALANCE



Classes A and D have significantly fewer images.

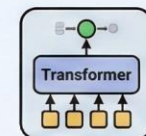
#### FUTURE WORK



Implement **Weighted Random Sampling** or **Class-Weighted Loss** functions.

✓ Balance dataset for better learning.

### LIMITATION 3: MODEL COMPARISON



**DeiT**  
(Sole Focus)

Focus solely on DeiT.

#### 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).