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TER5 PROJECT

Learning oncology biomarkers from histological tissue slide images using modern AI techniques.

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CONTENT TABLE

INTRODUCTION

- Whole Slide Images (WSIs) are large, high-resolution scans used in digital pathology.
- Detecting meaningful biomarkers within them is a complex visual task.
- We compare three different model families:

CNN: effective locally

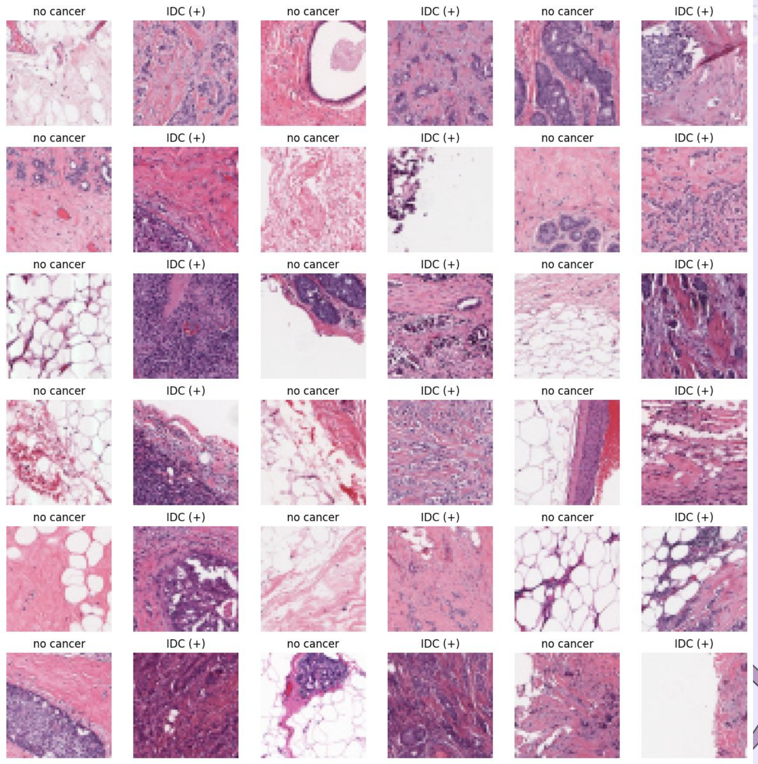
Transformers: good for global context

Foundation Models: trained on millions of patches

Which Database did we use?

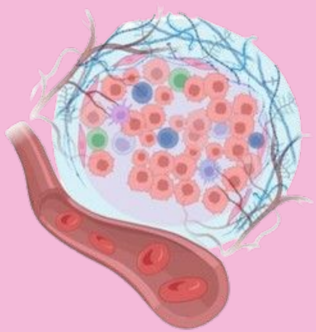
IDC Breast Cancer Dataset (Patch-based):

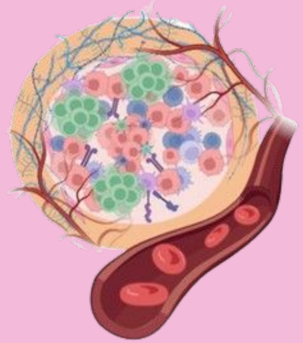
- **162 WSIs**
- **277,524 image patches (50 x 50 pixels)**
- **Binary classification: IDC-negative vs IDC-positive**
- **Extracted regions represent clinically relevant tumor zones.**



Objective

The aim is to classify the dataset in a binary way in order to distinguish images with infiltrating ductal carcinoma (IDC) from those without.

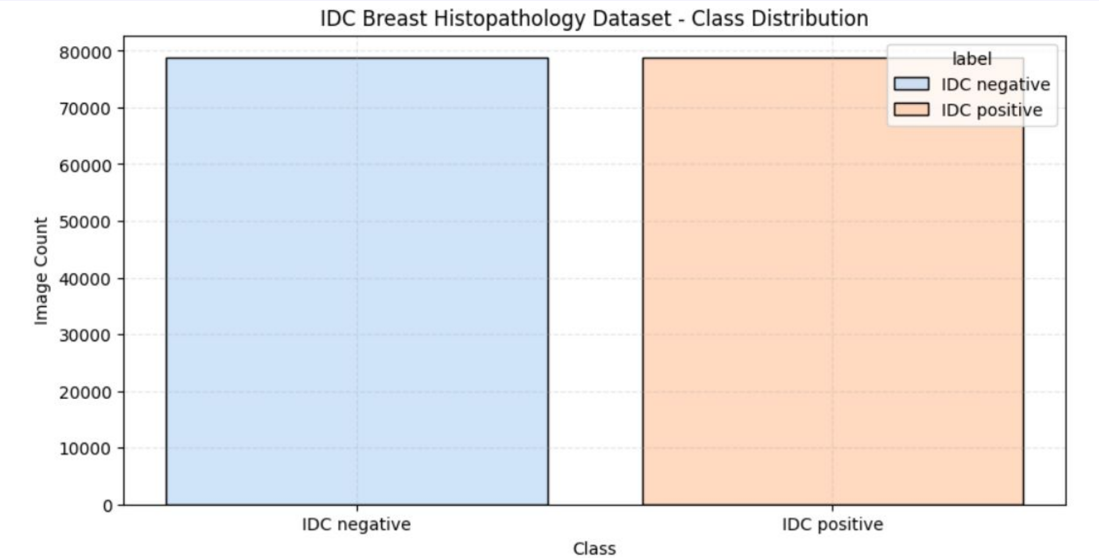




IDC negative:
This class corresponds to tumor-free tissue images, i.e. cases where no infiltrating ductal carcinoma (IDC) is detected.

IDC positive:
This class corresponds to tissue images that contain tumors, i.e. cases where infiltrating ductal carcinoma (IDC) is detected.

Class Distribution

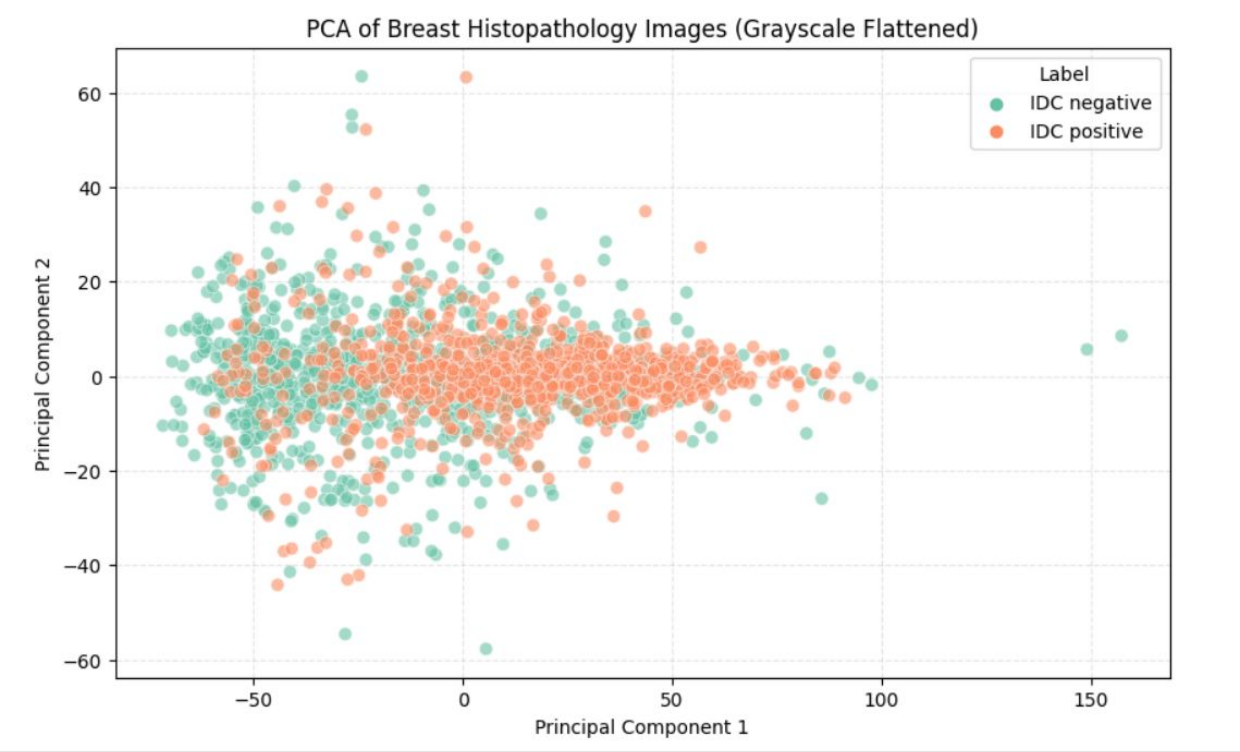


The two classes, *IDC negative* and *IDC positive*, are evenly distributed in the dataset, resulting in a well-balanced classification task.

VISUALISATIONS : PCA

The PCA visualization shows that the two classes, *IDC negative* and *IDC positive*,

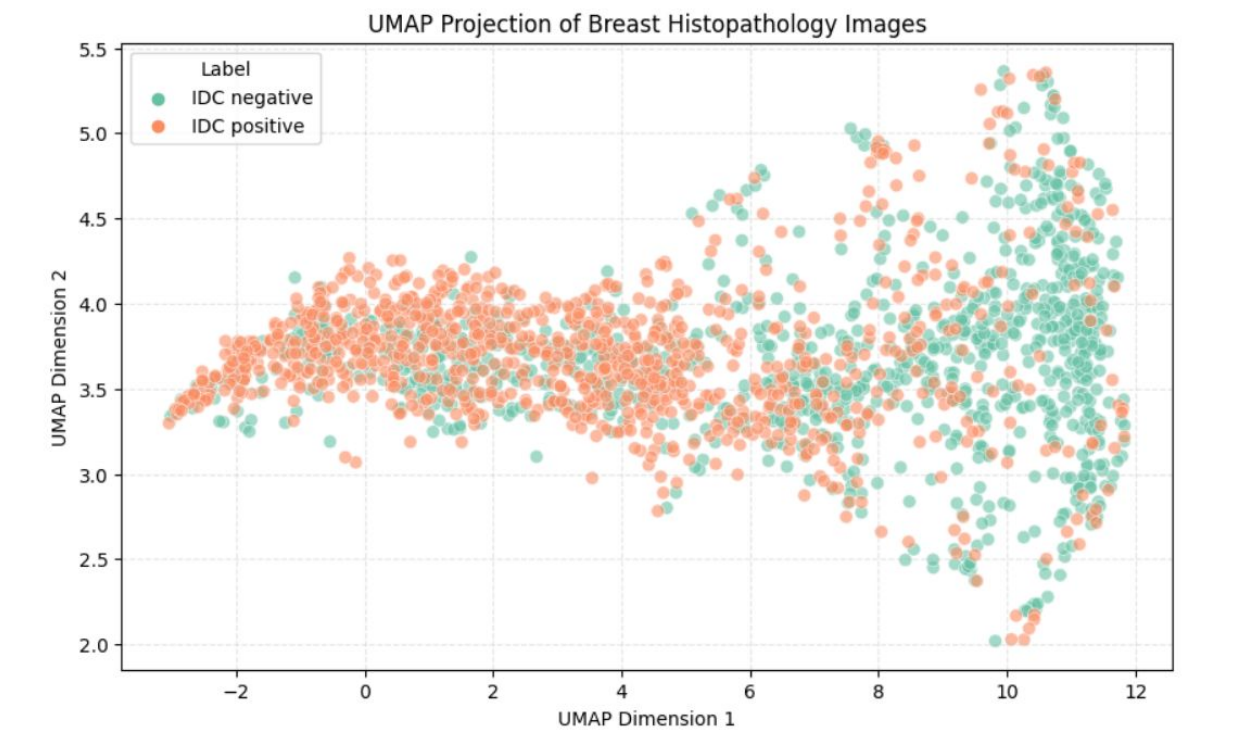
are largely intertwined in the reduced feature space.



VISUALISATIONS : U-MAP

This overlap likely reflects the subtle visual differences between tumor and non-tumor tissue,

which are difficult to capture without more advanced feature extraction methods such as CNN.



Which Pipeline did we use?

1- WSI → Patch extraction

Database contains the extracted patches

2- Feature embedding (via backbone model)

The extracted embeddings can serve as digital biomarkers, capturing and summarizing key histological features relevant to diagnosis.

3- Classification

Takes the extracted feature embeddings and assigns each patch to a specific category such as tumor or non-tumor based on learned patterns.

CNN models

EfficientNet: compound scaling, lightweight design

- **Accuracy: train 65% / test 58%**
- **Loss: train 18.0 / test 10.0**

Poor

ResNet: residual learning with skip connections

- **Accuracy: train 95.2% / test 84.4%**
- **Loss: train 0.73 / test 0.65**

Good

Transformers

ViT: patch tokenization + self-attention

- Accuracy: train 94% / test 85%
- Loss: train 0.65 / test 0.45

Good

CTransPath: CNN + Swin Transformer hybrid

- Accuracy: train 98% / test 85%
- Loss: train 0.9 / test 0.1

Very Good

Foundation Model

UNI: Unified Contrastive Learning for Histopathology, a general-purpose ViT encoder trained on 100M pathology patches

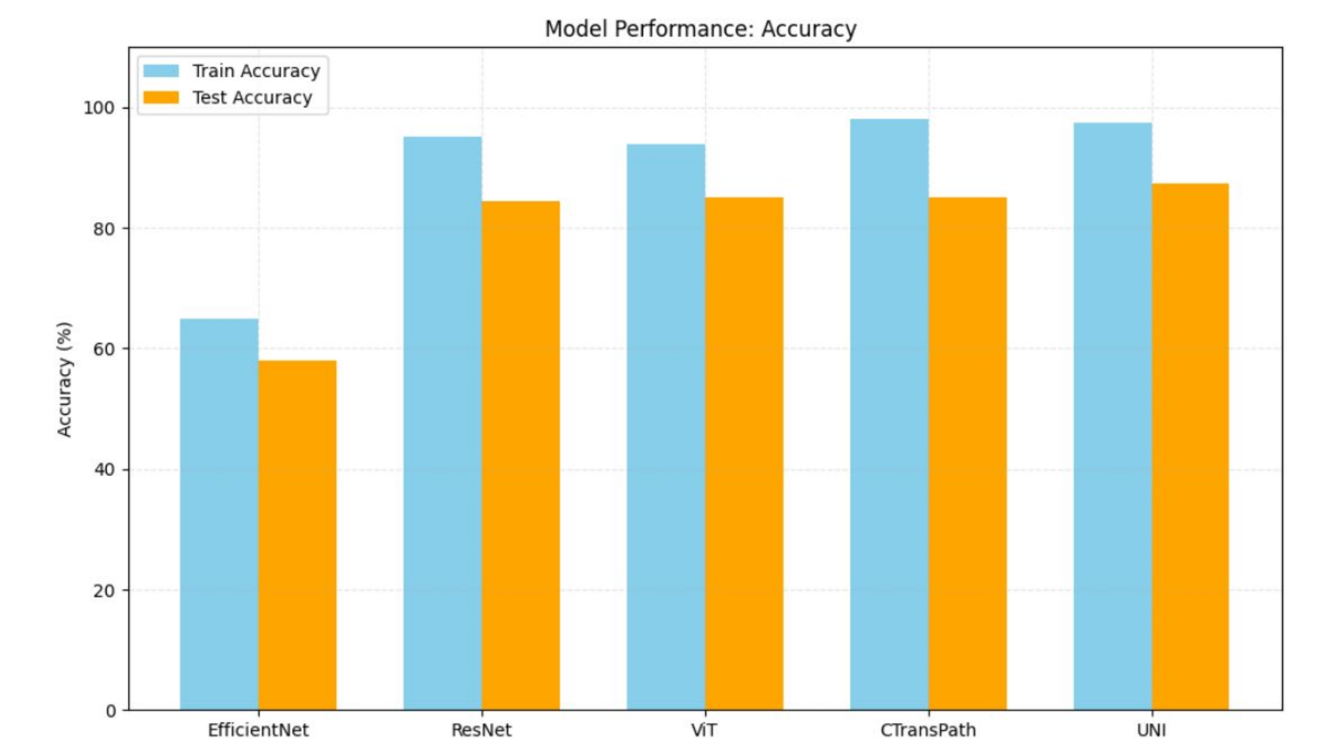
- **Accuracy: train 97.5% / test 87.5%**
- **Loss: train 0.54 / test 0.43**

Best

Results

	Train Acc	Test Acc	Train Loss	Test Loss
EfficientNet	65.0%	61.36%	18.00	10.00
ResNet	95.2%	84.4%	0.73	0.65
ViT	94.5%	85.0%	0.65	0.45
CTransPath	98.0%	85.0%	0.54	0.43
UNI	97.5%	87.5%	0.54	0.43

Results


Model Performance: Accuracy
Train Accuracy
Test Accuracy
Accuracy (%)
0
20
40
60
80
100
EfficientNet
ResNet
ViT
CTransPath
UNI

Study Limitations

- Limited GPUs → long training sessions (up to 20h per model)
- Difficulty loading WSIs (very large images)
- Lack of Model’s documentation (ex: UNI)
- Computational constraints, transformer based models require more compute time than it is practical.

Conclusion

- CNNs are fast and interpretable but lack global context
- Transformers achieve better spatial reasoning
- UNI outperforms others, but marginally
- EfficientNet underperforms on generalization
- GPU constraints limited hyperparameter tuning

Perspectives

01 **Broader datasets (e.g., multi-organ)**

02 **Patch selection optimization**

03 **Semi- or Unsupervised learning**

Thank You!

Thank you for your attention.

Questions?

Kaggle Notebooks

ResNet

EfficientNet

ViT

CTransPath

UNI