Improving Breast Cancer Diagnosis Through

Classification of Hematoxylin and Eosin Histopathological Images

"In collaboration with the Anti-Cancer Center of Sidi Bel Abbes"

Supervised by Pr. Sidi Mohammed BENSLIMANE, Dr. Nassima DIF

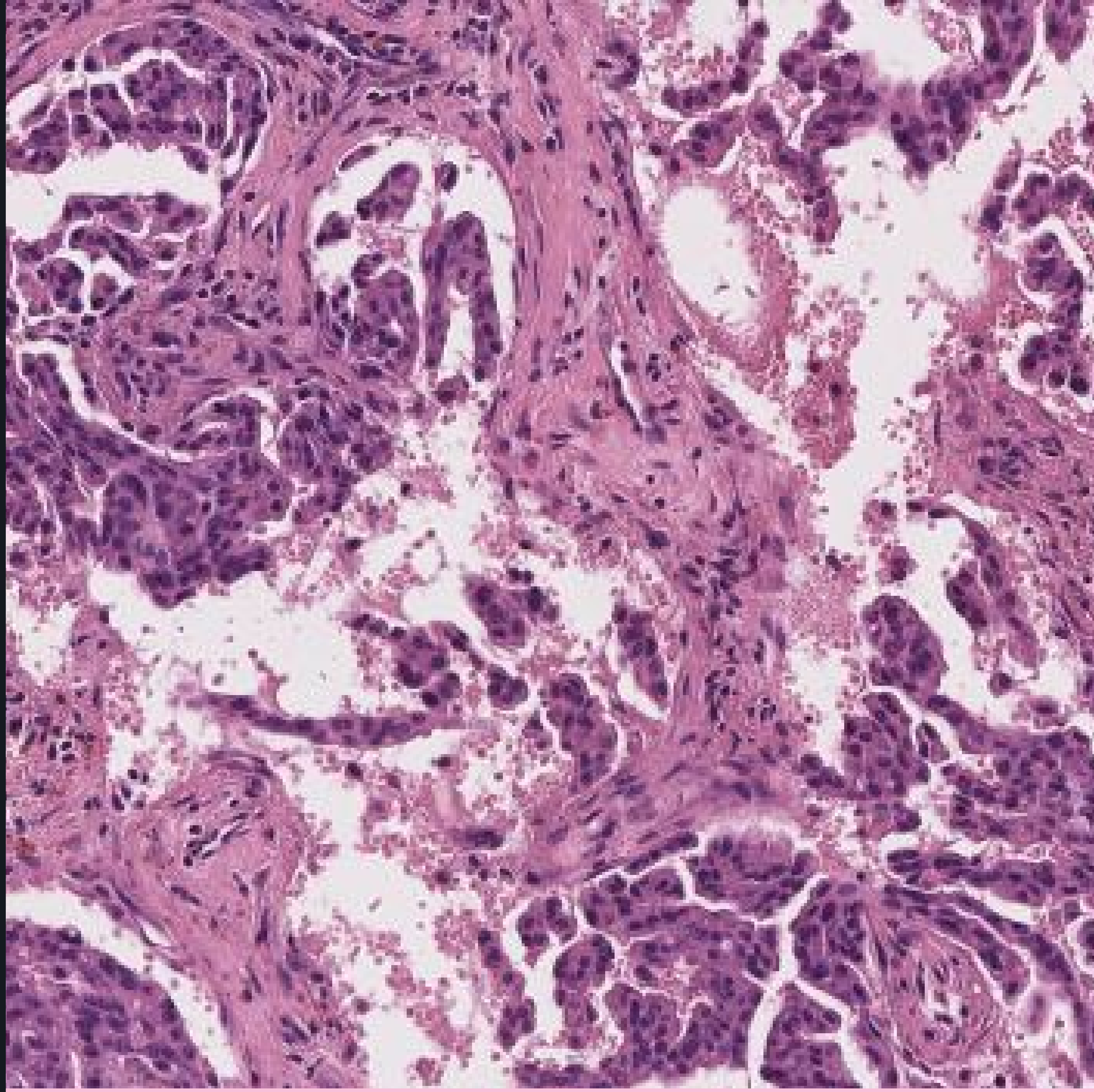
Artificial Intellignece and Data Science

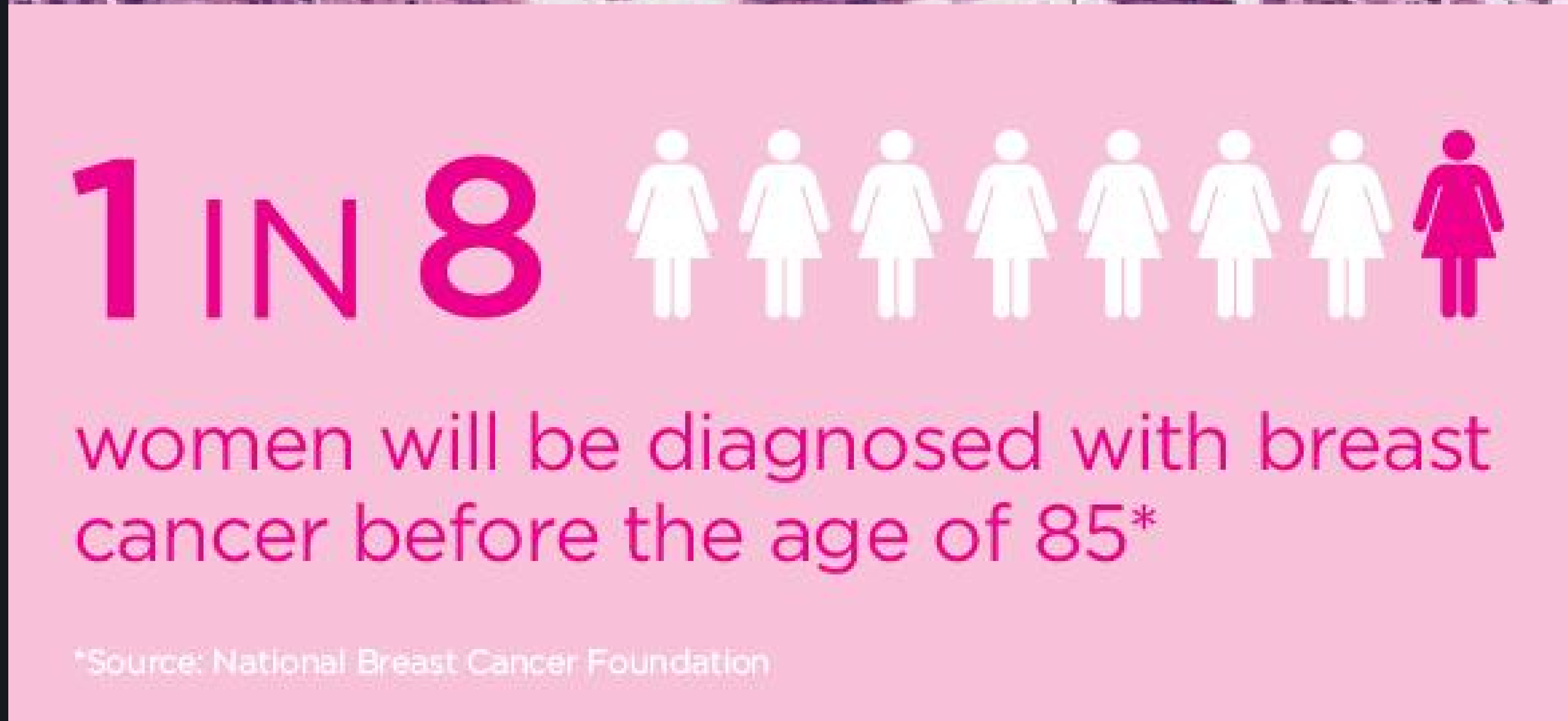
Introduction & motivation

Breast cancer is one of the most prevalent malignancies affecting women worldwide, with approximately **2.3 million** new cases diagnosed annually (World Health Organization - 2021).

Several factors contribute to the development of breast cancer, including genetic predisposition, hormonal influences, lifestyle factors, and environmental exposures.

Early detection of breast cancer is critical for improving patient outcomes and reducing mortality rates.





What is the challenge ?

Despite significant advancements in breast cancer diagnosis and treatment, several challenges persist in the field of medical AI.

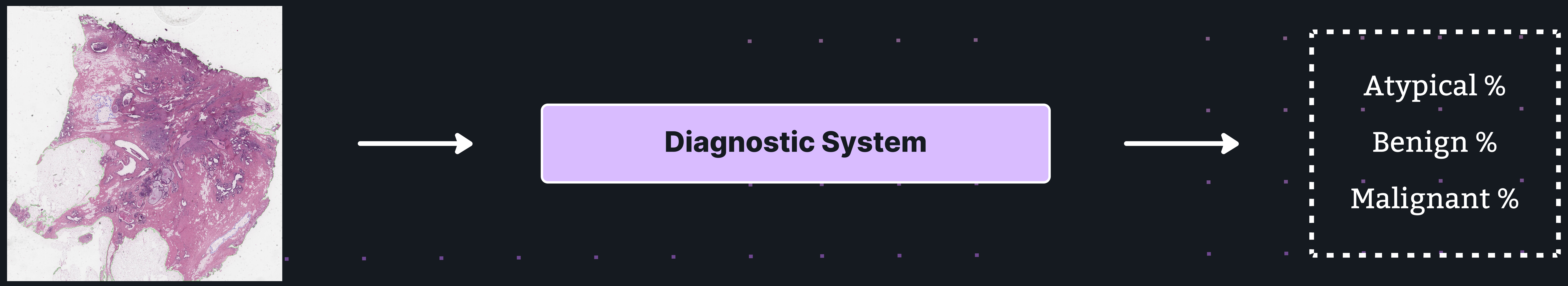
The main challenges were related to the **size of the histopathological images (Gigapixel)**. These extremely high-resolution images result in substantial computational complexity.

Another challenge is the **annotation of histopathological images**, which is a labor-intensive and time-consuming task requiring expert pathologists to accurately label the images.

What is the objective ?

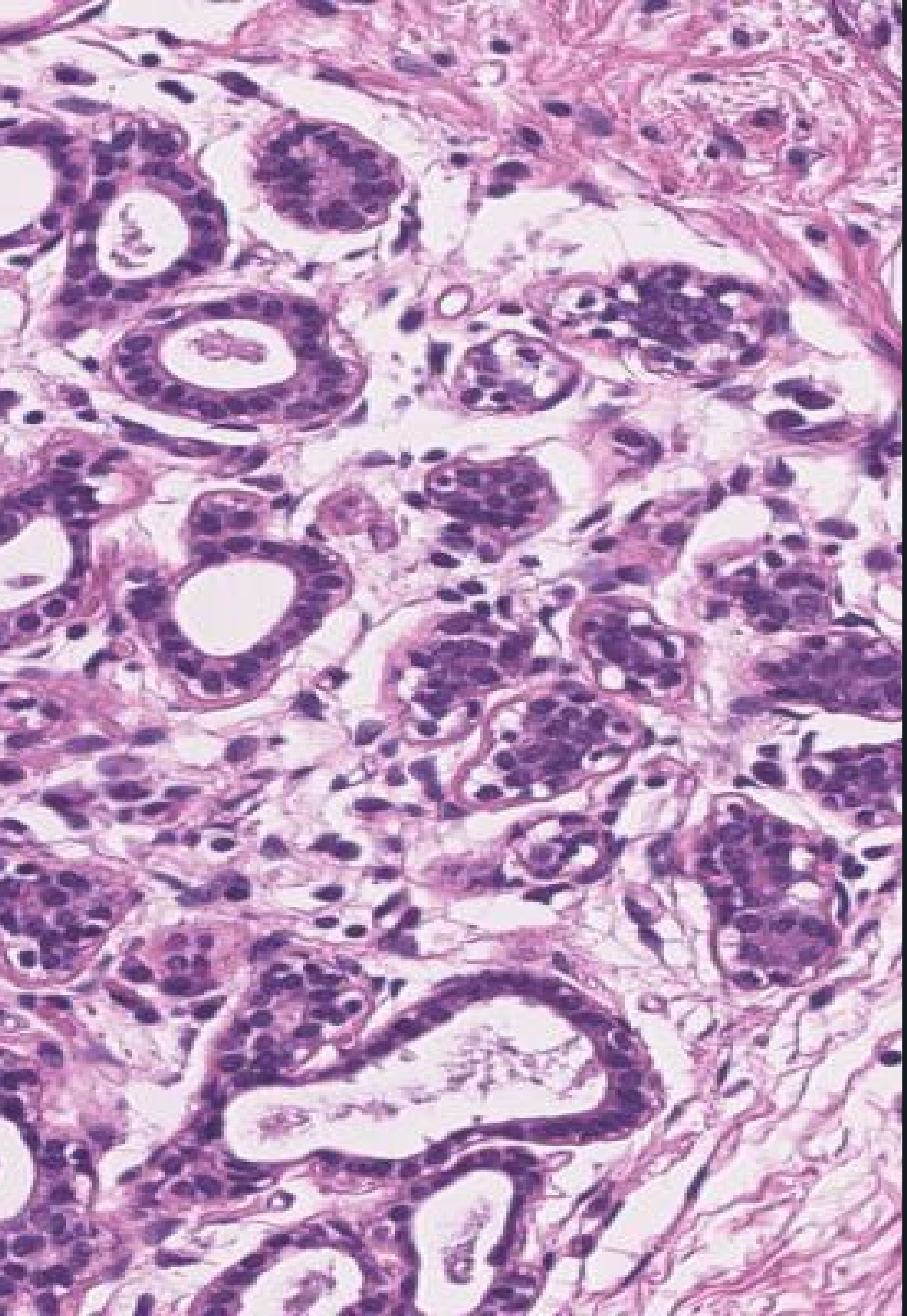
As part of our internship at **CAC SBA (Anti-Cancer Center of Sidi Bel Abbes)**, The primary objective of this project is to develop a computer-aided diagnostic system capable of accurately classifying histopathological images of breast tissue into three classes: **Atypical**, **Benign** and **Malignant**.

Another objective is to develop an information system that serves the dual purpose of facilitating the collection and storage of necessary patient data, as well as automating the process of retrieving patient information.



Whole Slide Image (WSI)

Model's Prediction



BRACS Dataset

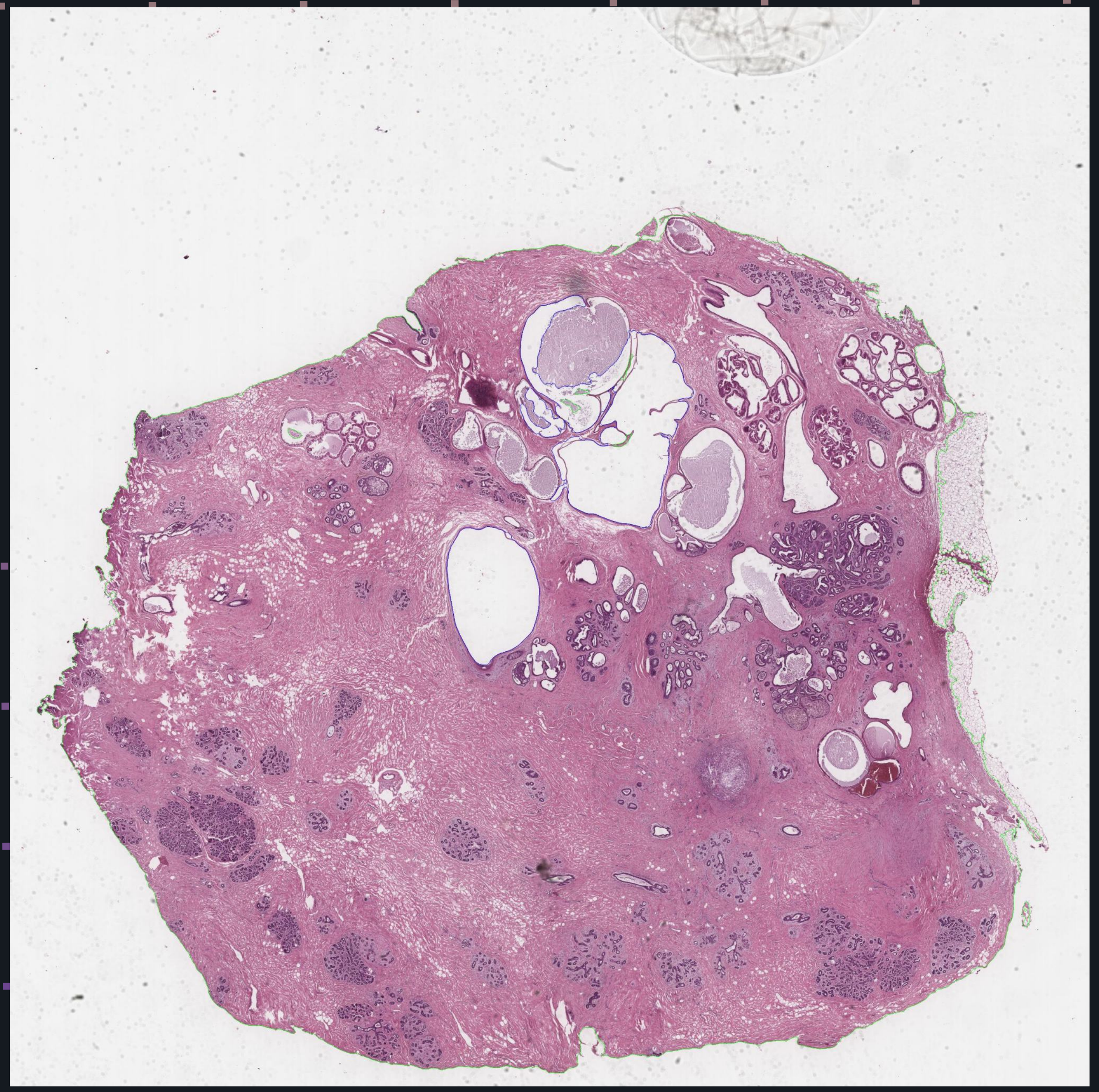
BReAst Carcinoma Subtyping (BRACS) dataset, a large cohort of annotated Hematoxylin and Eosin (H&E)-stained images to facilitate the characterization of breast lesions.

The BRACS dataset comprises both Whole Slide Images (WSIs) and Regions of Interest (ROIs) of **03 types** and **07 subtypes**.

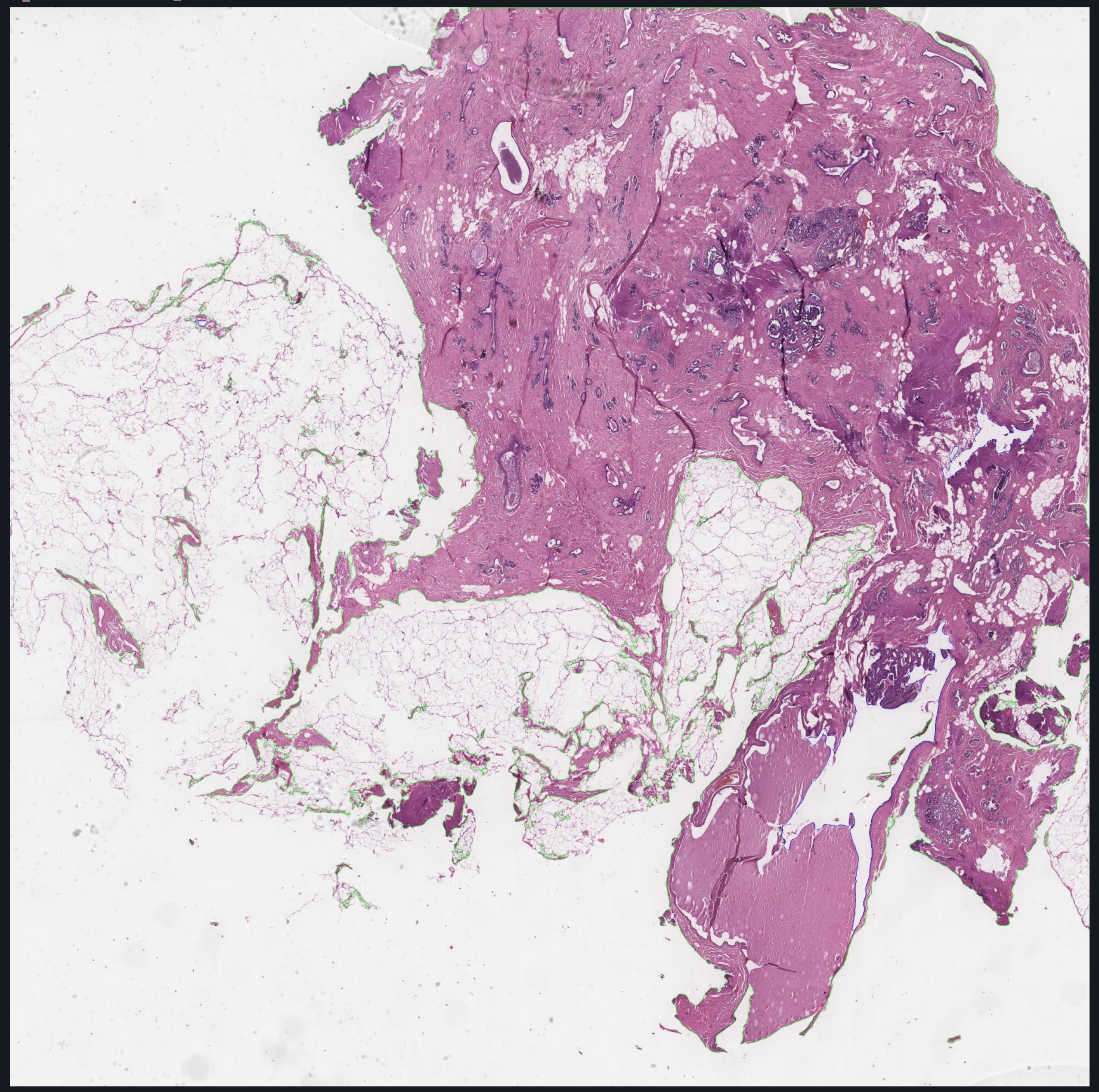
- **Atypical Tumors:** includes 2 subtypes (ADH, FEA)
- **Benign Tumors:** includes 3 subtypes (N, PB, UDH)
- **Malignant Tumors:** includes 2 subtypes (DCIS, IC)

Whole Slide Image (WSI)

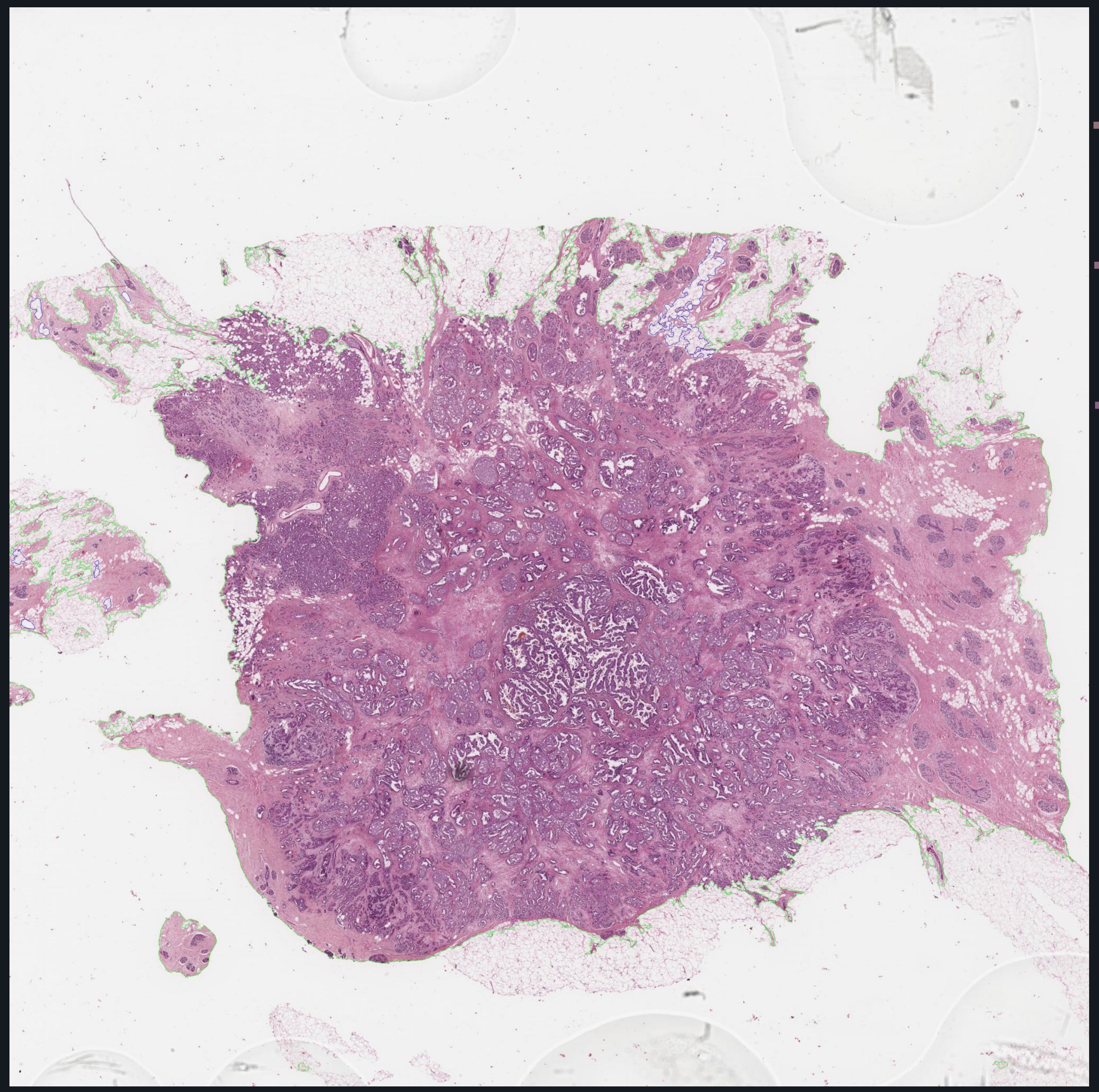
Whole Slide Images (WSIs) are digital images of entire histological slides, capturing the complete tissue section at high resolution (Gigapixels), and they have been obtained by scanning slides that were selected by a biologist of the pathological anatomy department.



Atypical Tumor
Atypical Ductal Hyperplasia (ADH)



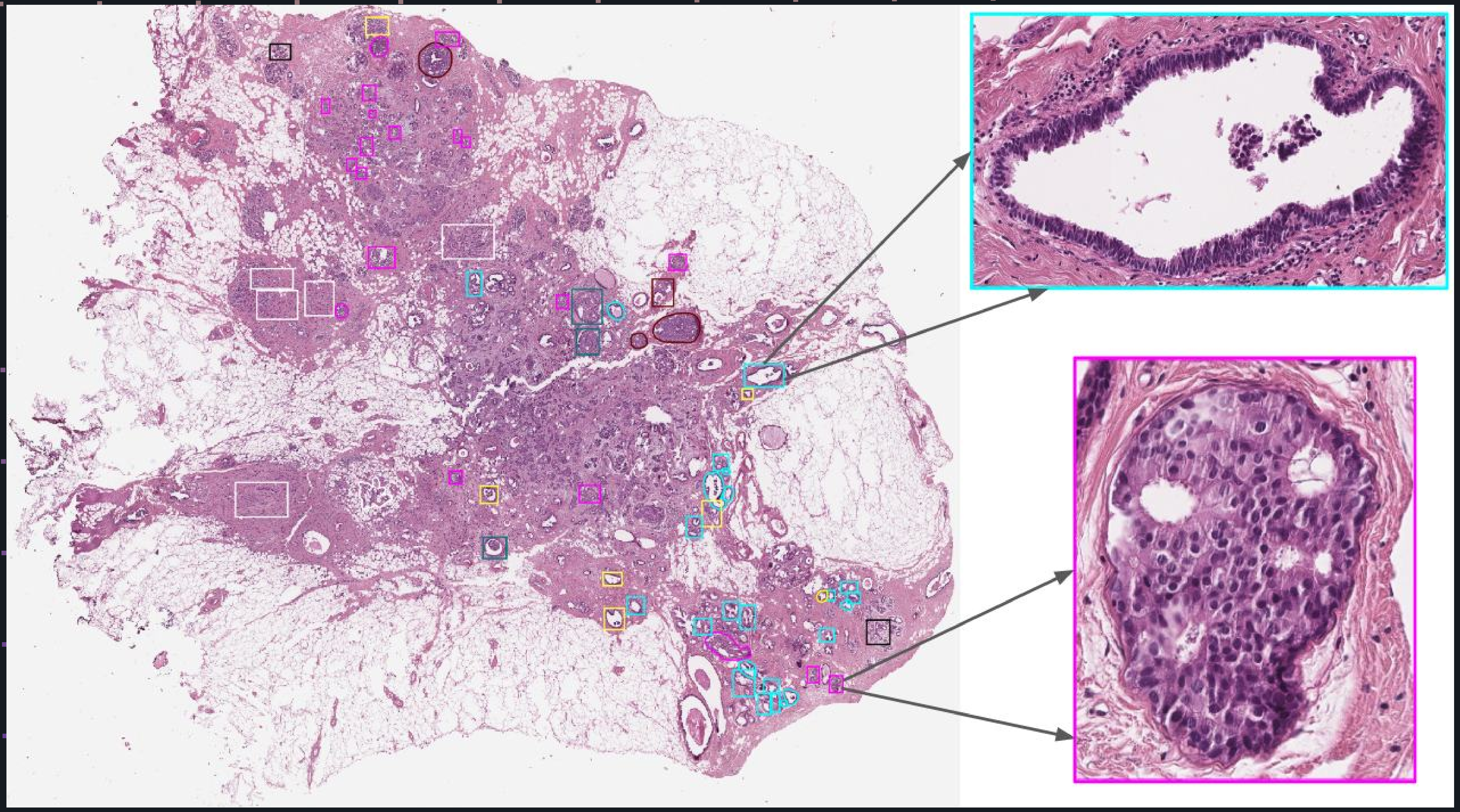
Benign Tumor
Usual Ductal Hyperplasia (UDH)

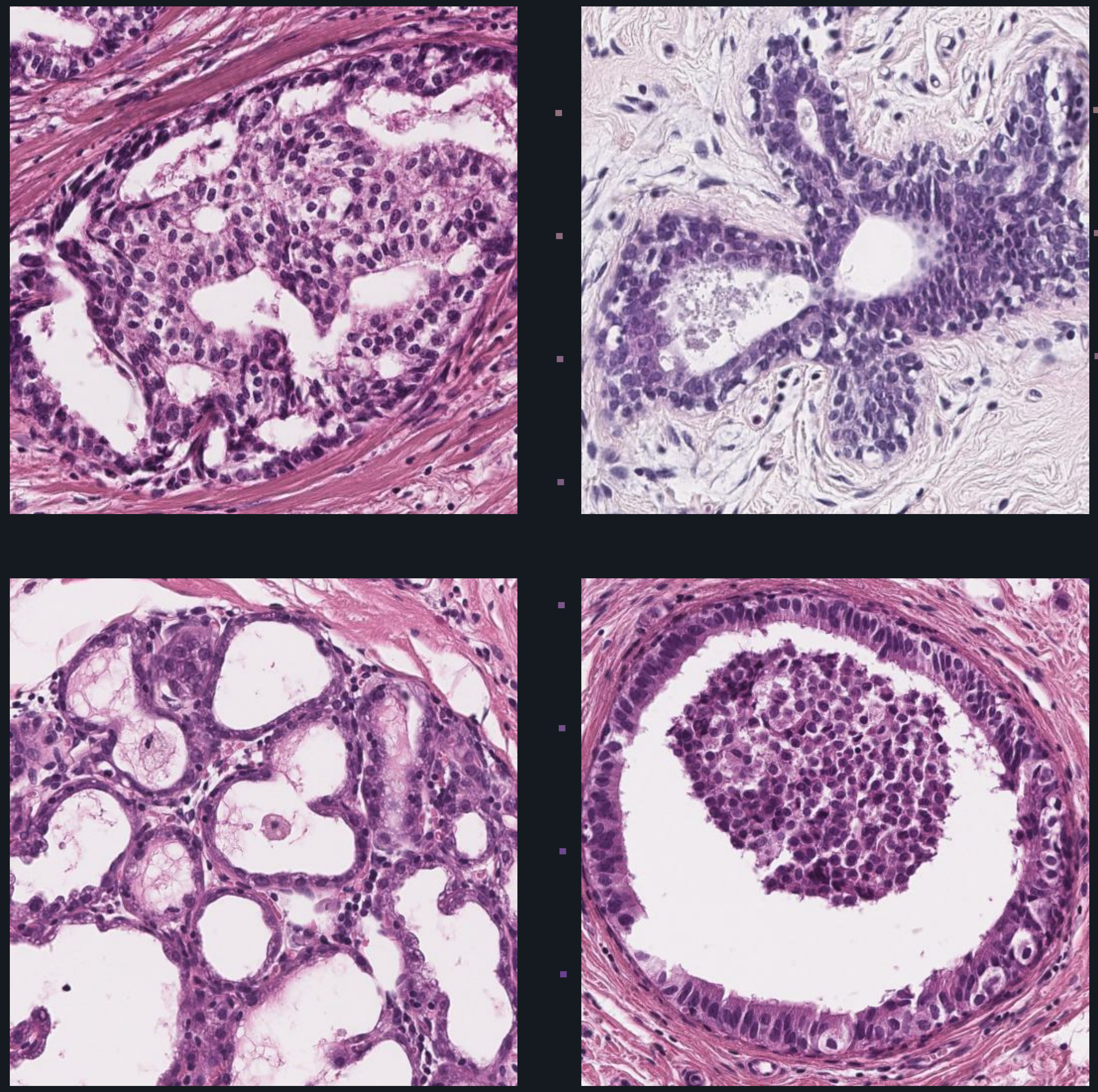


Malignant Tumor
Invasive Carcinoma (IC)

Region of Interest (ROI)

Regions of Interest (ROIs) represent carefully selected and annotated image patches that were extracted from the Whole Slide Images (WSIs), focusing on specific areas of interest within the vast expanse of the WSIs





Dataset description

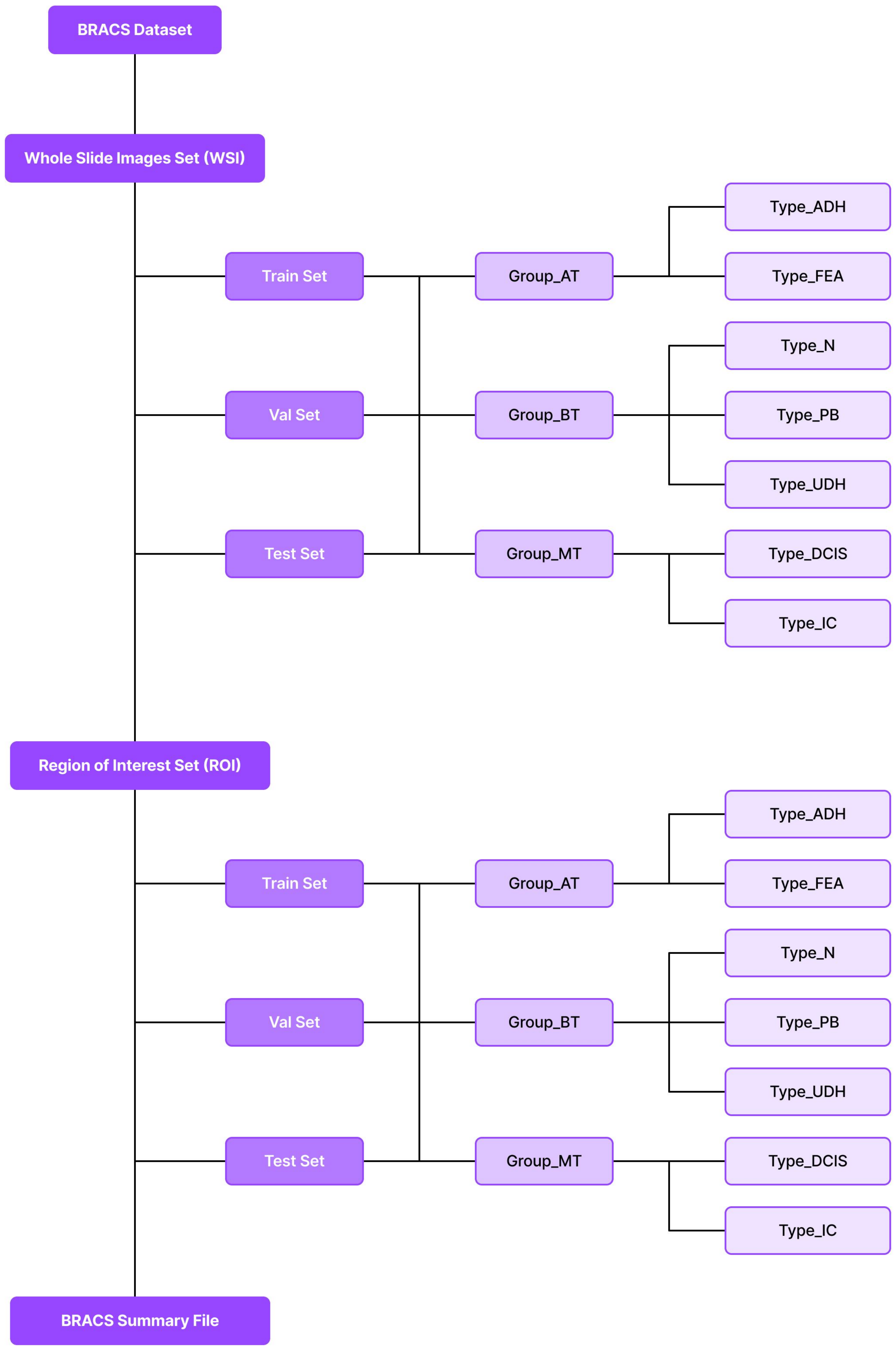
The BRACS dataset comprises a total of **547 WSIs** obtained from **189 different patients**.

The dataset also includes **4,539 ROIs** that were extracted from **387 WSIs** collected from **151 patients**.

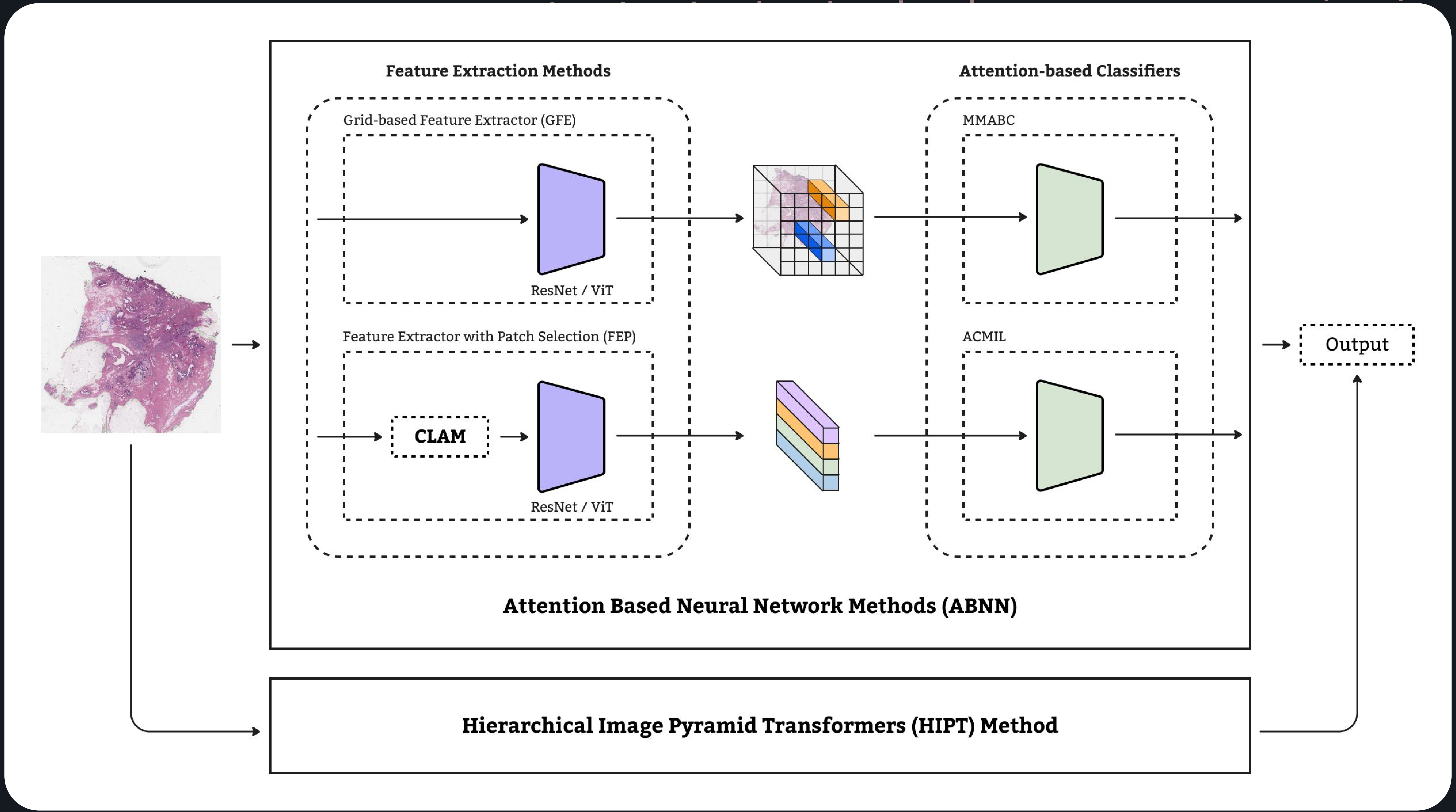
BRACS dataset provides pre-defined WSI- and ROI-level splits in train, validation and test sets.

Data split was generated such that all the WSIs extracted from a patient belong to the same set.

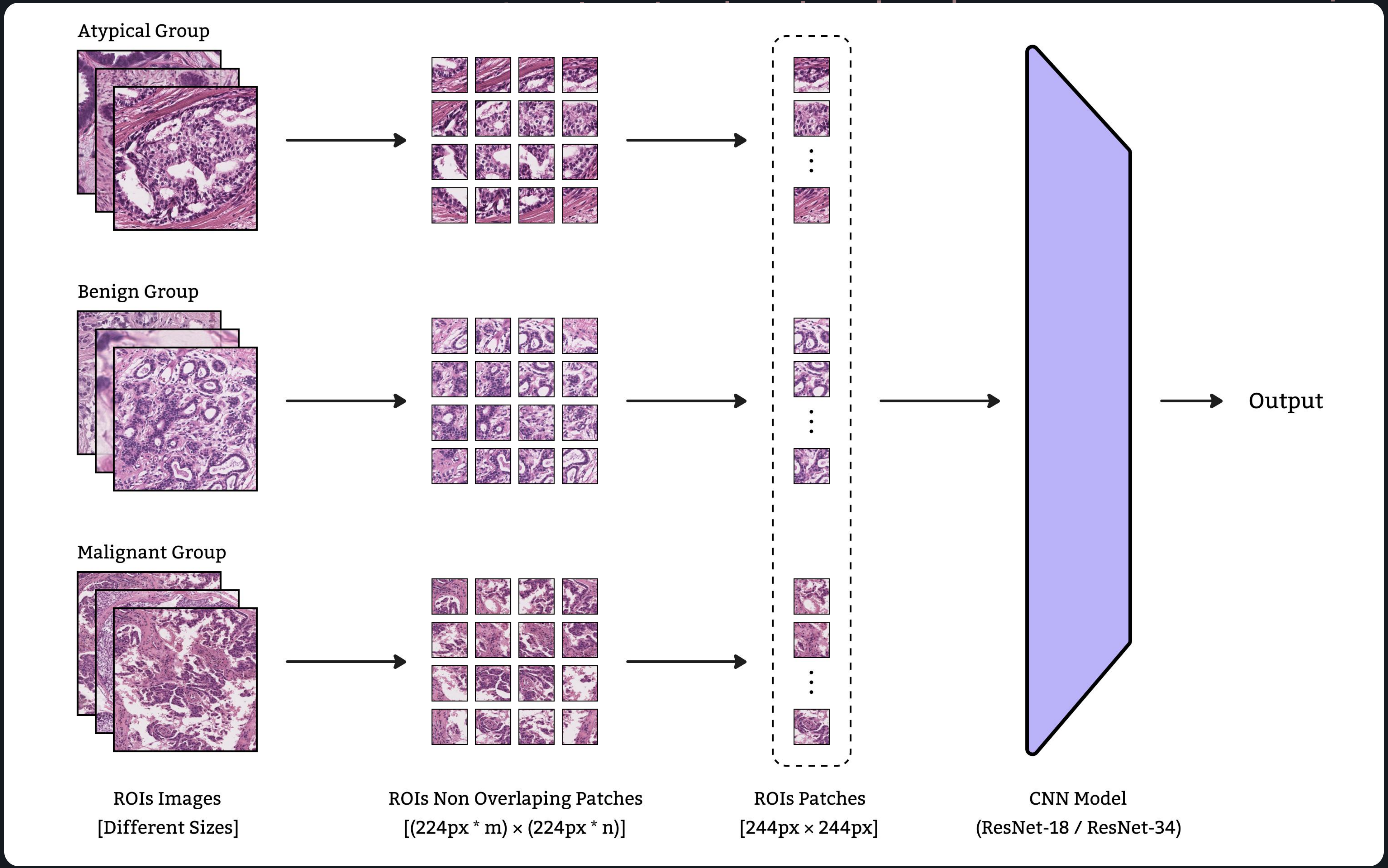
Similarly, all the ROIs extracted in a given WSI are assigned to the same split.



Methodology & Approaches



Preparing models for feature extraction

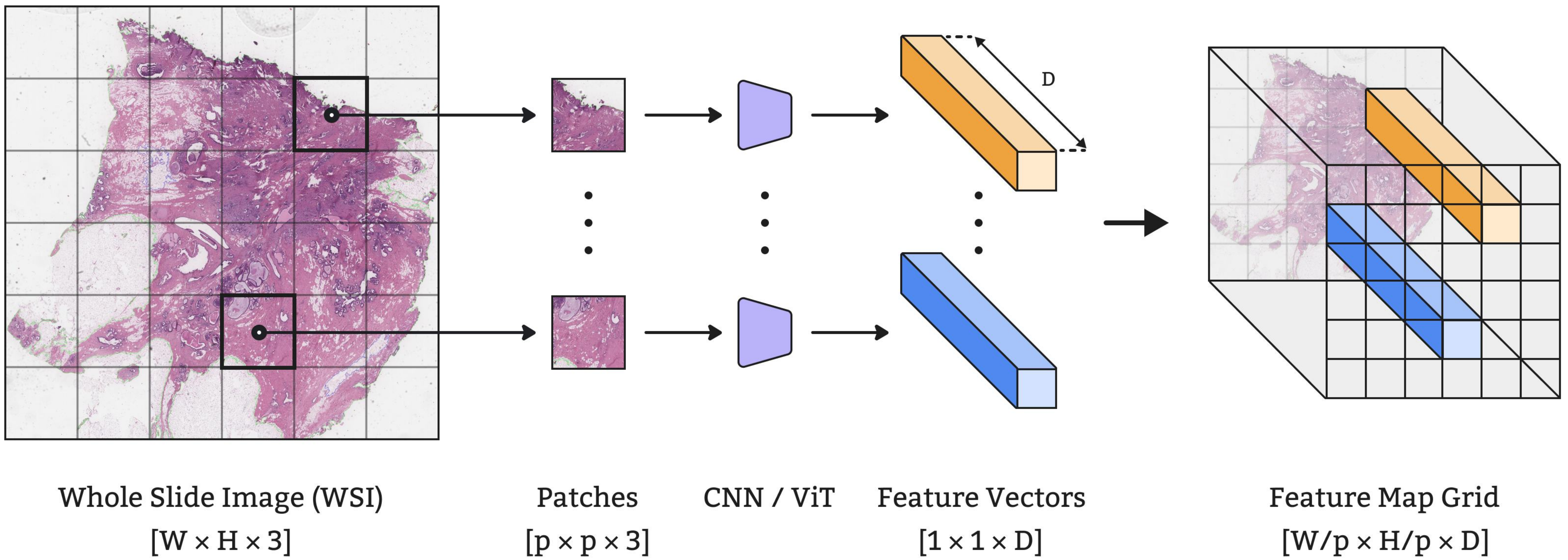


Feature Extraction Methods

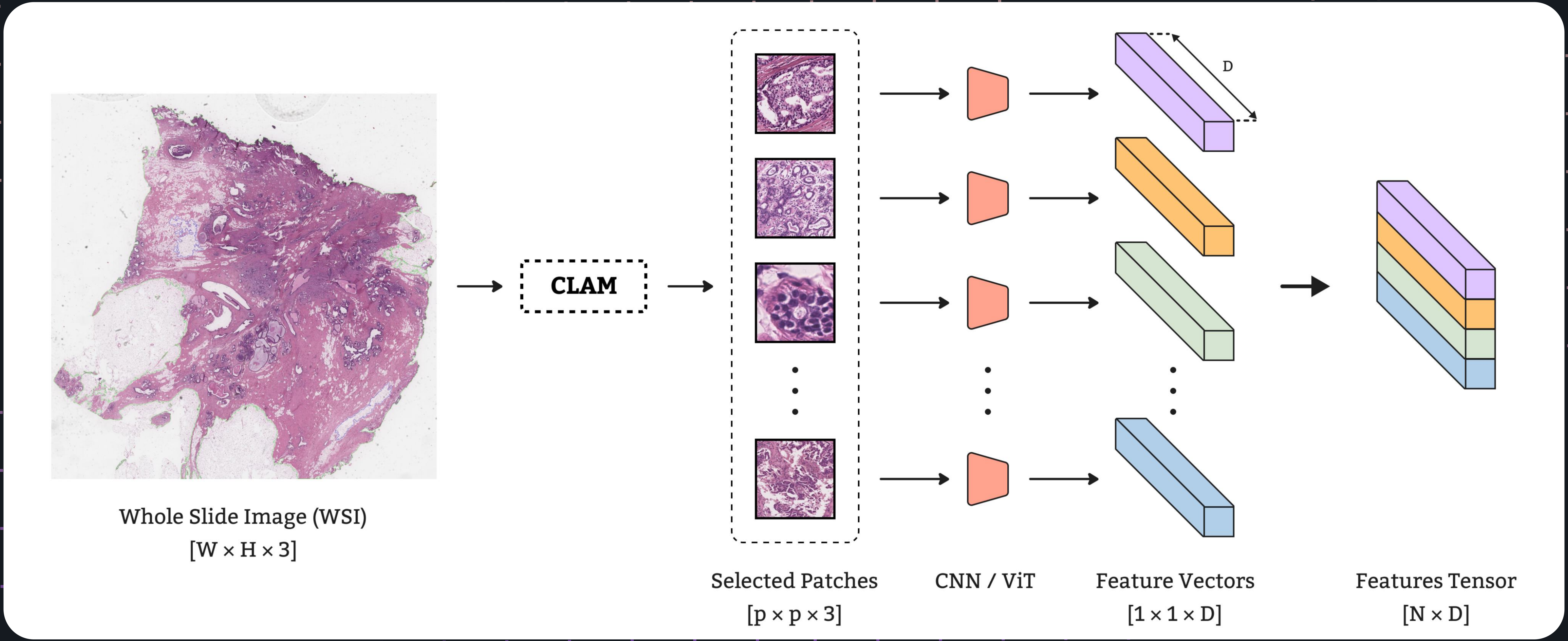
The feature extraction step involves processing the high-resolution gigapixel WSI to generate a more **compact representation** that can be processed by deep learning models. In the context of our project, two types of feature extraction were employed:

- **Grid-Based Feature Extraction (GFE)**
- **Feature Extraction with Patch Selection**

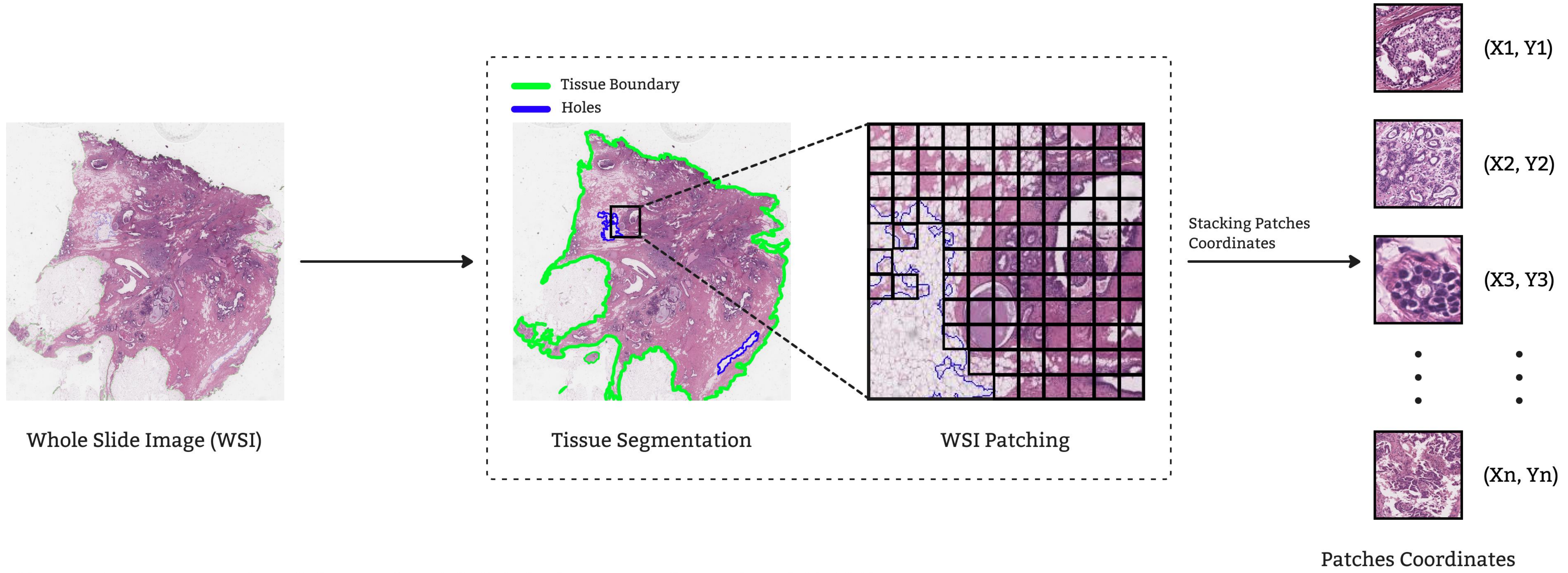
Grid-based Feature Extraction (GFE)



Feature Extraction with Patch Selection



Clustering-constrained Attention Multiple instance learning (CLAM)



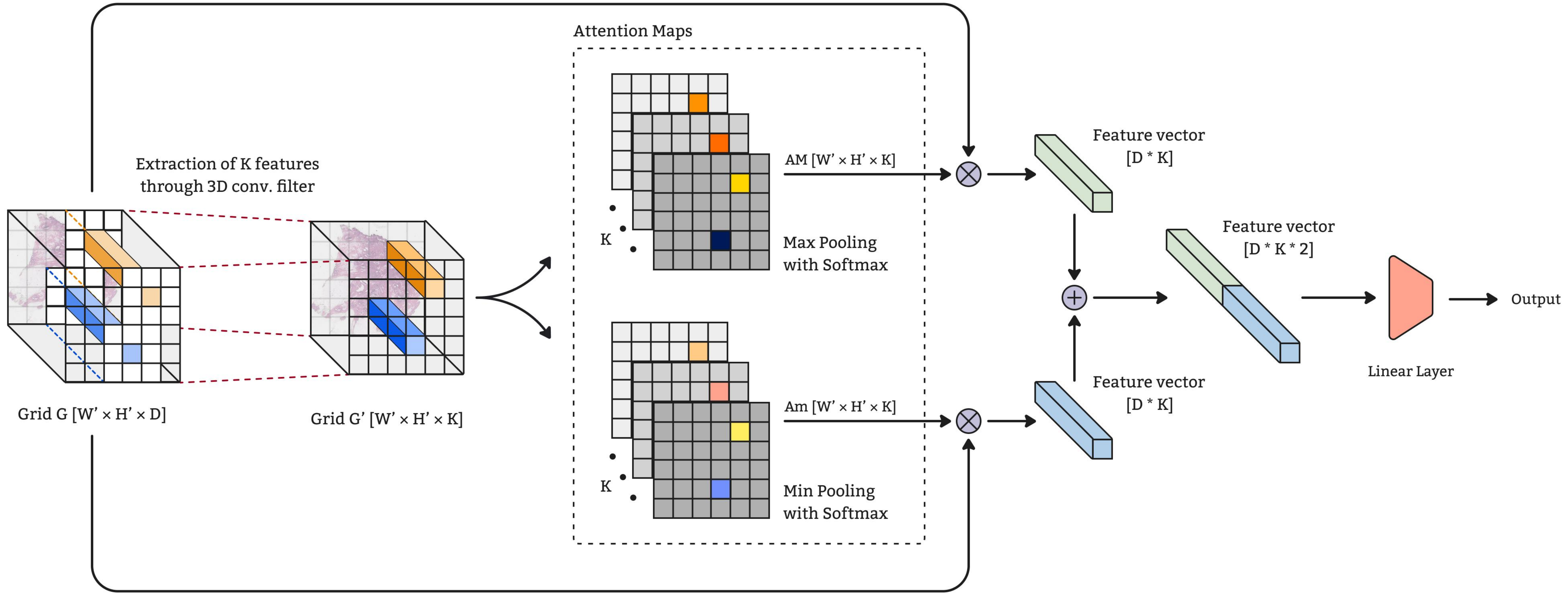
Clustering-constrained Attention Multiple instance learning (CLAM)

Attention-based Classifiers

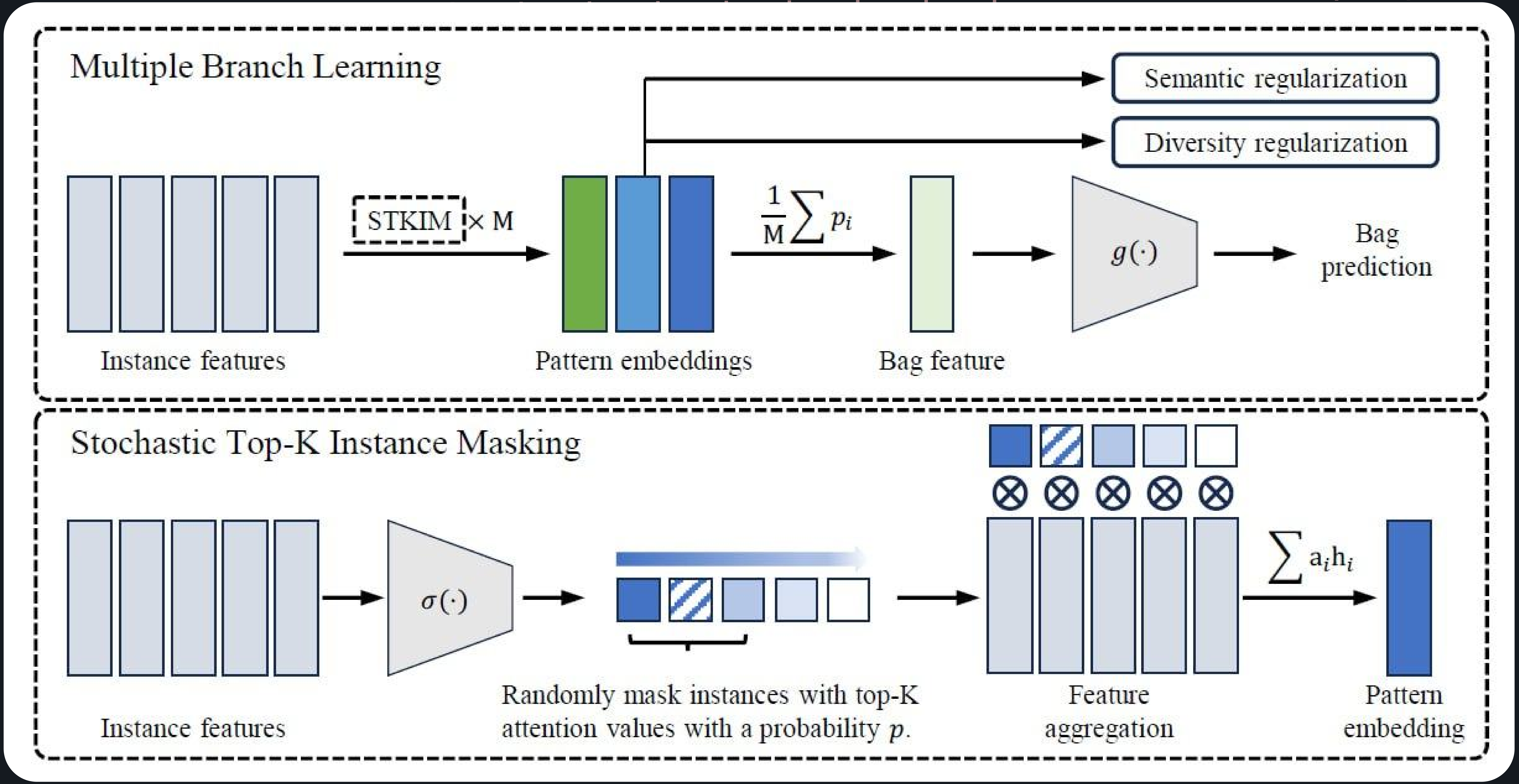
The compressed WSIs generated from the process of feature extraction are then used to train the attention-based classifiers. Two architectures were selected:

- **Min-Max Attention-Based Classifier (MMABC):** trained using GFE-generated compressed WSIs
- **Attention Challenging Multiple Instance Learning (ACMIL):** trained using patch selection-based generated compressed WSIs.

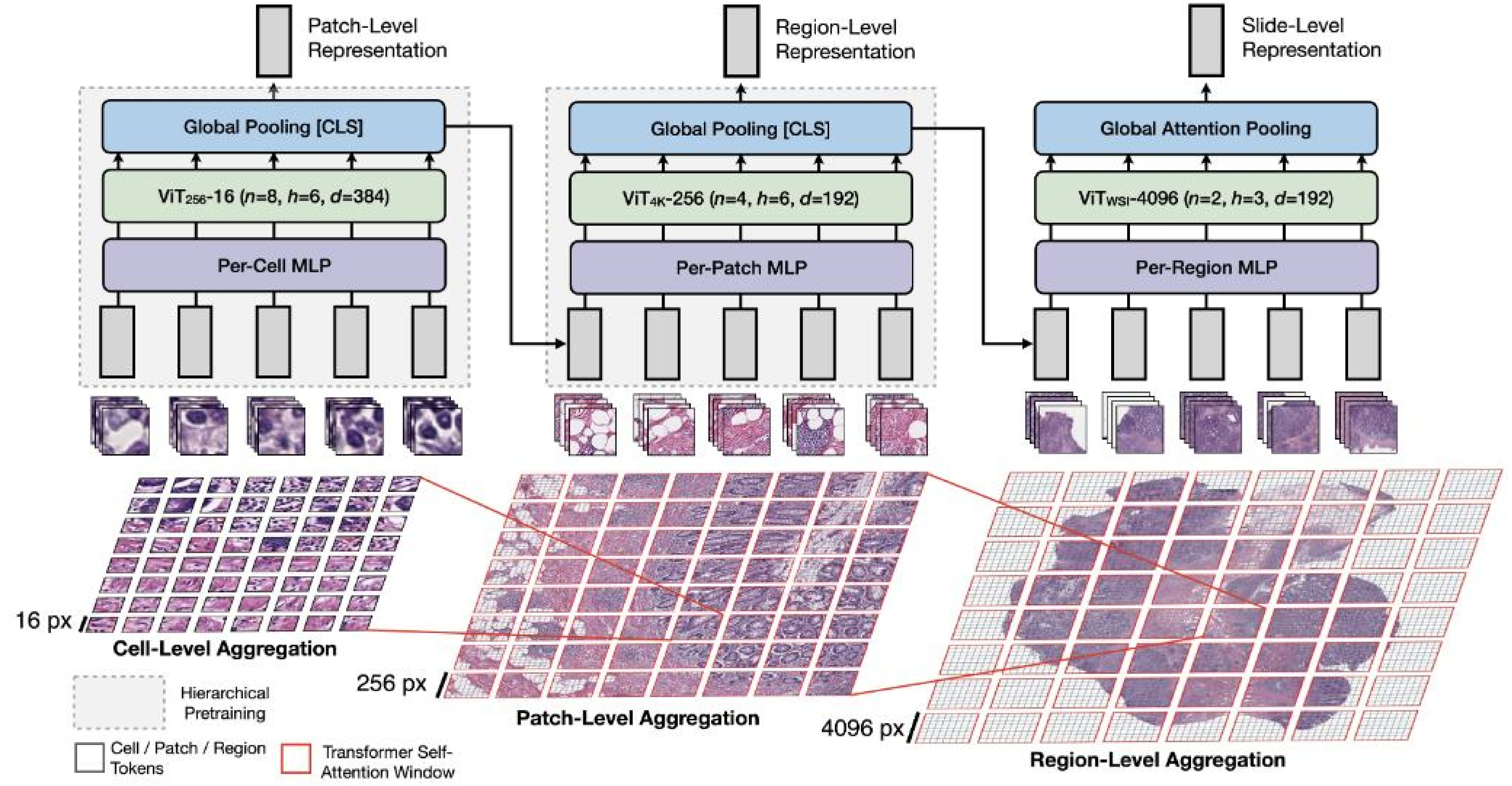
Min-Max Attention Based Classifier (MMABC)



Attention Challenging Multiple Instance Learning (ACMIL)



Hierarchical Image Pyramid Transformers (HIPT)



Training Experimentations

Firstly, we will highlight the outcomes of fine-tuning the feature extractors on The ROIs Dataset, followed by an examination of the classifiers' performance on the tensors extracted using those models and additional ones.

The experiments were conducted on an **NVIDIA GeForce RTX 3050 Ti Laptop GPU**, so consequently, the reported time corresponds to that particular device.

Feature extractors fine-tuning results

We experimented with fine-tuning **ResNet-18** and **ResNet-34** on BRACS' ROIs, and for each model, we experimented with different configurations that ranged from changing hyper-parameters to changing the number of layers to fine-tune.

Model	Hyperparameters	Config 1	Config 2
ResNet-18	Initial weights	ImageNet	ImageNet
	Batch Size	256	64
	Learning rate	0.001	0.001
	Optimizer	ADAM	SGD
	Sampler	Random	Balanced
	Weight decay	None	0.001
	Decay rate	None	None
	Dropout	None	None
	Depth (Fine-tuning)	2	3
	Epochs	20	10
	Average Epoch time (min)	14	16.5

Model	Hyperparameters	Config 1	Config 2	Config 3
ResNet-34	Initial Weights	ImageNet	ImageNet	kather100k
	Batch size	128	64	64
	Learning rate	0.001	0.001	0.0001
	Optimizer	ADAM	SGD	ADAM
	Sampler	Random	Balanced	Balanced
	Weight decay	None	0.1	0.1
	Decay rate	None	None	None
	Dropout	None	None	None
	Depth (Fine-tuning)	2	3	3
	Epochs	20	10	10
	Average Epoch time (min)	22	27	27

Feature extractors fine-tuning results

ROIs Classification Results (soft-voting)

Model	Configuration	accuracy	precision	recall	f1 score
ResNet-18	Config 1	0.461	0.543	0.470	0.396
	Config 2	***0.624***	***0.651***	***0.640***	***0.617***
ResNet-34	Config 1	0.340	0.442	0.370	0.231
	Config 2	0.540	0.614	0.566	0.523
	Config 3	0.543	0.570	0.522	0.487

ROIs Classification Results (hard-voting)

Model	Configuration	accuracy	precision	recall	f1 score
ResNet-18	Config 1	0.463	0.535	0.471	0.397
	Config 2	***0.621***	***0.632***	***0.631***	***0.612***
ResNet-34	Config 1	0.340	0.421	0.370	0.233
	Config 2	0.557	0.610	0.578	0.541
	Config 3	0.542	0.551	0.520	0.480

Patches Classification Results

Model	Configuration	accuracy	precision	recall	f1 score
ResNet-18	Config 1	0.579	0.492	0.459	0.460
	Config 2	***0.632***	***0.563***	***0.559***	***0.557***
ResNet-34	Config 1	0.555	0.460	0.405	0.382
	Config 2	0.622	0.548	0.534	0.536
	Config 3	0.592	0.518	0.500	0.495

WSI Classifiers results

We trained three different architectures on the task of classifying WSIs (MMABC, ACMIL, HIPT-WSI).

MMABC and **ACMIL** were trained on the compressed WSIs generated using different feature extractors:

- **ResNet-18** & **ResNet-34** (fine-tuned on BRACS' regions of interest).
- **ResNet-50** (trained on the Kather100k Dataset)
- **ViT-S/16** pre-trained using DINO on a substantial collection of 36,666 WSIs

While the **HIPT-WSI** was trained on the features generated from **HIPT-4096** level.

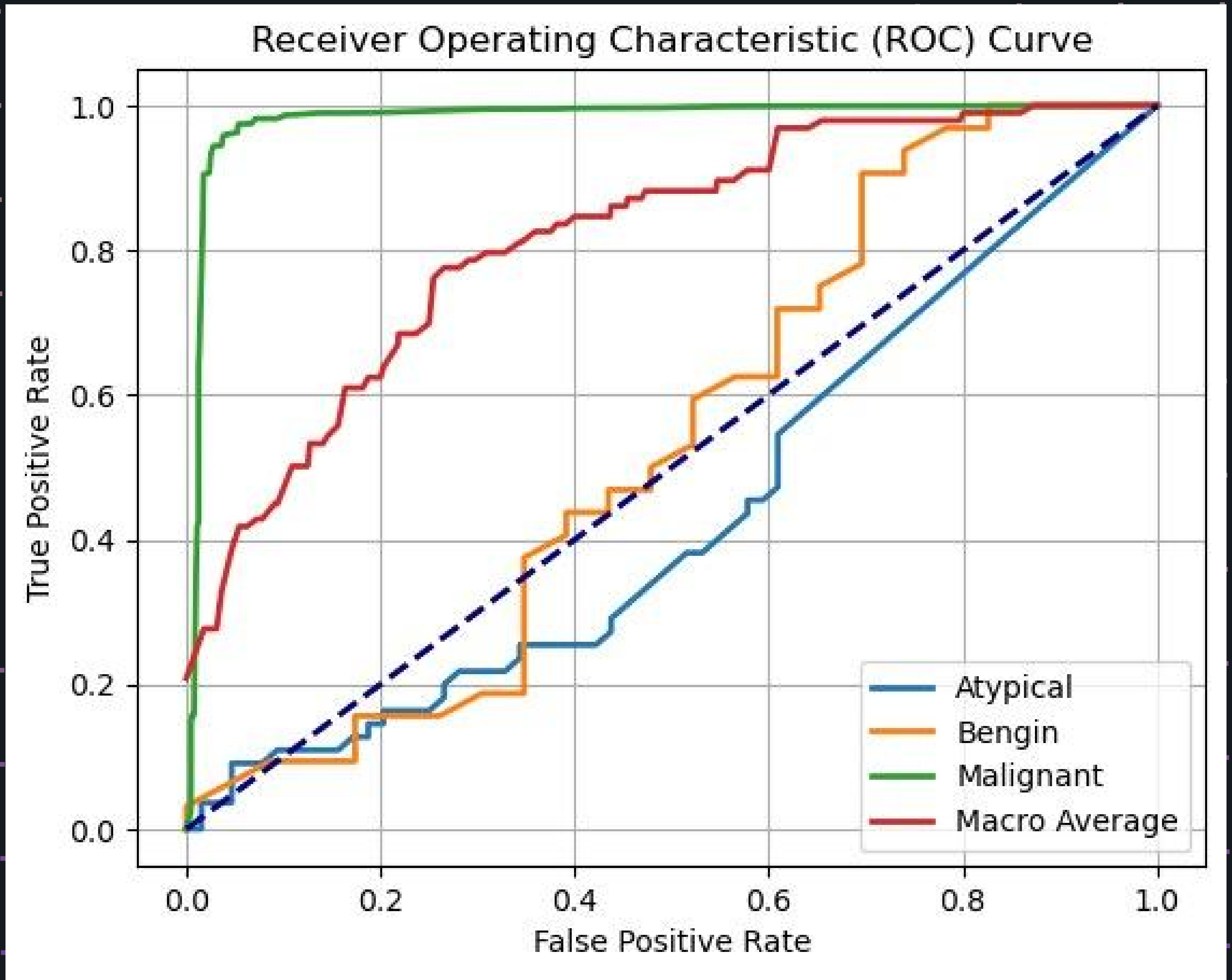
WSI Classifiers results

In this section we evaluate the performance of different architectures (**MMABC** & **ACMIL** & **HIPT**) trained on compressed WSIs generated using different feature extractors.

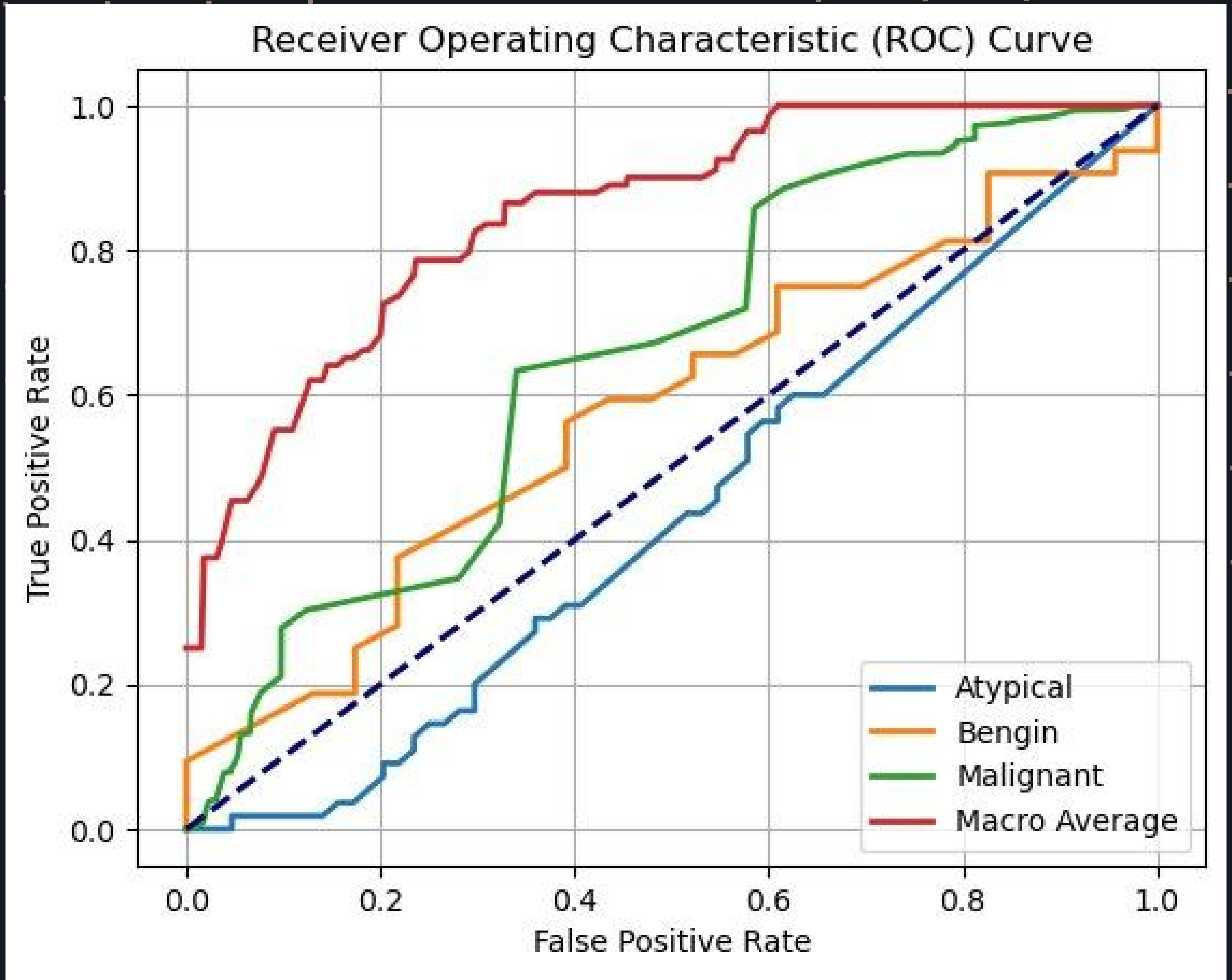
Model	Feature Extractor	LR Decay	AUC	F1 Score	Accuracy	Precision	Recall
MMABC	ResNet-18	no	0.78	0.52	0.62	0.54	0.56
	ResNet-34	no	0.81	0.53	**0.66**	0.56	0.60
	ResNet-50	no	0.73	0.46	0.55	0.58	0.51
	ViT-S/16	no	**0.86**	0.52	0.63	0.51	0.57
ACMIL	ResNet-18	no	0.76	0.52	0.55	0.51	0.52
		yes	0.79	0.48	0.63	0.43	0.57
	ResNet-34	no	0.77	0.55	0.59	0.55	0.56
		yes	0.77	0.44	0.57	0.38	0.52
	ResNet-50	no	0.67	0.40	0.51	0.36	0.46
	ViT-S/16	no	0.82	0.56	0.63	0.56	0.59
		yes	0.84	**0.65**	**0.66**	**0.65**	**0.65**

Model	Data Augmentation	AUC	F1 Score	Accuracy	Precision	Recall
HiPT	No	0.77	0.56	0.62	0.56	0.58
	Yes	0.81	**0.68**	**0.72**	**0.73**	**0.68**

ROC Curves of the best models



Best Model of the HIPT Method



Best Model of the ABNN Methods

Information System for data collection

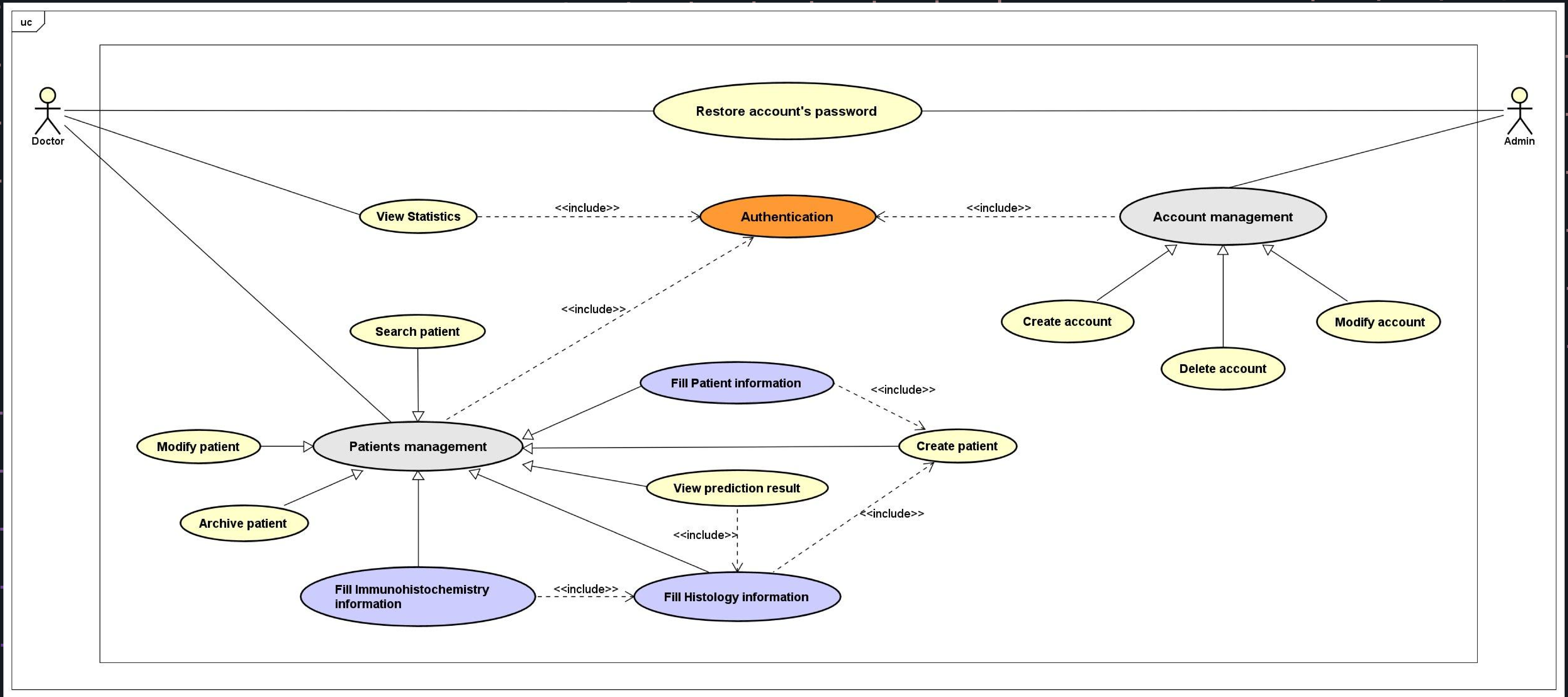
Anti-Cancer Center of Sidi Bel Abbes

The Anti Cancer Center of Sidi Bel Abbes (CAC SBA) is one of 25 centers across the country, which are dedicated to the diagnosis and treatment of cancer, it was established in 2017 under the direct supervision of the Algerian Ministry of Health and Population.

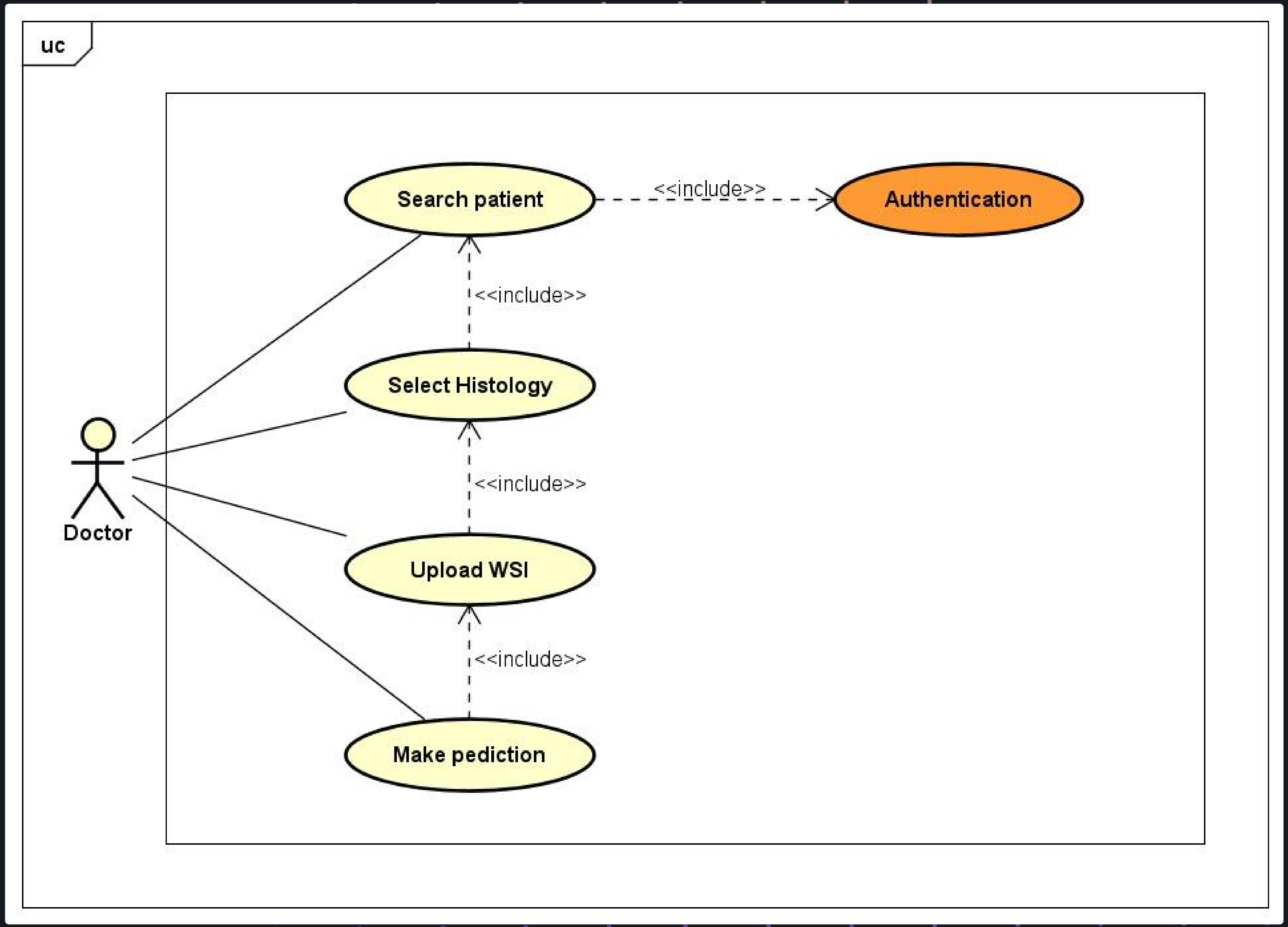
Information System overview

The system is divided into two parts, a **web application** in which the doctor manages patients files, and a **desktop application** in which the medic uploads a WSI of a breast pathology and makes a prediction using the best AI model amongst our experimentations.

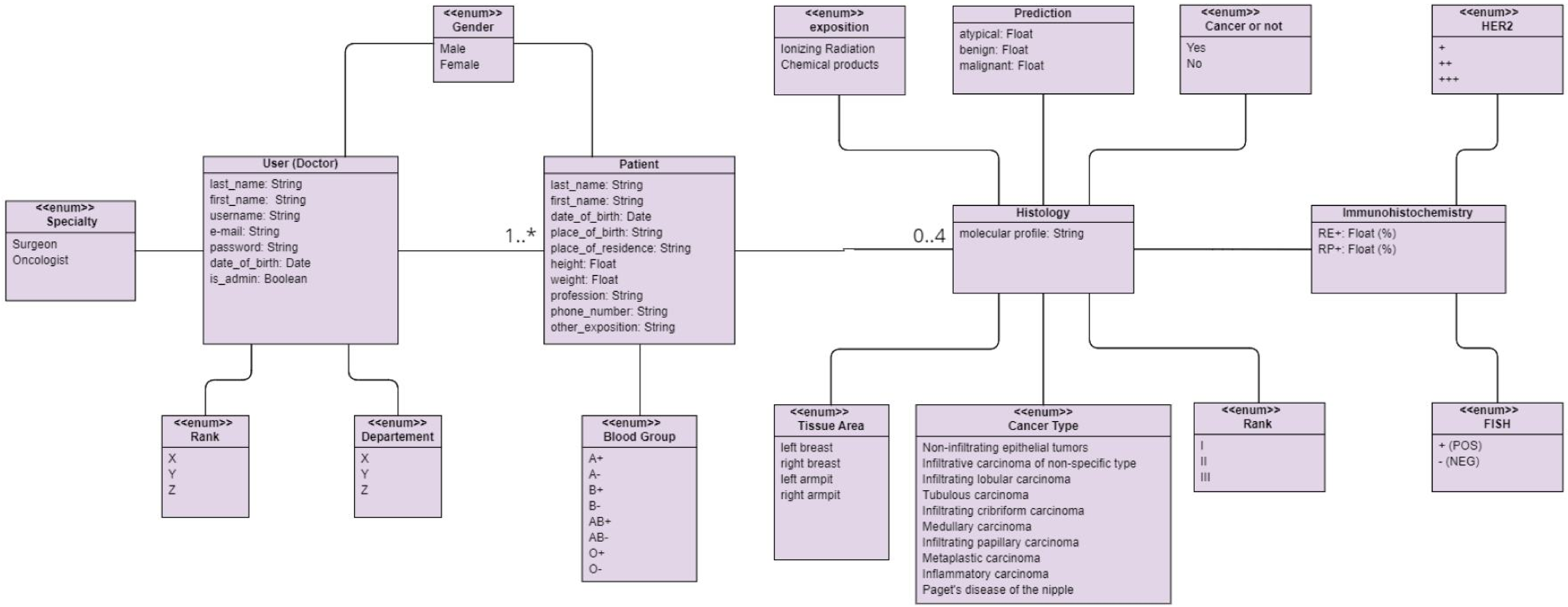
System Conception



System Conception



System Conception



Used tools (Diagnostic System)

Python
High-level programming language

Pytorch
Preprocessing, training and evaluation of Deep Learning Models

OpenSlide
Library used to read Whole Slide Images (WSIs)

Tkinter
Python interface for deployment

Used tools
(Information System)

React JS
JavaScript framework

Tailwind CSS
CSS framework

Axios
HTTP client

PostgreSQL
Database management

PostgreSQL
Server side web framework

Let's take a closer look with a live demo!

Summary & Conclusion

This multidisciplinary project aimed to develop an effective and robust system for breast cancer detection in whole slide histopathological images (WSIs).

The project explored and evaluated diverse deep learning architectures and techniques (**MMABC**, **ACMIL**, **HIPT**) using different feature extractors (**ResNet-18**, **ResNet-34**, **ResNet-50** and **ViT-S/16**).

The results demonstrate the potential of these techniques in addressing the challenges of breast cancer detection in histopathological images, which could have far-reaching implications, empowering healthcare professionals with a powerful tool for early detection and accurate diagnosis.

Thanks for your attention!

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