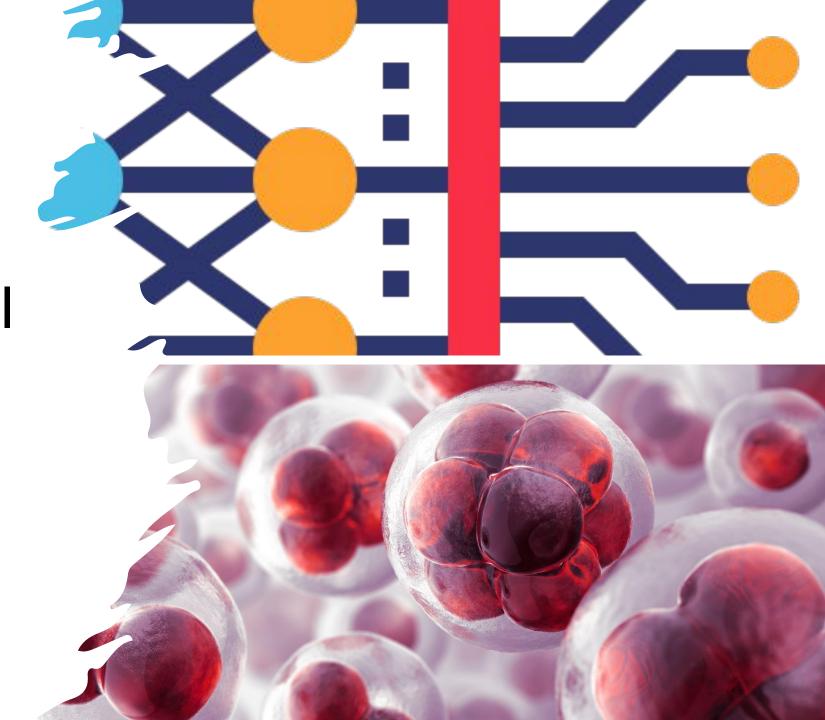
Invasive Ductal Carcinoma Classification



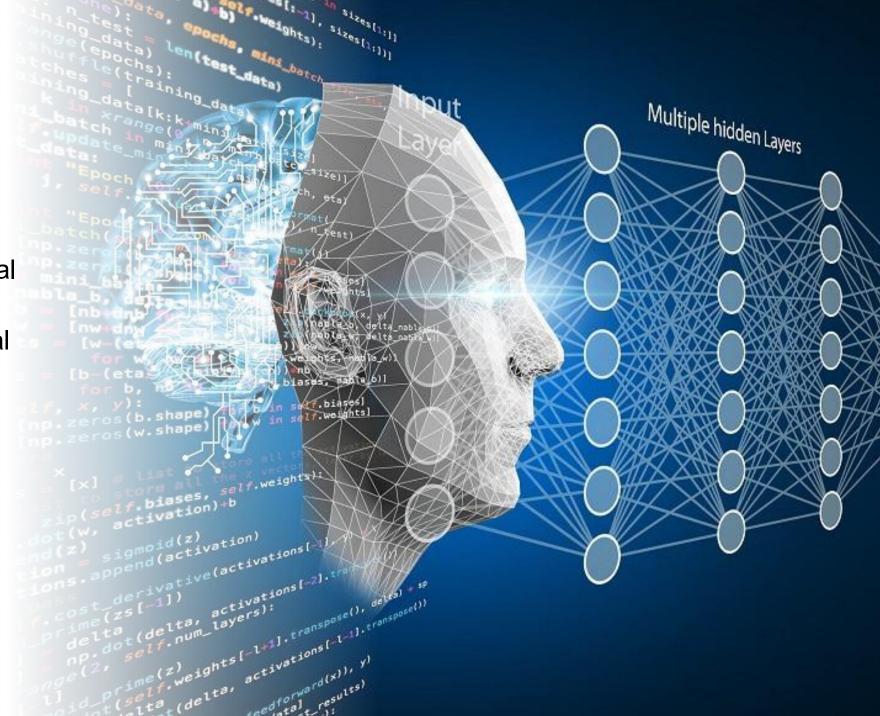
## Team

 Implementation of original project with fasAl library Alessandro Tiveron Francesco Ferronato Mattia Tortelli Virgolini Niccolò Brusadin



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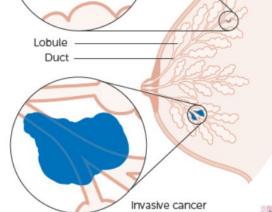
- Description of the Original Project
- Limitations of the Original Project
- Objective
- Method
- Results



# Data Overview and Task

Original Dataset: 162 whole-mount slide images of Breast Cancer specimens

Patch Extraction: 277,524 patches (50 x 50 pixels) Class Distribution: 198,738 IDC negative 78,786 IDC positive



Localised L

dass0



dass1



class0

Filename Format: u\_xX\_yY\_classC.pn g

- •u: Patient ID (e.g., 10253\_idx5)
- •X: x-coordinate of patch
- •Y: y-coordinate of patch
- •C: Class (0 for non-IDC, 1 for IDC)

Objective: Classify patches into IDC negative (0) and IDC positive (1) using fastAl and CNN

Challenge: Utilize the dataset to develop a robust model for accurate Breast Cancer classification









# Description of the Original Project

#### **Methodology:**

•FastAl implementation of Transfer Learning Approach

#### **Data Exploration:**

- Organized Kaggle dataset into patient folders
- Each patient folder contains 2 subfolders 'class 0' and 'class 1'

#### **Data Loading:**

•ImageDataBunch setup with validation, augmentation, and normalization

#### **Transfer Learning:**

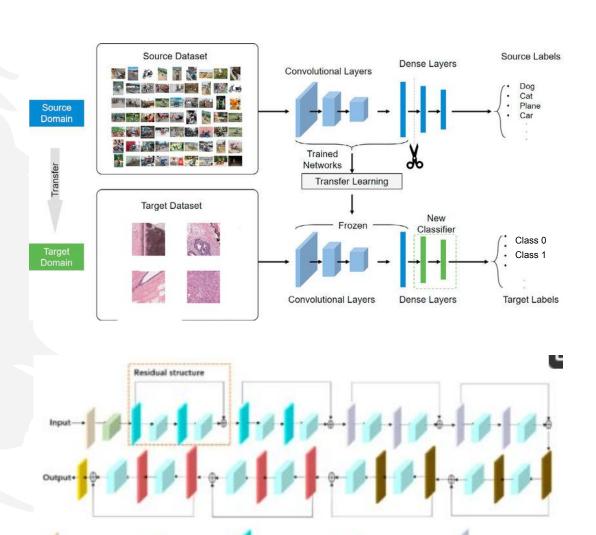
- •Adopted pre-trained ResNet18 on ImageNet
- •Focus on fine-tuning last layer

### Model Implementation:

 Implemented with cnn\_learner() using pre-trained ResNet18

#### Learning Rate Optimization:

•Optimized using Ir\_find(), one-cycle training, and refined learning rates

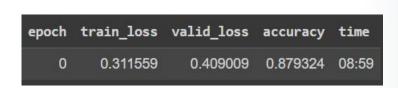


Norm + Relu Sum 3 x 3 Conv. 128 filters

7 x 7 Conv, 64 filters Norm + Relu + Pool 3 x 3 Conv, 64 filters

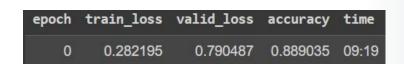
3 x 3 Conv. 256 filters 3 x 3 Conv. 512 filters Fully connected + Softmax

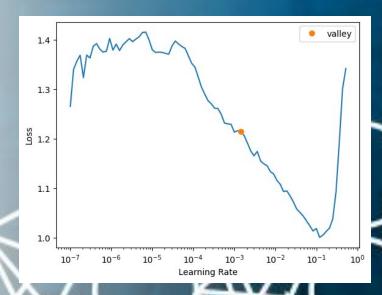
Performance of model trained with fit\_one\_cycle policy (for 1 epoch??) (Ale?)

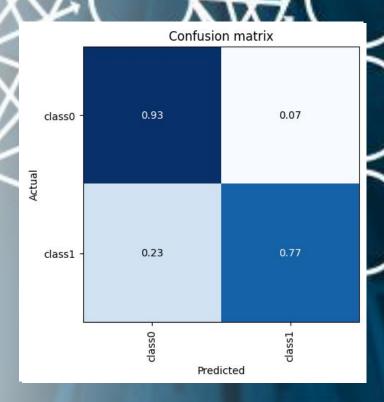


Performance improved after unfreezing and optimizing hyperparameters

0







# Limitations of the Original Project

Outdated fastAl library version

Data preparation

Lack of test set

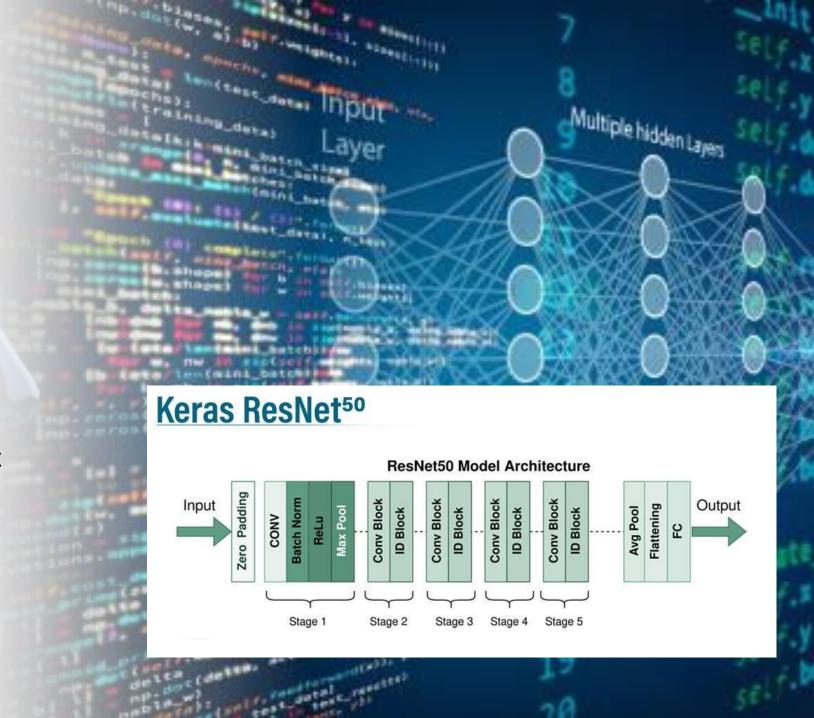
Unbalanced classes

# Train model on Training Set Tweak model according to results on Validation Set Pick model that does best on Validation Set Confirm results on Test Set

V7 Labs

## Objective

- Understanding the original project
- Transition from fastAl to Keras
- Implement the latest fastAl libraries
- Enhance robustness with a test set, balance classes
- Exploring ResNet50's potential



# Methods: Pre-training



#### **Library Utilization:**

A Keras user-friendly implementation (to control data augmentation and preprocessing)



#### **Data Preprocessing:**

Organizing histopathology images into 70% training and 15% validation and 15% test set



#### Class Imbalance Handling:

Weights assigned to prioritize correct classification of class 1



#### Augmentation and Preprocessing:

With RandomFlip(), RandomRotation() and RandomZoom()

# Methods: Model Training optimization



#### 1. Finding Optimal Learning Rate

Identify the best learning rate for model training.



#### 2. Unfreezing Model Parameters

Unlock all hyperparameters for comprehensive training



#### 3. Re-evaluating Learning Rate Post-Unfreezing

Reassess the optimal learning rate after unfreezing parameters



#### 4. Fine-Tuning

Define model convergence with unfrozen parameters

## Methods: Models



Transfer Learning with EfficientNetV2S:

EfficientNetV2S, pretrained on ImageNet, as first model implementation



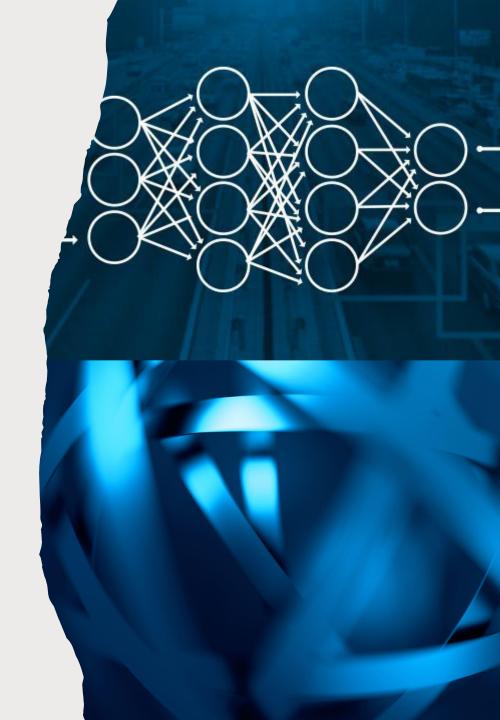
Transfer Learning with ResNet50:

Exploration of ResNet50 for binary classification as an alternative approach

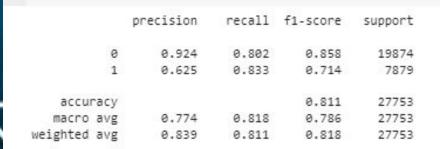


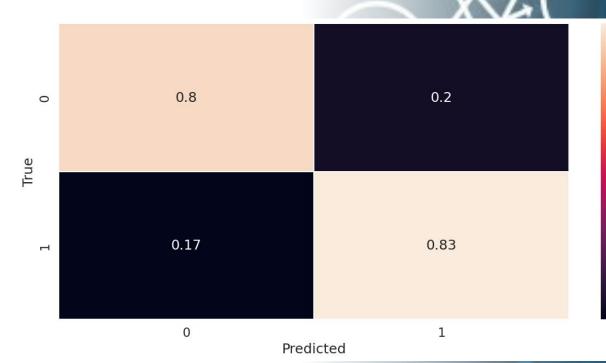
Performance Evaluation:

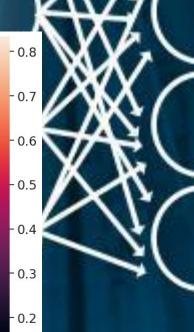
Predictions and evaluation on an external test set after 5 epochs



 Performance of EfficientNetV2s on test set







•Examples of cancer classification (Attendo immagini del codice runnato)





loss

0.0 0.5 1.0 1.5 2.0 2.5 3.0 3.5 4.0

0.6

0.5

0.3

Performance on test set of ResNet50 trained for # epochs

⊟	precision	recall	f1-score	support
0	0.953	0.841	0.893	4138
1	0.687	0.893	0.777	1622
accuracy			0.855	5760
macro avg	0.820	0.867	0.835	5760
weighted avg	0.878	0.855	0.860	5760

0.865

0.860

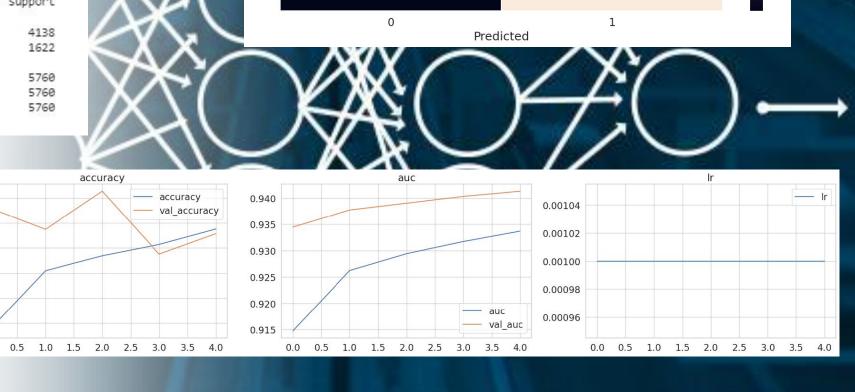
0.855

0.850

0.845

0.840

accuracy



0.84

0.11

- 0.8

- 0.7

- 0.6

- 0.5

- 0.4

- 0.3

-0.2

0.16

0.89



# Conclusion (da confermare)



# High Accuracy with ResNet50:

ResNet50 demonstrates precision in predicting IDC and non-IDC cases as original project



#### **Improved Robustness:**

Results are significantly enhanced with the implementation of a dedicated test set and balanced classes