AI Applications on biomedical images and signals

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OUTLINE

01.

INTRODUCTION

02.

RESEARCH FIELDS

03.

DISCUSSION

MEET OUR TEAM

ARTIFICIAL INTELLIGENCE IN BIOMEDICINE

AI-based algorithms can mine vast amounts of data from electronic health records, medical images, genomic data, and other sources. This is important because AI-based solutions can support medical care and decisions and it has an important role in personalized medicine.

RESEARCH FIELDS

01. Melanoma skin cancer images

02. ECG signals

03. Breast cancer classification

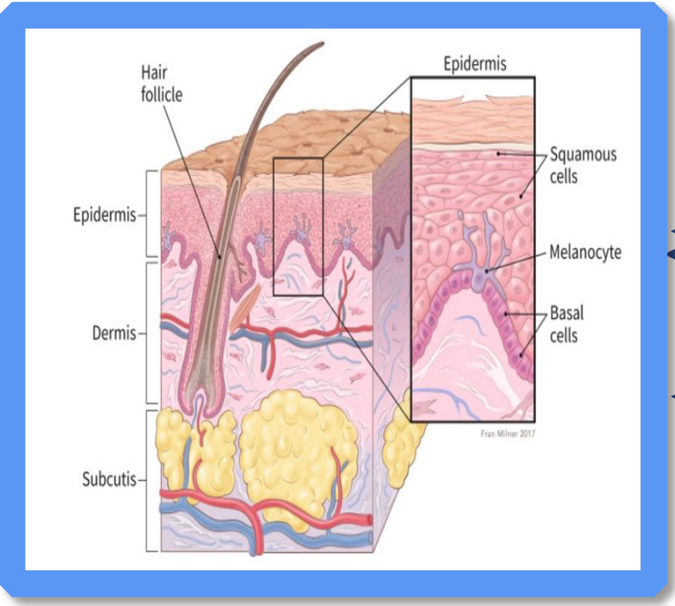
01.

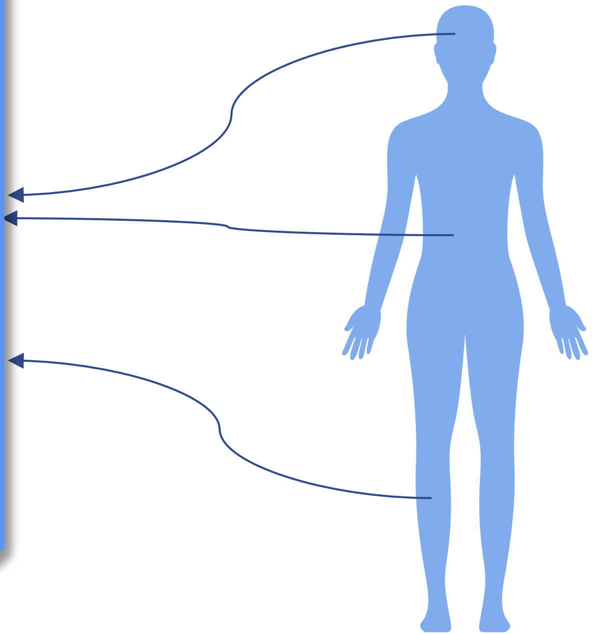
MELANOMA CLASSIFICATION

1. Minimization of False Negative Rate (NFR)
2. CNNs design employing Genetic Algorithms (GA)
3. Cloud Approach for melanoma detection
4. Real Time support

The Melanoma Detection Problem

Melanoma





Sun exposure

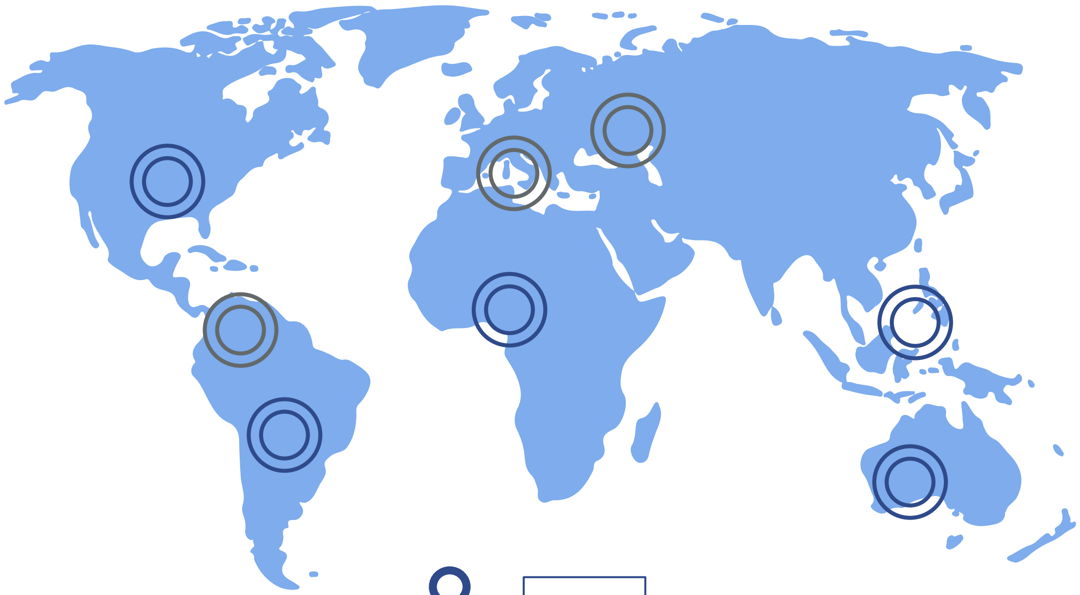
Indoor tanning

Moles

Family History

Race or ethnicity

Prevalence (American Cancer Society)



2.6% for Whites

0.1% for Blacks

0.6% for Hispanics

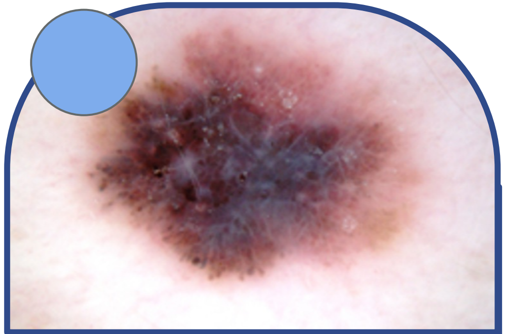
before age 50

The risk of melanoma increases as people age

Early diagnosis is very important!

Dataset for melanoma detection

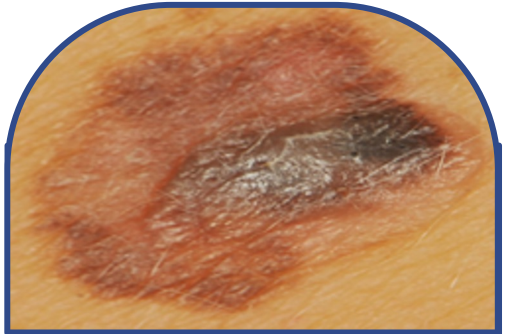
Dermatological



HAM 10000 dataset

High resolution

Clinical



MEDNODE dataset

Low resolution

- Anatomical area
- Clinical and pathological data
- Familiarity
- Diagnosis

I.

Minimization of FNR

ROAD MAP

01

Data selection

MED-NODE
(clinical images)

02

Methods

9 CNNs: Alexnet, DenseNet, GoogleNet Inception V3, GoogleNet, MobileNet, ShuffleNet, SqueezeNet, VGG16

03

Generation of datasets

4 datasets: INA, NIA, IA, NINA

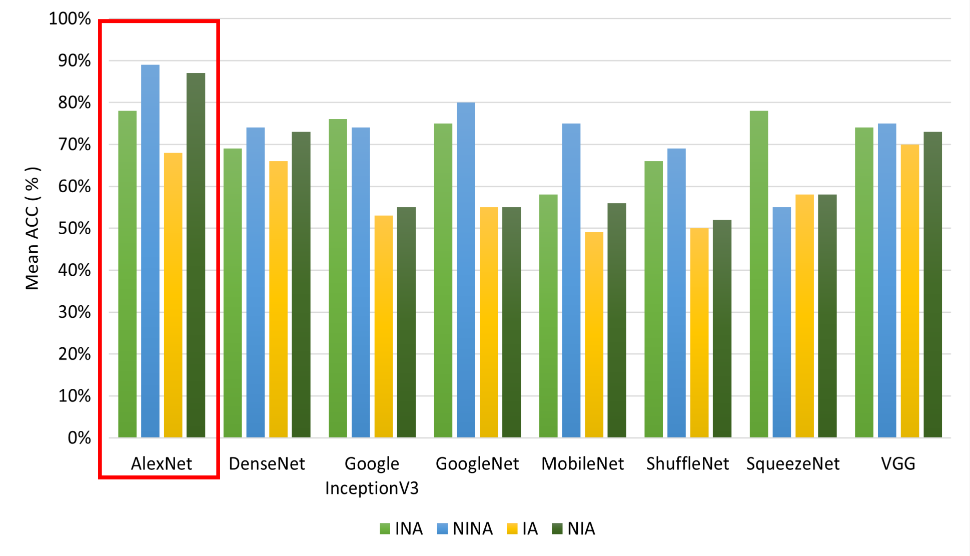
04

Data augmentation & pre-processing

IIQ and OTSU segmentation

05

Evalutation & Results



Results

All tested neural networks perform better without data augmentation, with **AlexNet** and SqueezeNet achieving a maximum accuracy of 78%. Without pre-processing and data augmentation, AlexNet performed best with 89%, 75% and 82% of accuracy, sensitivity, and specificity, respectively.

IIQ not active							
Net	**Data Augmentation**	**SN**	**SP**	**PPV**	**FDR**	**FNR**	**FPR**
AlexNet	None	0.87	0.90	0.86	0.15	0.13	0.10
	Yes	0.84	0.91	0.87	0.14	0.16	0.09
DenseNet	None	0.56	0.82	0.77	0.23	0.29	0.18
	Yes	0.64	0.74	0.56	0.44	0.19	0.26
Google InceptionV3	None	0.73	0.76	0.62	0.38	0.27	0.24
	Yes	0.39	0.60	0.29	0.71	0.57	0.40
GoogleNet	None	0.79	0.82	0.72	0.28	0.21	0.18
	Yes	0.45	0.63	0.48	0.52	0.54	0.37
MobileNet	None	0.81	0.72	0.45	0.55	0.14	0.28
	Yes	0.32	0.61	0.29	0.71	0.37	0.38
ShuffleNet	None	0.61	0.74	0.60	0.40	0.35	0.26
	Yes	0.36	0.60	0.45	0.55	0.52	0.39
SqueezeNet	None	0.23	0.43	0.43	0.57	0.22	0.27
	Yes	0.43	0.62	0.41	0.59	0.41	0.37
VGG	None	0.58	0.83	0.76	0.24	0.27	0.17
	Yes	0.82	0.59	0.40	0.60	0.07	0.24

Results

VGG can guarantee the lowest FNR at the expense of global accuracy, whereas AlexNet can guarantee comparable FNR to VGG but with the highest global accuracy

2.

CNNs design employing Genetic Algorithms (GA)

ROAD MAP

01

Data selection

ISIC
(dermoscopic
images)

02

Pre-processing

contrast enhancement
for coloured images routine (rgbCER) and
k-means segmentation

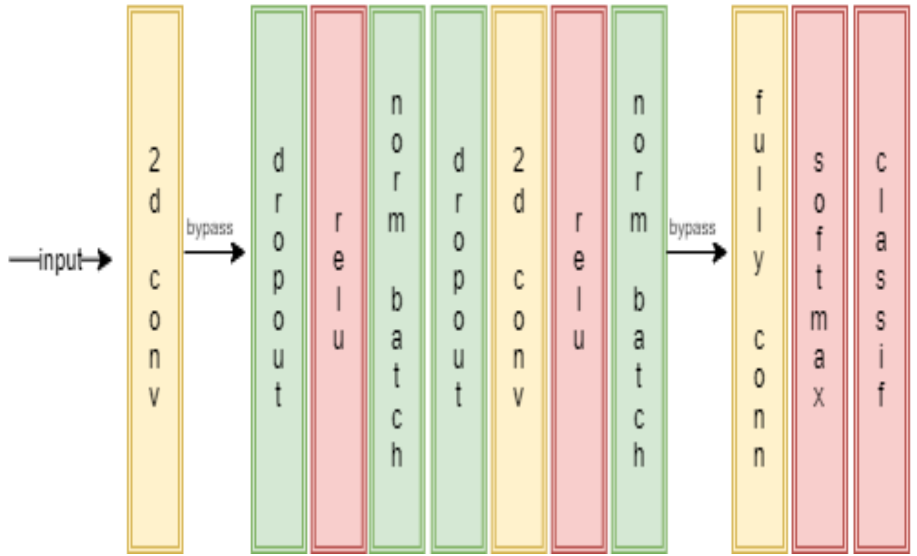
03

Methods

Design of CNNs
with GA

04

Evalutation & Results



Results

The hybrid approach to melanoma detection CNN design achieves 94% accuracy, 90% sensitivity, 97% specificity, and 98% precision.

The proposed method could improve melanoma classification by eliminating the need for user interaction and avoiding a priori network architecture selection

3.

Cloud Approach for melanoma detection

ROAD MAP

01

Data selection

MED-NODE
(clinical images)

02

Methods

3 CNNs: Alexnet, GoogleNet Inception V3 and GoogleNet

Three layers architecture

03

Generation of datasets

4 datasets: MD1, MD2, MD3 and MD4

04

Pre-processing

Data Augmentation and OTSU segmentation

05

Evalutation & Results

Goals

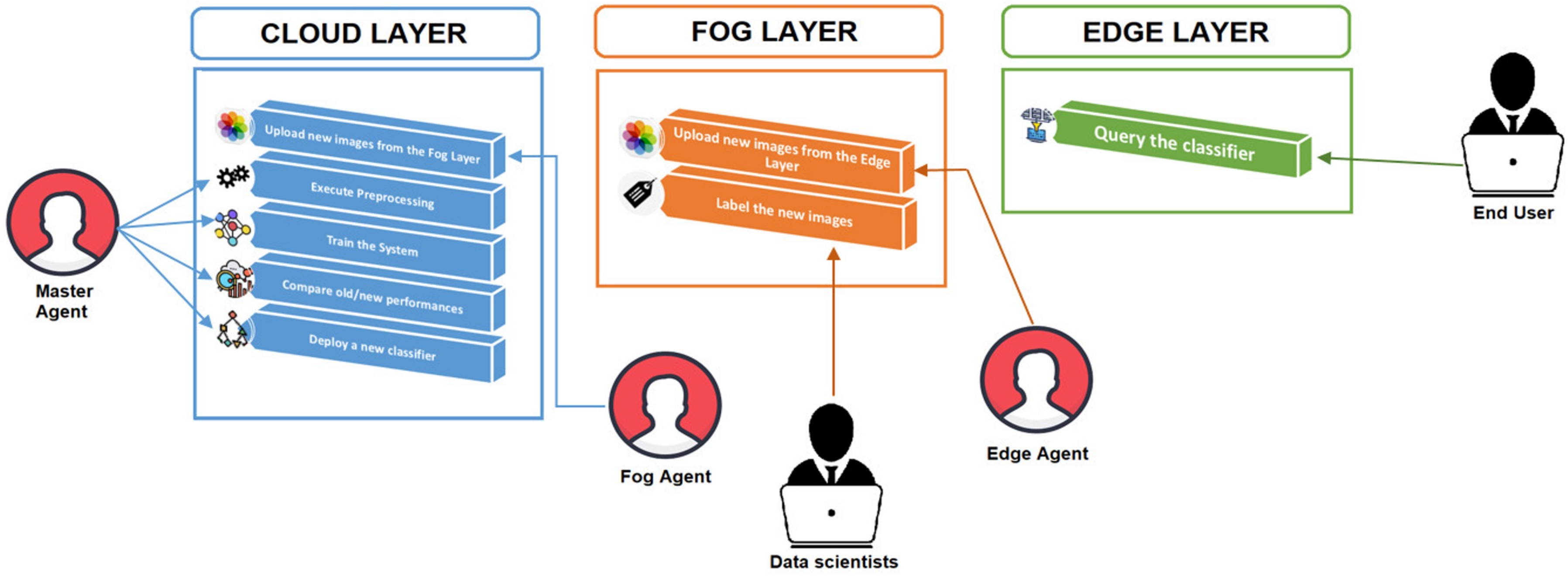
1.

**Our goal
was to show how the datasets
structure modifications could cause a
drop in the overall
system performance**

2.

Design the architecture to allow automatic classifier retraining and deploying to show that a distributed and cooperative system is needed to deploy a melanoma classifier robust against Transfer Learning issues.

Three layers architecture



WITH OTSU SEGMENTATION

Net	Data Augmentation	ACC (min)	ACC (max)	ACC (mean)	ACC (sd)
AlexNet	None	**0.65**	**0.94**	0.78	0.06
	Yes	0.44	0.91	0.68	0.08
Google InceptionV3	None	**0.56**	**0.94**	**0.76**	0.07
	Yes	0.32	0.74	0.53	0.09
GoogleNet	None	**0.60**	**0.91**	**0.75**	0.07
	Yes	0.32	0.74	0.55	0.09

WITHOUT OTSU SEGMENTATION

Net	Data Augmentation	ACC (min)	ACC (max)	ACC (mean)	ACC (sd)
AlexNet	None	0.68	**1**	0.89	0.05
	Yes	**0.76**	0.97	0.87	0.05
Google InceptionV3	None	**0.56**	**0.94**	**0.74**	0.07
	Yes	0.32	0.71	0.55	0.07
GoogleNet	None	**0.65**	**0.94**	**0.80**	0.06
	Yes	0.30	0.76	0.55	0.09

Results

The best result is obtained for the **AlexNet** network **without data augmentation** and with and without the applied segmentation

4.

Real Time support

ROAD MAP (I)

01

Real-time data acquisition

02

Continuous tracking

to track the device's position with respect to the patient skin to determine the distance and the device orientation

03

Image Pre-processing

04

Feature extraction and classification

05

Rendering and pose estimation

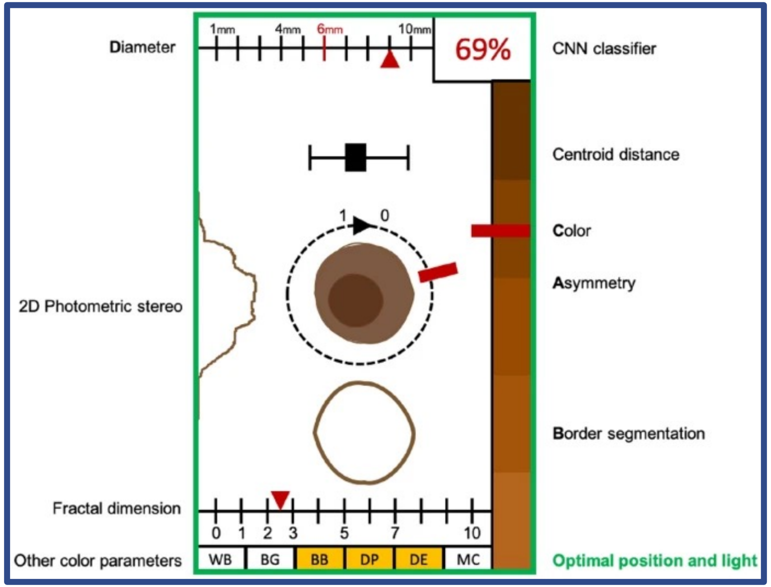
The evaluated features are combined with the original image

06

Displaying

The augmented image is shown in the dermatologist camera view

A sketch of the visualization layout



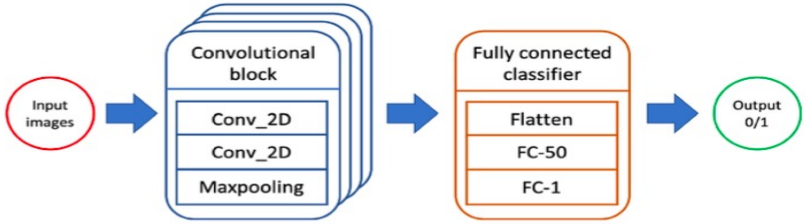


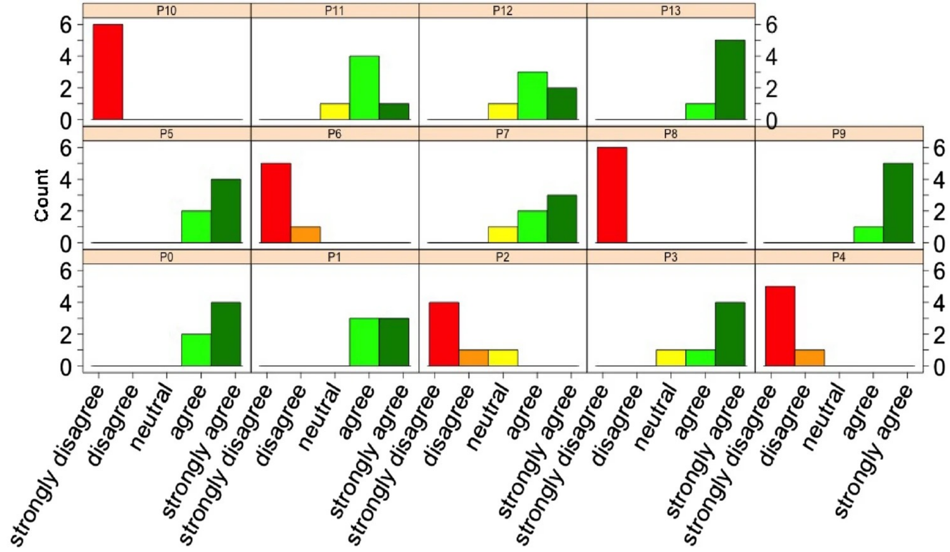
Fig. 5 The Convolutional Neural Network architecture

Table 2 The CNN classification results

Accuracy	Sensitivity	Specificity
78.8%	91.3%	73.0%

Results

To analyze the classification results of the adopted CNN model we computed accuracy, sensitivity, and specificity. The CNN classifier obtained an accuracy average result of 78.8%.



ID	Question
P0	The tasks to perform were clear
P1	I think that I would like to use this system frequently
P2	I found the app unnecessarily complex
P3	I thought the app was easy to use
P4	I think that I would need the support of a technical person to be able to use this app
P5	I found the various functions in this system were well integrated
P6	I thought there was too much inconsistency in this app
P7	I would imagine that most people would learn to use this system very quickly
P8	I found the app very cumbersome to use
P9	I felt very confident using the system
P10	I needed to learn a lot of things before I could get going with this system
P11	Is the loading time of the augmented skin lesion information during the lesion analysis satisfactory
P12	The metaphors for depicting the skin lesion features during the lesion analysis are easy to understand
P13	Overall, I'm satisfied of the support offered by the tool in the skin lesion examination
P14	Open comments

Usability

The dermatologist perceptions were collected at the end of the experiment through the Post-Experiment questionnaire. The participant perception of the system Usability has been collected by using the standard Italian version of the System Usability Scale (SUS) questionnaire, is a Likert Scale which consists of 10 questions. Each question is ranked from 1 (disagree vehemently) to 5 (strongly agree).

02.

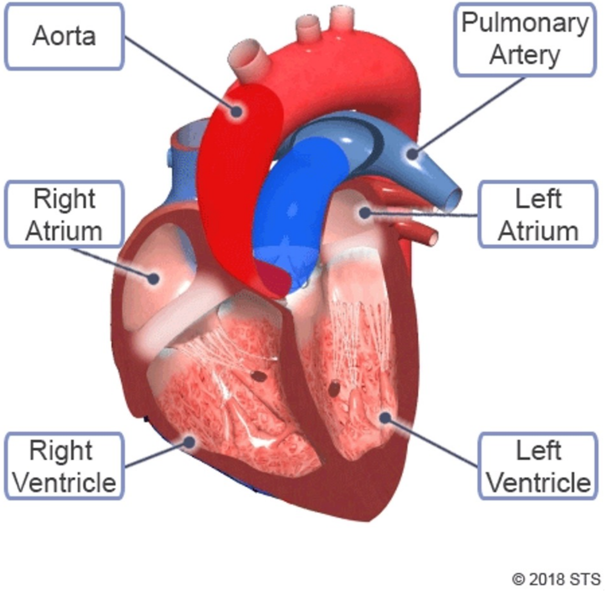
Classification of ECGs

1. Classification of Premature Ventricular Contractions

2. Identification of a Pattern in Premature Ventricular Contractions

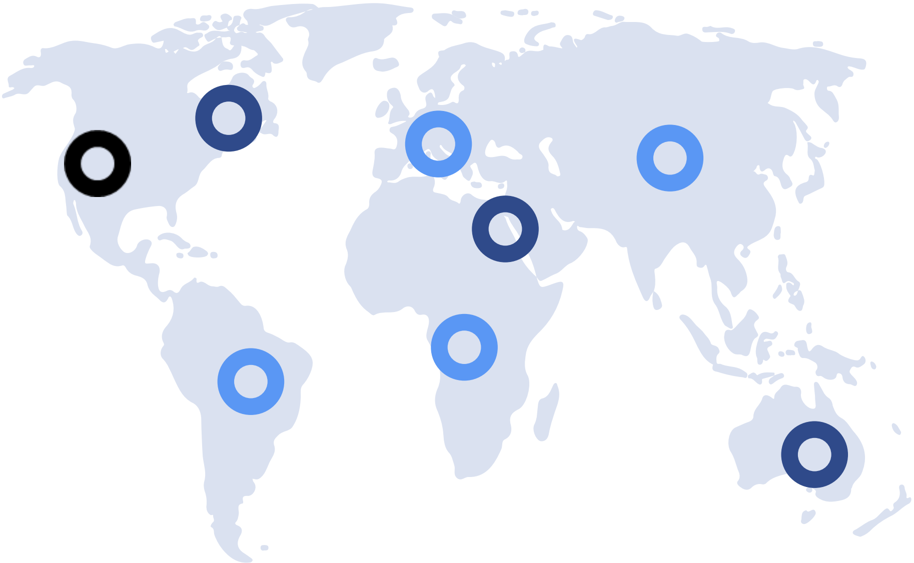
Cardiovascular Disease

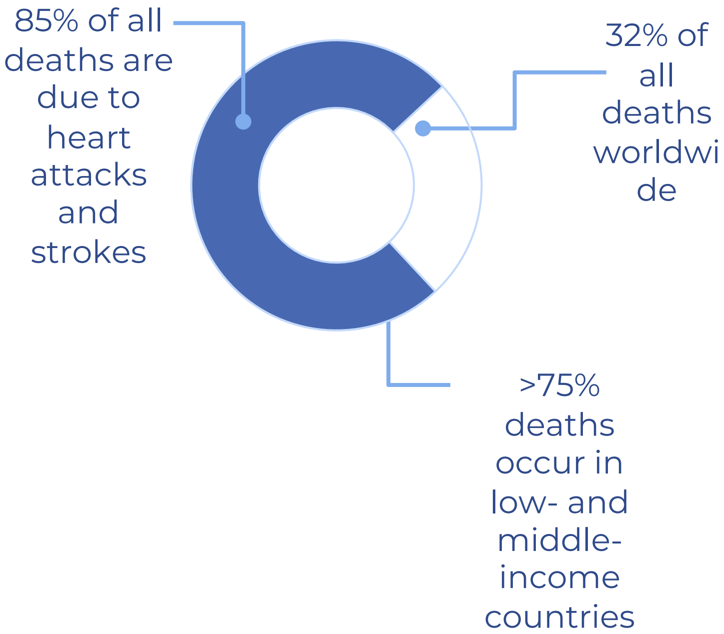
The Heart



The heart is a muscle,
divided into four heart chambers, which beats and continuously pump blood to the rest of the body.

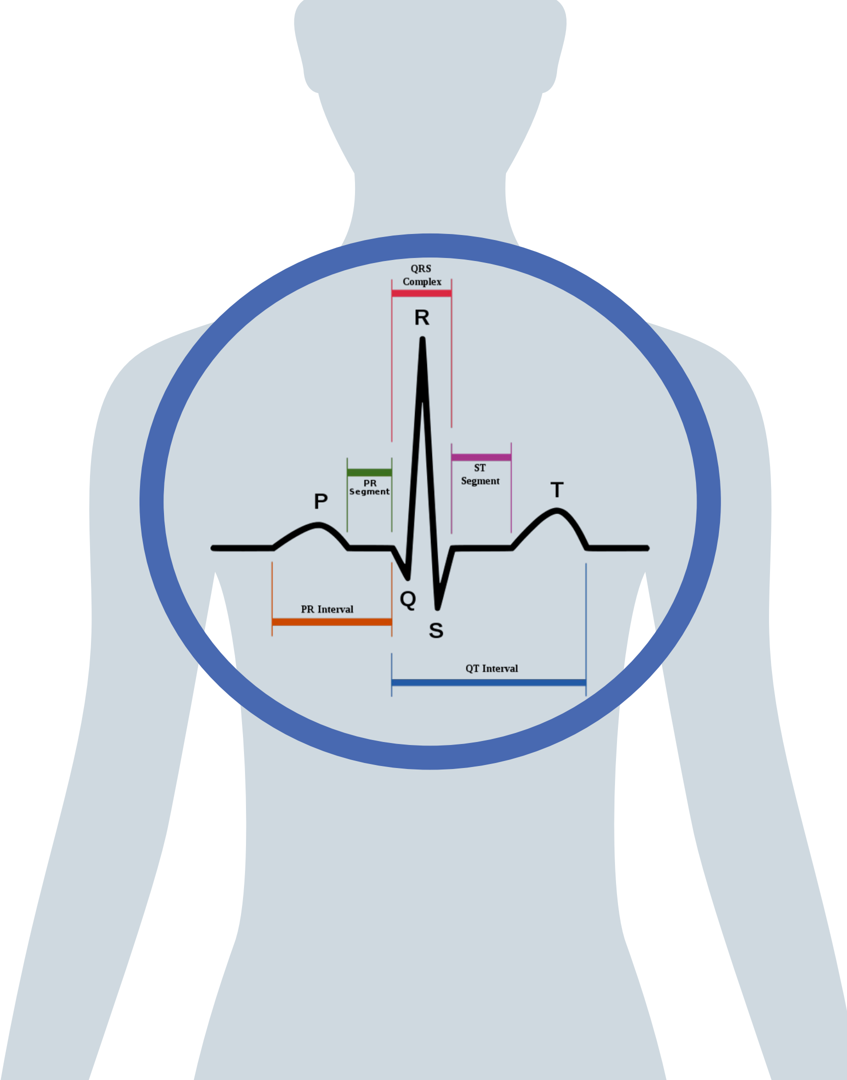
Prevalence (American Cancer Society)





Electrocardiogram

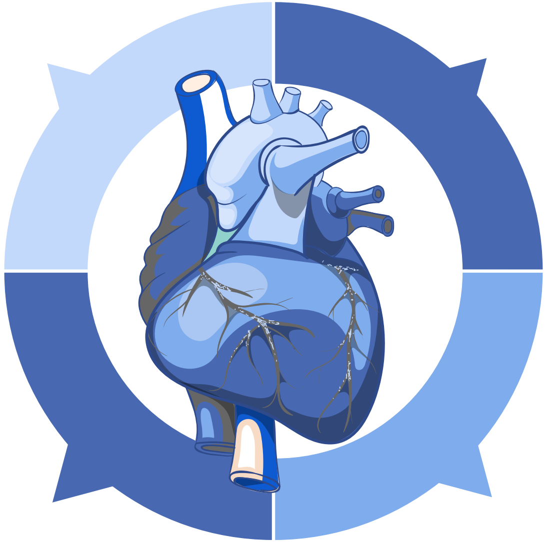
The electrocardiogram is the main tool to determine the electrical activity of the heart.



PVCs

Start in the ventricles

Beat sooner than the next expected heartbeat

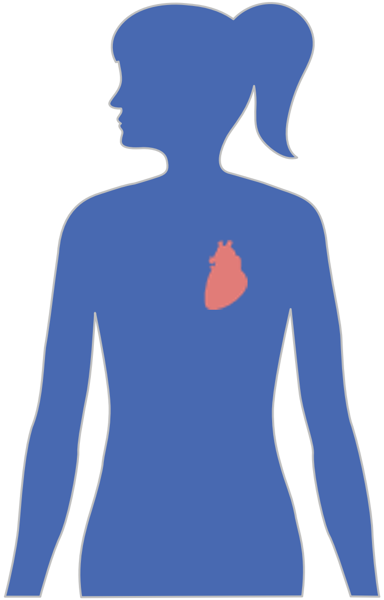


Heart diseases or changes in the body can make cells in the lower heart chambers electrically unstable

Unhealthy lifestyle choices make people more likely to develop pvc.

Dataset for ECGs

MIT-BIH
Arrhythmia Database



Duration	I dataset	II dataset
169 milliseconds	Unbalanced dataset (75000 non-PVC, 14000 PVC)	Balanced dataset (14000 non-PVC – 14000 PVC)

Health Record

1-lead ECG RGB images

1975

half-hour ECG recordings from 47 people

1979

I.

Classification of Premature Ventricular Contractions

ROAD MAP

01

Data selection

MIT-BIH
Arrhythmia Database

02

Methods

6 classifiers: Decision Tree, Random Forest,
Long-Short Term Memory (LSTM),
Bidirectional LSTM,
ResNet-18, MobileNetv2, ShuffleNet

03

Generation of datasets

2 datasets: original and
balanced dataset

04

No pre-processing & Transfer Learning

05

Evalutation & Results

Table 11. Final results (1st experiment).

Models	ACC	SE	SP	PRE	F1	AUC
MobileNetv2	0.9990	0.9930	0.9996	0.9958	0.9944	0.9963
ResNet-18	0.9984	0.9902	0.9991	0.9909	0.9905	0.9947
ShuffleNet	0.9967	0.9727	0.9990	0.9893	0.9809	0.9858
BLSTM	0.9941	0.9592	0.9974	0.9592	0.9653	0.9783
LSTM	0.9938	0.9562	0.9973	0.9709	0.9635	0.9767
Random Forest	0.9927	0.9322	0.9987	0.9865	0.9586	0.9654
Decision Tree	0.9871	0.9234	0.9934	0.9335	0.9284	0.9584

Table 12. Final results (2nd experiment).

Models	ACC	SE	SP	PRE	F1	AUC
MobileNetv2	0.9909	0.9895	0.9923	0.9923	0.9909	0.9909
LSTM	0.9884	0.9860	0.9908	0.9909	0.9885	0.9884
ResNet-18	0.9860	0.9874	0.9846	0.9846	0.9860	0.9860
ShuffleNet	0.9853	0.9832	0.9874	0.9873	0.9852	0.9853
BLSTM	0.9846	0.9839	0.9853	0.9853	0.9846	0.9846
Random Forest	0.9804	0.9804	0.9804	0.9804	0.9804	0.9804
Decision Tree	0.9642	0.9601	0.9684	0.9682	0.9641	0.9643

Results

In both experiments, **MobileNetv2** reaches high performance and promising results for PVCs' final diagnosis.

The final results showed 99.90% of accuracy in the first experiment and 99.00% in the second one, despite no feature detection techniques were used

2.

Identification of a Pattern in Premature Ventricular Contractions

Working Hypothesis & Goal

The classification for PVCs detection
gave very high performances (99%ACC).
However, we do not know *the patterns a priori*

Main challenge associated with the detection of PVCs: identifying common patterns.

ROAD MAP

01

Data selection

MIT-BIH
Arrhythmia Database

02

Pre-processing

Noise removal, conversion in BW image, extraction of ECG wave

03

Methods

ECG waves comparision

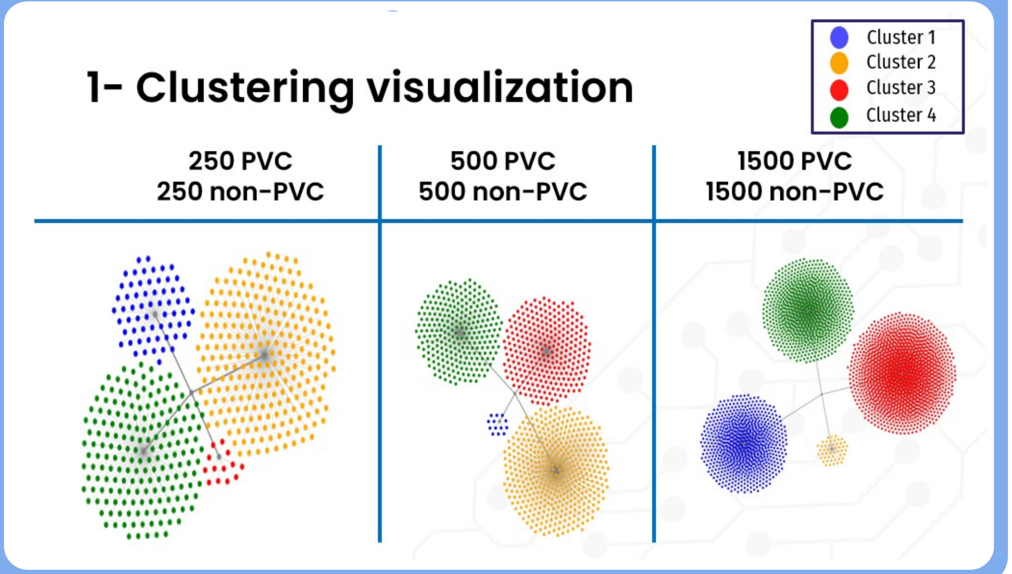
04

Clustering

05

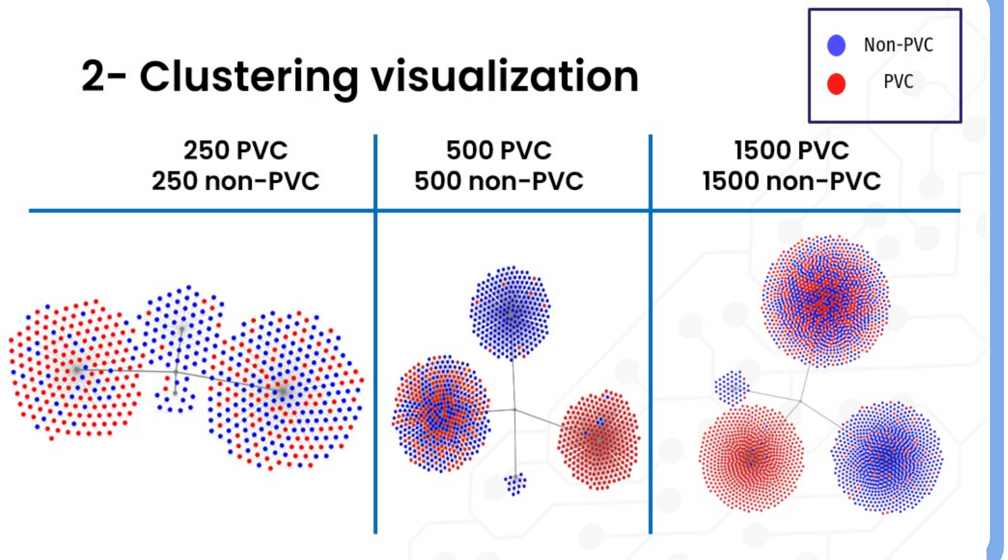
Evalutation & Results

Results



The final results showed the presence of three large and one smaller cluster. This configuration is repeated as the dataset size increases.

It is important to note that the original dataset also contains ECG signals from extremely rare disorders. Specifically, non-PVC signals are not labeled adequately in the dataset



Results

We notice a distinction between PVC and non-PVC that is inefficient due to the significant mixed presence in the various clusters. Indeed, the prevalence of blue and red nodes in all four clusters is immediately visible because the non-PVC classes contain a wide range of arrhythmias, not just healthy people. Increasing the number of ECGs in the dataset results in a clearer display and less overlapping of the two labels of the dataset.

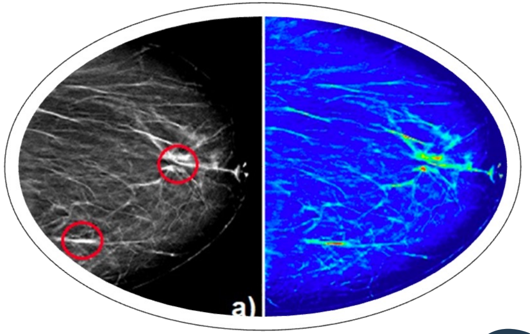
Most of the red nodes, i.e. PVCs, are located in a single cluster: this clearly indicates a common pattern among the PVCs.

03.

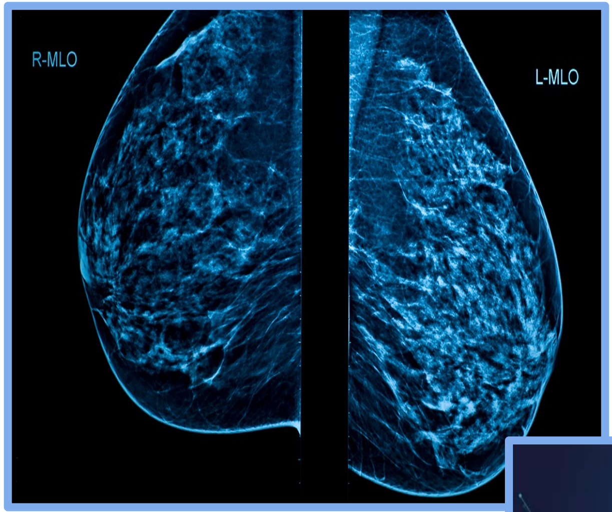
Breast cancer classification

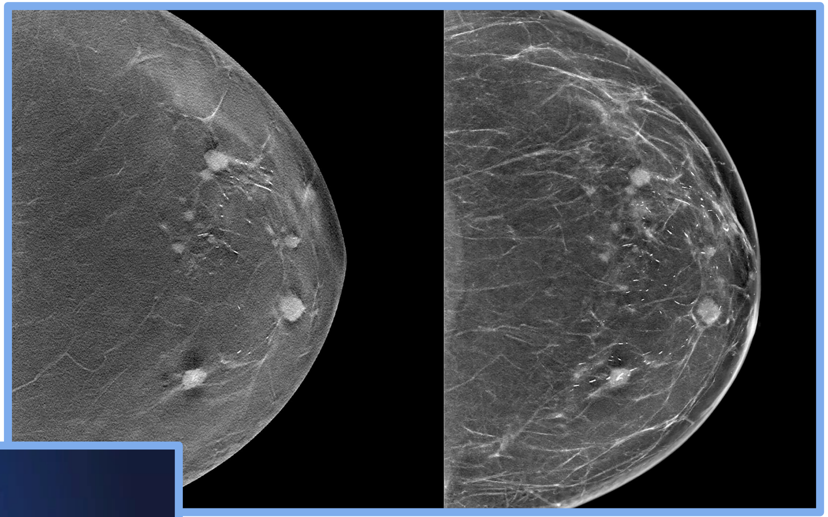
1. DCNN for digital breast tomosynthesis (DBT) classification

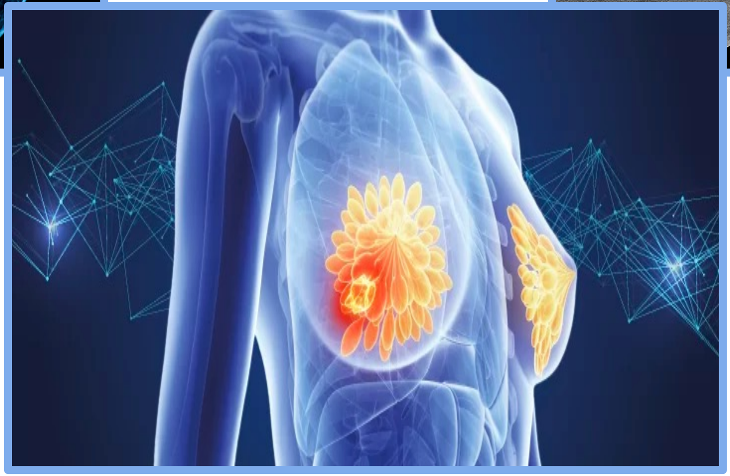
2. EGAN for DBT data augmentation



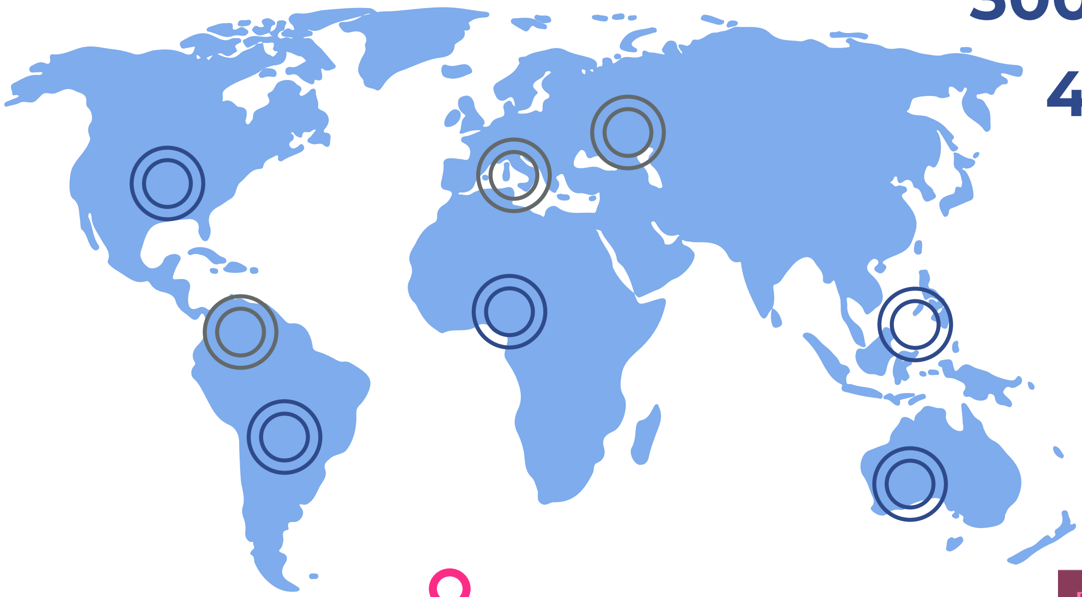
Breast Cancer







Prevalence (American Cancer Society)



300.590 new cases (2023)

43.700 new deaths (2023)

19.6 death rates (2016-2020)

Mammography & DBT

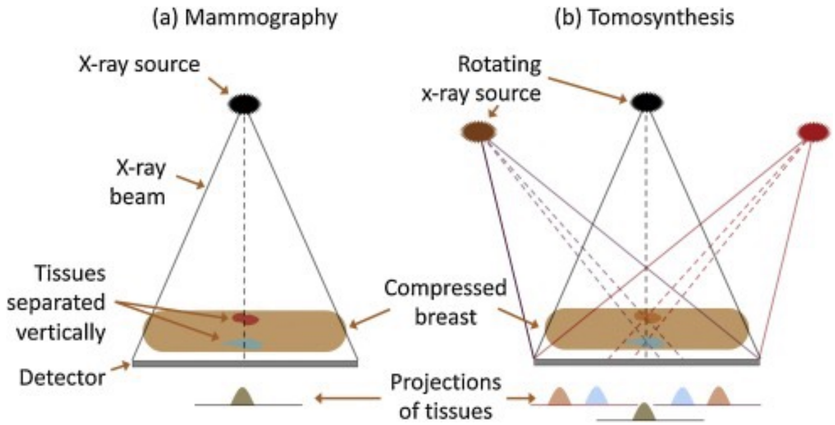


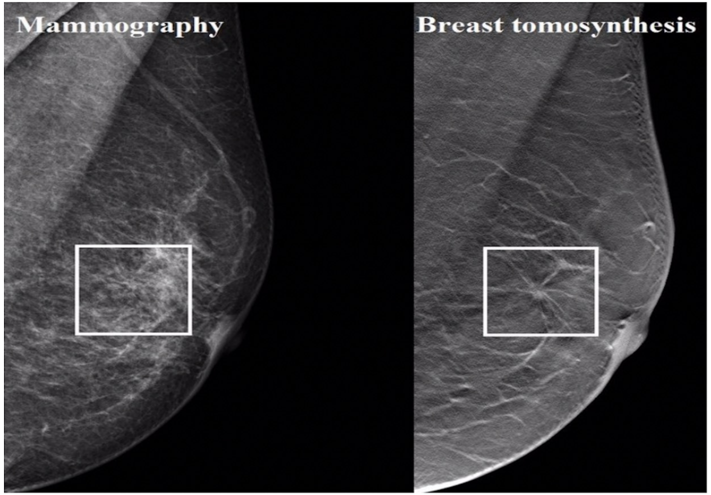
Fig.? Comparison between a) standard Digital Mammography acquisiton and b) Digital Breast Tomosynthesis.

Digital mammography is the most effective method for early detection of breast cancer, but it has limitations, especially for dense breasts.

Digital breast tomosynthesis (DBT) offers 3D representation and clearer localization of possible lesions, but interpreting DBT exams can be complex.

DBT

Digital breast tomosynthesis (DBT) exams are complex, consisting of tens of image slices and presenting challenges to building datasets due to privacy restrictions, costs, and manual efforts required to process them. Balancing non-balancing datasets is also difficult, particularly when a particular class is more abundant than others.



I.

DCNN for DBT images classification

ROAD MAP

01

Data selection

DBT images

02

Methods

DBT-DCNN

03

Evalutation & Results

04

Grad-CAM

to highlight pixels in all DBT slices of a given exam that were more relevant for the final classification task performed by the network

Results

	TP (#)	TN (#)	FP (#)	FN (#)	acc (%)	s (%)
TL-AlexNet	940	249	208	9	84.6	99.0
TL-VGG19	832	215	242	17	74.5	87.7
DBT-DCNN	948	374	83	1	94.0	99.0

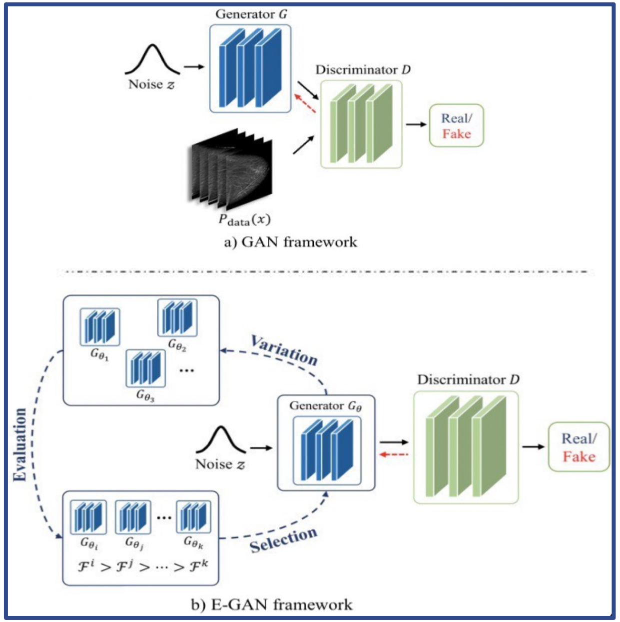
To improve the performance of DBT exam analysis, computer-aided detection (CAD) systems have been developed. A deep convolutional neural network (DBT-DCNN) was developed to classify the presence or absence of mass lesions in DBT exams and compared to popular architectures.

The study found that the DBT-DCNN performed better in terms of sensitivity and specificity and had the potential to reduce false positives.

2.

EGAN for DBT data augmentation

EGAN for DBT data augmentation (I)



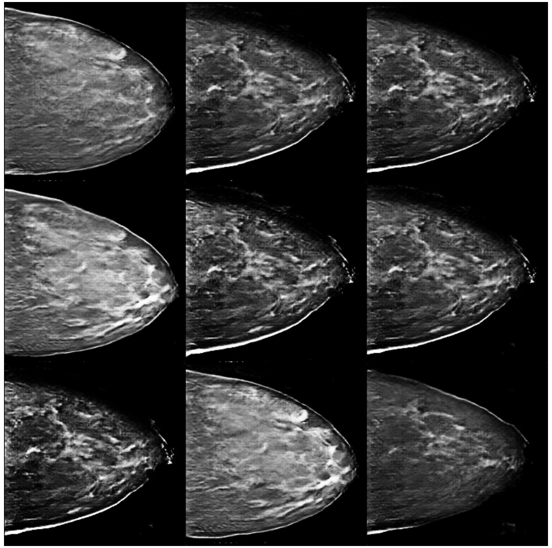
To address the challenges on DBT datasets, data augmentation techniques, particularly generative models such as GANs, are necessary. However, GANs often experience training difficulties such as gradient vanishing and mode collapse.

A new GAN architecture, Evolutionary GAN (E-GAN), has been designed to optimize the generator through an evolutionary approach.

EGAN for DBT data augmentation (II)

E-GAN has been applied to increase the data of a DBT image dataset to generate more "sick" slice samples to balance the starting dataset.

The results represent a starting point for the development of future architectures in charge of 2.5D or even 3D.



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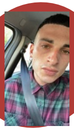

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Thanks for the attention!