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#### A comparative study of different deep learning architectures for breast cancer histology images classification

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# UMONS A comparative study of different deep learning architectures for University of Mons breast cancer histology images classification

Imane Nedjar<sup>1</sup>, Saïd Mahmoudi<sup>2</sup>, Mohammed Amine Chikh<sup>1</sup>

<sup>1</sup> Biomedical Engineering Laboratory Tlemcen University ,Tlemcen, Algeria
 <sup>2</sup> Computer Science Department, Faculty of Engineering University of Mons ,Mons, Belgium

## Introduction

•The given statistics of death by breast cancer each year are still anxious. This have pushed the scientific community to propose several method to improve the process of diagnostic and treatment.

Method

•As the histological image analyses represent a critical step to decide the state of cancer, we have proposed a statistical comparison between different deep learning architectures, for the prediction of cancer types in breast histology image.

#### Dataset

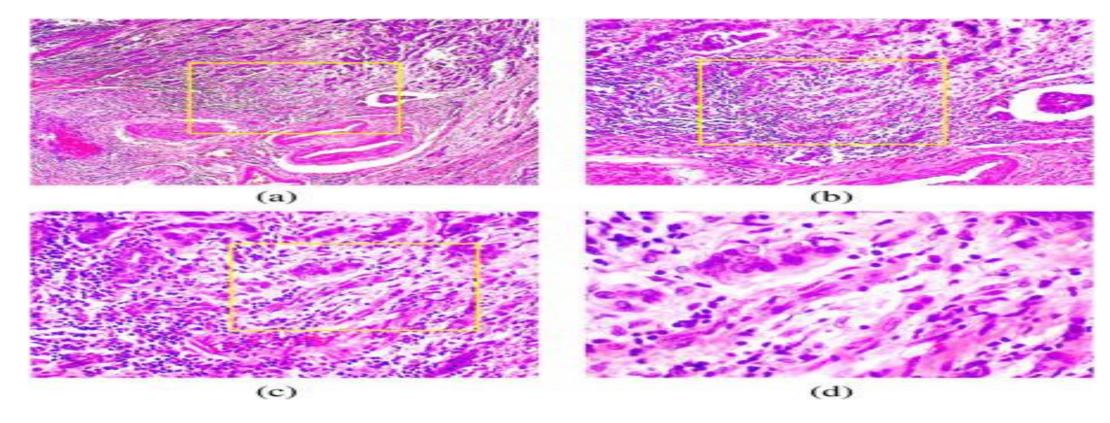
### The deep learning architectures

•The deep learning architectures are know by their efficiency in the medical image classification [1-2].

•As each architecture is different from others .We have tested 11 architecture to select whose that are adequate to the classification of breast cancer histological images.

•The architectures tested are : Xception,VGG16,VGG19,ResNet,InceptionV3,InceptionResNetV2,MobileN et,MobileNetV2,DenseNet121, DenseNet169, NASNetMobile [3]. •The BreaKHis database is used to evaluate the deep learning architectures.

•The database is composed of 7909 images divided into benign and malignant tumors.



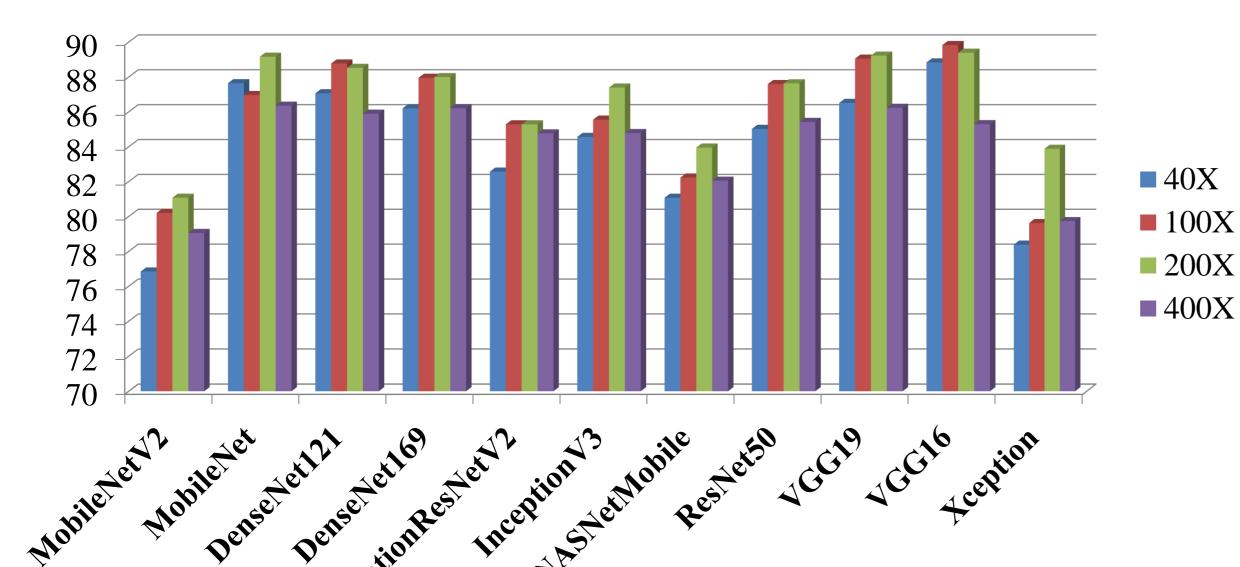
**Fig 1.** Slide of breast malignant tumor (stained with HE) seen in different magnification factors: (a) 40×, (b) 100×, (c) 200×, and (d) 400×. [4]

•The measures used in the experiments are performed on the basis accuracy at image level and patient level as was used in [5].

Patient Score = 
$$\frac{Nrp}{Nnp}$$
 Patient - accuracy =  $\frac{\sum Patient Score}{Np}$   
Image - accuracy =  $\frac{Nr}{Nall}$ 

Results

•Where : Np be the number of total patients, and Nnp the number of cancer images of patient P. Nrp and Nr are the correct image classified. Nall the number of cancer images of testing set.



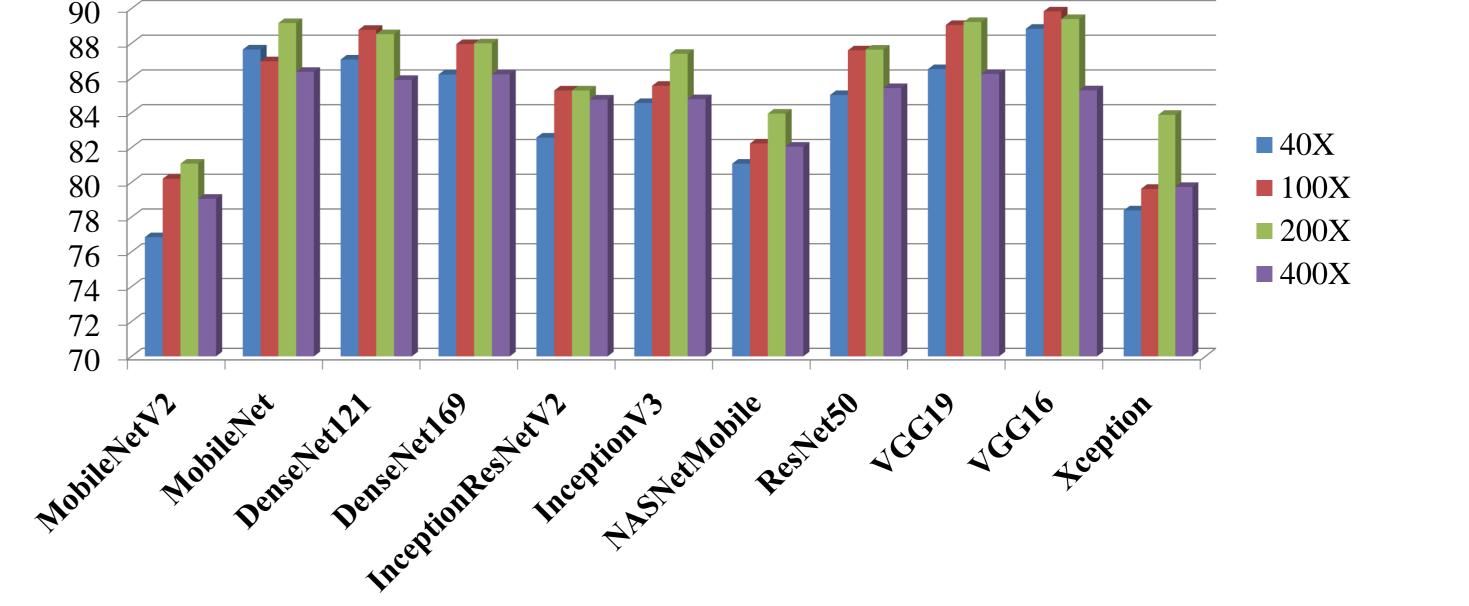


Fig 3. Patient accuracy using 10 epochs for different magnification factors

•The accuracy of Image and Patient obtained ,show that there is a small different in the results given by the architectures.

•The best result are given by VGG16 for 10 epochs, followed by MobileNet.

•In following Table we used 30 epochs to train both VGG16 and MobileNet.

•At Image accuracy MobileNet architecture out perform VGG16 in the majority of magnifications, however at Patient accuracy, VGG16 achieved a good performance.

	Image Accuracy				Patient Accuracy				
	40	100	200	400	40	100	200	400	
MobileNet	88,59	89,00	89,90	86,41	89,22	89,10	89,11	85,49	

Fig 2. Image accuracy using 10 epochs for different magnification factors

**VGG16\_** 88,13 89,39 89,52 84,77 **89,47 90,03 89,84** 84,08

**Table 1.** Image and Patient accuracy using 30 epochs for different magnification factors

### Conclusion

We have presented a statistical studies of different deep learning architectures for breast cancer histology images classification.
The obtained results shows that the MobileNet and VGG16 out performs the other architectures.

•We are working on the two architectures to developed an efficient architecture for breast cancer histology images classification by using the advantages of MobileNet and VGG16.

### References

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[3] https://keras.io/applications

[4] Spanhol F.A., Oliveira L.S, Petitjean C, and Heutte L, "A Dataset for Breast Cancer Histopathological Image Classification," IEEE TRANSACTIONS ON BIOMEDICAL ENGINEERING, vol. 63, no. 7, 2016.
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