

ML Classification Methods Comparison for Breast Cancer Diagnosis in Clinical Application Field

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Abstract. With the development of computing resources, deep learning method has made great progress in the field of image recognition. And as a result, deep learning-based image detection methods have been able to make great breakthroughs in medical fields such as disease recognition, microbiological testing, bacterial quantification, and tumour detection. With the advancement of in the ML field, the computer-aid diagnosis system has been improving. This paper reviews basic CAD ML system, and the recently improved DL system. In general, both methods offer the ability to assist the medical expert in giving them opinions. Deep learning, on the other hand, shows promising improvement in breast cancer diagnosis, but still with some limitations, such as requirement of high computational power and cost, as well as data scarcity. The accuracy rate of DL can reach up to 97%, which is the best in the field. Thus, both effectively reduce false positive rate of detecting breast cancer, improving the performance for detection and diagnosis.

Keywords: Machine Learning, Deep Learning, Brease Cancer, CAD.

1. Introduction

Machine Learning (ML) is an application method of Artificial Intelligence (AI) that learn for themselves [1]. It gives the system's ability to learn and improve from experience without being explicitly programmed. ML has become more popular in the medical area; this growing interest is accelerated by low-cost memory and cheaper spend. It is particularly vital in medical imaging research, data exploration and mining, nature language processing, image recognition, and prediction. This paper focus on breast cancer prediction and diagnostics [2].

One of the most dreadful diseases for women is breast cancer, it caused more death than any other diseases. There are 17.1 million new cases of breast cancer in 2018, according to the record of international agency for cancer research (IARC) and American Cancer Society [3]. The IARC statistics show that 25% of women in developing countries were diagnoses with different stages of breast cancer, and many died due to late prediction. As stated by American Cancer Society, developing countries are 82% of the world population and they have most of the death case worldwide (53%), about 626,700 deaths were reported in 2018 [4].

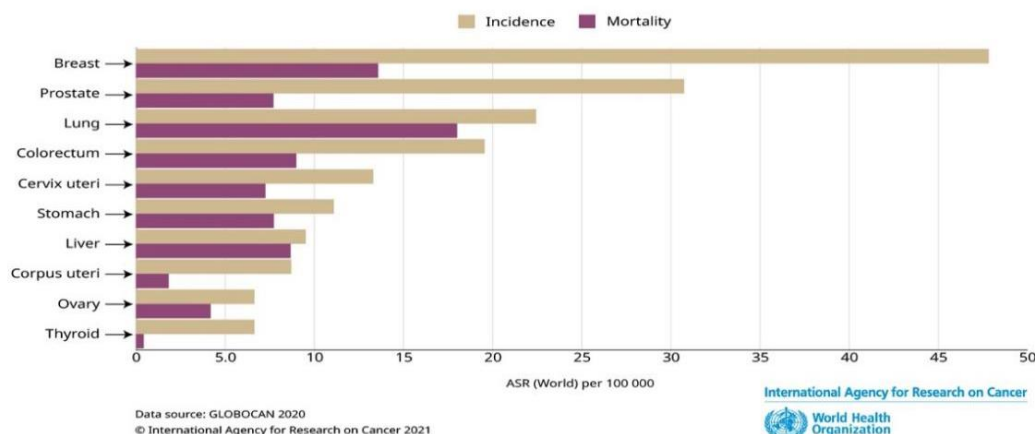


Figure 1. Comparison of 10 most common cancer types of Mortality and Incidence rate for all ages

In this paper, we compare the conventional machine learning technique with deep learning technique by comparing their performance on different datasets and their efficiency in detecting malignant masses. The goal is to introduce breast cancer and machine learning techniques by showing the recent advancements in the area, data extracted from recent studies will be presented and discussed.

Machine Learning Methods (Computer Aid Detection- CAD)

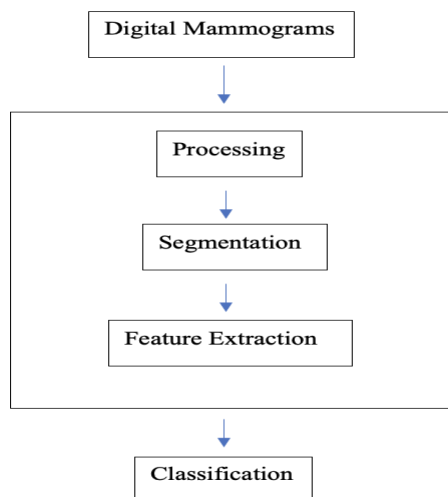


Figure 2. Conventional Machine Learning Pipeline

1.1. Processing

This is critical in a CAD system. In this step, the unnecessary and unwanted objects are eliminated from the mammograms. As shown in Figure 4, part a) is the original mammogram image, the annotation is removed in part b), pectoral muscle is removed in part c) by region growing, and pectoral muscle is removed by adaptive segmentation [6].

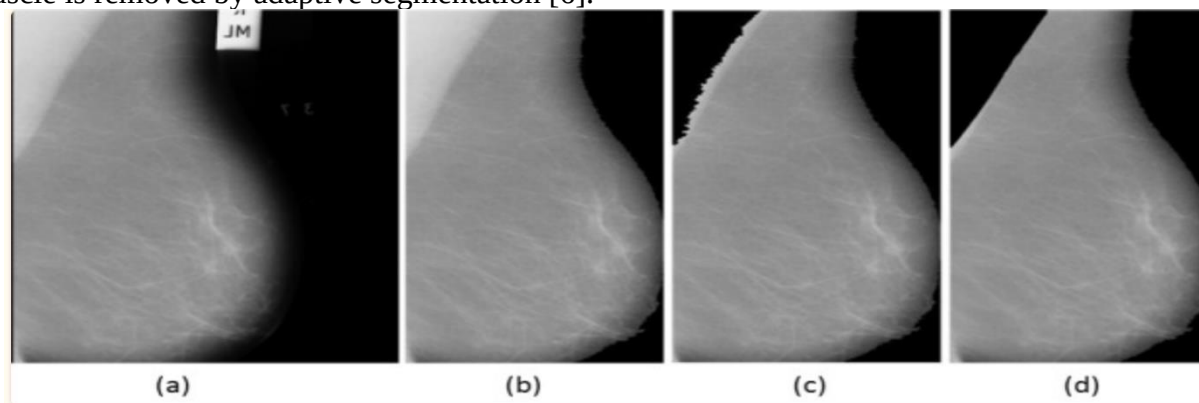


Figure 3. Visualization of the processing steps

1.2. Image Enhancement Techniques

This is used to improve the quality of mammogram, done by adding more contrast for easier readability [7]. This step focus the low-contrast regions by improving the image quality and helps achieve high diagnostic performance. These regions are concealed in surrounding tissues, which lead to a misdiagnosis. The image enhancements technique makes it easier for the system to detect these subtle abnormalities. However, some methods will add distortions to the image, thus the machine only accept those method that would maintain a similar appearance [8].

1.3. Segmentation Technique

Segmentation must be well focused and precise since it will directly impact the result from detecting and extract the features from the abnormal tissues. The fundamental steps involve dividing

the breast from the background, aiming to differentiate the breast from other objects. It is vital to keep the breast characteristics prior they are being further processed [9-12].

To extract Region of Interests with benign/malignant masses, mammograms are being partitioned into many nonoverlapping regions. During detection, the false positive rate will increase, but will be removed during classification stage.

This step uses Chan-Vese method, which is a recursively refined segmentation algorithm with resized segmentation image for each recursive step.

1.4. Feature Extraction Technique

Feature Extraction helps to characterize the features of a particular region. To do that, those properties are utilized (including mass size, boundaries, and density). Most features are not vital when studies. However, when combined with other ones, they might become helpful and vital for the classification step. This step has mainly three categories: morphological, textural, and features of multiple resolutions [13]. The digital medical image recognition (DMIR) is suitable for this purpose.

1.5. Classification Technique

This is the last step of the pipeline. It is highly dependent on other intermediate and previous steps. The classifier will remove the redundant and keep the most critical ones. Recent studies have shown that, the SVM model is the most commonly used classifier, scaling a 94% accuracy rate [14].

The SVM model will follow three phases, teacher image, training, and testing. The training data is obtained manually from the previous Chan-Vese segmentation process, based on the False positive and False negative rate of the segmentation result. Then, their window size is changed to one of the following size (7x7), (9x9), (11x11), and (13x13) to be written in training file. Mainly into (x,y) format where x represents the rows of window size of the image, each x variable is representing an observation of an individual image, y represents the class of images. The class is recorded as either 0 (non-nodule) or 1 (nodule).

1.6. Testing and Training Results

	Training data		Testing data	
	Nodule	Nonnodule	Nodule	Nonnodule
Number of images	11	17	46	96
Total number of images	28		142	

Figure 4. testing and training data

This training and testing was based on UKMMC (UKM Medical Centre) Dataset. Figure 4 shows the data and number of images used in this process.

	Result (predicted)	
	Nodule pixel	Nonnodule pixel
Ground truth (actual)		
Nodule pixel	TP	FN
Nonnodule pixel	FP	TN

Figure 5. Confusion Matrix

Accuracy can then be calculated based on Figure 5. Formulas as followed.

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN}$$

$$Specificit(SP) = \frac{TN}{TN + FP}$$

With all data analysed together, quantitative results are shown in the following table.

	FP rate	SP	AC	NRM	OVERLAP
Without the rejection model	0.196	0.803	0.803	0.099	0.800
With the rejection Model (7 × 7 × 7 × 7)	0.058	0.941	0.938	0.031	0.933
With the rejection model (9 × 9 × 9 × 9)	0.051	0.948	0.944	0.028	0.940
With the rejection model (11 × 11 × 11 × 11)	0.044	0.955	0.950	0.025	0.946
With the rejection model (13 × 13 × 13 × 13)	0.040	0.959	0.954	0.023	0.950

Figure 6. Quantitative analytics

Deep Learning Method

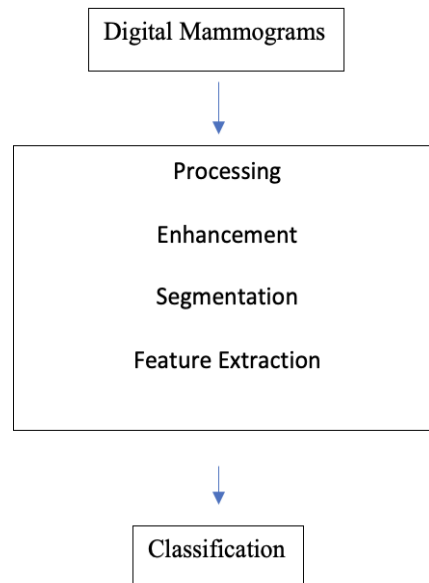


Figure 7. Deep Learning Pipeline

1.7. Convolutional Neural Network for Breast Mass Detection Methods

Riddli et al were able to implement a faster operating CNN model (R-CNN) for classifying malignant pathology. The suspected regions were refined by fine-tuning the hyperparameters. This method scored high on public INbreast database classification result. However, its major limitation is that the testing scale is too small to match the large testing task sometimes [15].

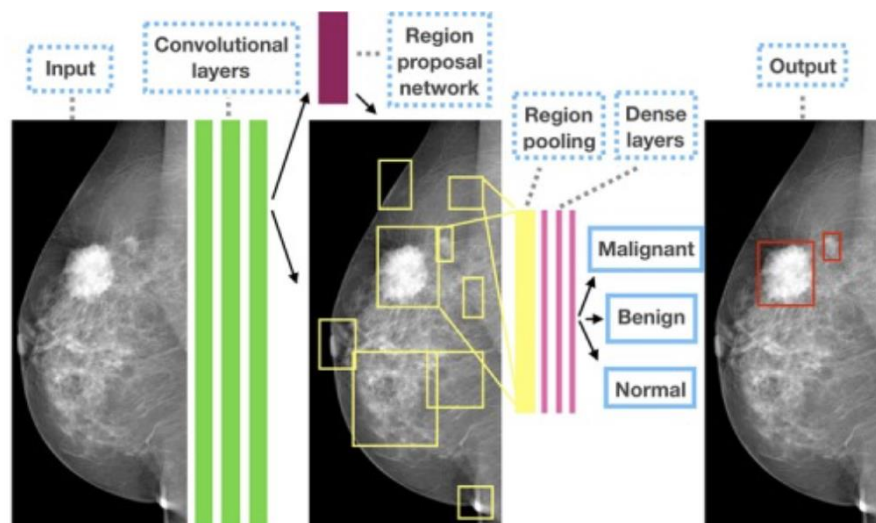


Figure 8. Sample results of mass detection and classification

2. Compare and Discussion

Table 2. Compare and Contrast of Machine Learning and Deep Learning

Method	Advantage	Disadvantage
Machine Learning	1. Less computing power	1. Lower Accuracy rate (Maximum rate of 90%). 2. Limited to dataset. 3. Limited to the density.
Deep Learning	1. Higher accuracy rate (Can reach up to 97%). 2. Advanced algorithms.	1. Large amount of Data. 2. High annotation costs. 3. Specialists dependent. 4. High computing cost.

Machine Learning method was introduced first to the industry, it is now considered traditional and commonly used by doctors for giving them a second opinion. However, the method suffer from many limitations such as its ability to be only used on certain dataset or for certain breast cancer mass density. Sometimes, the rare cases of breast cancer, for example, unusual location of the malignant mass or those mass that looked benign but became malignant in the long run. These masses tend to be ignored by the Machine Learning detection method.

Therefore, scientists started bringing deep learning to the game. It did use some advanced algorithm and achieved higher than ever accuracy rate (some can even go above 97%). But in the meantime, the advanced algorithm requires people with more prior knowledge, and cost a fortune of computational power, not to mention its high installation cost and annotation cost.

All in all, the ceiling for the deep learning method is high, there will be a lot of room for advancement. On the other side, the growth of the Machine Learning method is limited and are likely to be replaced over time since accuracy rate is what is valued the most in this field. Meanwhile, more research and studies are done on the hybrid of the two methods, which has also been showing great results.

3. Conclusion

With the development of computing power, deep learning has made great progress in the field of image recognition. And as a result, deep learning-based image detection methods have been able to make great breakthroughs in medical fields such as disease recognition, microbiological testing, bacterial quantification, and tumour detection. Both the ML methods and the DL methods are

considered breakthrough in the clinical field. However, heterogenous breast density make masses more difficult to detect by traditional ML method. The traditional ML method is limited to certain dataset and certain density of mass. Deep learning, on the other hand, shows promising improvement in breast cancer diagnosis, but still with some limitations, such as requirement of high computational power and cost, as well as data scarcity. The accuracy rate of DL can reach up to 97%, which is the best in the field. In conclusion, future scope of the development of ML and DL methods maybe is to hybrid the two and perform data augmentation for the method to reduce the computational cost.

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