Breast Cancer Detection Using Machine Learning Algorithms

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Summary

This paper presents a computer-aided design (CAD) system that detects breast cancers (BCs). BC detection uses random forest, AdaBoost, logistic regression, decision trees, naïve Bayes and conventional neural networks (CNNs) classifiers, these machine learning (ML) based algorithms are trained to predicting BCs (malignant or benign) on BC Wisconsin data-set from the UCI repository, in which attribute clump thickness is used as evaluation class. The effectiveness of these ML algorithms are evaluated in terms of accuracy and F-measure; random forest outperformed the other classifiers and achieved 99% accuracy and 99% F-measure.

Keywords:
breast cancer; cancer detection, UCT; classification; machine learning

1. Introduction

BC[1] forms in breasts and makes some of the cells grow abnormally especially those of the milk-producing ducts, it may occur in women and men. Its symptoms include: strange lumps and thickening, change the appearance, shape, size, skin of breast, appearance of an inverted nipple, etc.

According to the Global Cancer Statistics 2020 published in February 2021 [1], BC is the most widely spread cancer (11.7% of total cases), moreover, according to the 2021 annual cancer report published at the website of the Jordanian ministry of public health, the BC is the most spread cancer among Jordanians (the number of cases is 1279 i.e 21.3% of the total cases).

BC is one of the common cancers in women that is considers as one of the very life-threating cancers around the global. According to the cell appearance, BC is classified into (i) invasive ductal carcinoma and (ii) ductal carcinoma in situ, the former is the most dangerous as it may surround all the tissues of breasts and it may cause deaths to the majority of BC patients [2].

BC [3] is one of the common cancers that threaten lives of many women globally. In Jordan, it is among the common malignancy that causes deaths for many Jordanian women and it is the third cause of death after lung and colorectal cancers, moreover, it dramatically increases the health opportunities in many other Arabian, European and American countries. BC publications in Jordan [4] are relatively limited, as the number of published paper in PubMed is only 85 papers between 1985 and 2019. Masses and any other asymmetry areas in breast may indicate the existence of BCs. Masses are most common symptoms of BCs, however, they might be hidden within the overlapping tissues of the breast, this makes their detection a challenging job, moreover, some of the tissues of breast are very similar to the mentioned masses. This misdetection may delay the diagnosis of BCs and may lead to additional painful tests. These mammography disadvantages lead to the usage of CAD where the mass detection, segmentation and classification accuracy can be significantly improved. As BCs are among the fatal diseases, moreover, it is known that classical approaches examine the lesions of breast using time consuming and inefficient methods. Instead, CAD may help radiologists to better investigate mammograms, these CAD systems use computer technologies and related advanced intelligent algorithms in detect abnormalities in mammograms, as a result, CAD systems may serve as second opinion criteria in BC detection and very promising roles in the processes of the early detection of BCs and to help in reducing death rates among BC patients in cost-effective manners, thus, CAD systems and related artificial approaches have motivated thus research. CAD is believed to be useful in BC detection and diagnoses. Therefore, radiologists and physicians are looking forward to using such effective clinical applications in detecting BCs to early detection and diagnosis of BCs to maximize successful treatment options and opportunities. On the other hand, it is

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[1] https://www.khcc.jo/en/cancer-types/breast-cancer

known that many countries promote prompt screening methods to early detecting the initial symptom of BCs and may imaging approaches are used to identify BCs in these screening methods; the popular screening approach include (i) mammography: the most significant scheme of early detection for BCs, (ii) ultrasound: is a popular scheme which is not effective for solid breasts, and (iii) thermography: the most effective scheme especially when diagnosing smaller cancerous masses. However, due to the intrinsic difficulties associated with imaging techniques, on one hand, many approaches are proposed to enhance image processing techniques, on the other hand, many researchers Are motivated by the need for efficient and accurate techniques to early detect BCs so as to maximize the successful medication opportunities. This paper promotes the usage of ML algorithms to automatically detect BCs on mammograms, as it is known that ML is a research arena that is capable to deal with complex tasks and to improve performance diagnosis in many classification tasks. These ML algorithms include Random Forest, Ada Boost, Logistic Regression, Decision Tree, Naïve Bayes and Deep learning.

The rest of this paper is organized as follows: section II presents the recent related work, section III presents the implemented ML algorithms, section IV presents results and related discussions, and finally, conclusion and future work are presented in section V.

2. Related Work

In [5], ensemble learning methods are used to predict BCs such AdaBoost, Random Forest, and XGBoost, their results indicate that random forest achieves 97% accuracy. In [6], Support vector machine (SVM) achieved 96.25% accuracy in predicting BCs on Wisconsin BC dataset. In [7], metric assessments are used to build a discriminator of benign and malignant tumors.

In [8], an advanced Mamdani fuzzy inference is designed to predicting a benign or malignant tumors and is able to handle complex cancers with higher performance. In [9], a novel majority voting based hybrid classifier is implemented to enhance the accuracy of predicting BCs, however, their proposed method achieved only 79% accuracy. In [10], a comparison on a group of ML algorithms to detect BCs is conducted and concluded that AdaBoost achieved an accuracy at 98.77. In [11], using Wisconsin BC dataset, many ML algorithms are evaluated in detecting BCs and concluded that random forest and SVM achieved 96.5% accuracy.

In [12], a combination of AdaBoost and random forest is implemented to classify BCs, a comparison between their proposed hybrid algorithm and other classifier such as SVM is conducted, results shown that the accuracy of ensemble based algorithms enhanced by 4.3%, with the highest increase up to 9.8%.

In [13], mortality aspect of BCs in India is investigated with respect to many risk parameters such as the characteristics of demography, life style, water intake, etc., and an ensemble algorithm (Bagoost) is used to predict BCs for Malwa women in India, and achieved an accuracy of 98.21%.

In [14], an ensemble algorithm that combines multiple classification methods to classify benign and malignant tumor on UC Irvine ML repository, and their stacked ensemble classifier achieved an accuracy of 97.20%. In [15], a comparison study of many ML based method to predicting BCs including deep learning, and concluded that the highest accuracy is achieved by deep learning (96.99%), in [16], the achieved accuracy by neural networks is 96.2%, in [17], convolutional neural network (CNN) achieved 97.66% accuracy, in [18], a deep learning algorithms achieved 99.73% accuracy in predicting BCs, CNN in [19] achieved an accuracy that varies from 84-92%. To sum up, the best predicting accuracy was achieved by CNN.

3. Machine Learning Algorithms

ML makes computer systems learn and act similar to humans by learning to progressively improve their performance on a specific task. ML algorithms [20] are used to serve many applications such as classification, feature selection and clustering, etc. Learning a desired function "f" that connect each attribute set "x" to one of the specified class Labels "y" is the problem of classification. A classification model is another name for the target function. A classification algorithm (also known as a classifier) is a method for creating classification models from a data-set. Each method employs a learning mechanism that identifies a model so as to best fit the training attributes and related class label. Such learning mechanisms are to both match the input data and correctly corresponding class label in the testing data-set. As a result, the aim of learning is to generalize, i.e. to handle any data-set in the future. Regarding application of ML algorithms in classification of cancer, ML algorithms effectively distinguish between Benign and Malignant, assisting the physician in making a diagnosis, moreover, for ML classifiers, identifying the subset of features is critical.

There are many ML techniques that are commonly used in BC classification, progression monitoring, treatment, and prediction, such as Support Vector Machine, Decision Trees, Naïve Bayes, k–Nearest Neighbors, Adaptive Boosting, traditional Neural Networks, Probabilistic Neural Network, Recurrent Neural Network and Conventional Neural Networks [21-33] [34]. The ML algorithms used in this study are briefly explained below:

3.1 Random Forest

Growing a group of trees and allowing them to vote on which class is the most popular lead to remarkable improvements in classification accuracy. Random forest [35] is a set of classifier trees that are based on independent sets of parameters, in which each tree register has a single vote for the most popular class with respect to a given input. Using a random selection of features to split each node makes random forest classifiers accurate. The following techniques are to randomize trees:

- Bagging, where each tree is trained on a random subset of training data, these subsets are selected uniformly and randomly with replacement.
- Boosting, in which classifiers are given a vote weight proportional to their performance and random subsets of samples are sampled in order from a distribution that favors data on which preceding classifiers in the sequence failed.
- Arcing, which is same as boosting however, it does not include vote weighting at the end.

The main steps of the random forest are the following:

- Step-1: Select a random sample of some size from the data with replacement.
- Step-2: Take a random sample of predictors without replacing them.
- Step-3: Build the data's first categorization and regression tree partition.
- Step-4: Repeat the second step for each additional split until the tree reaches the desired size. Noting that pruning is not recommended.
- Step-5: Repeat the previous steps as many times as possible.

3.2 AdaBoost

Ada Boost [36] is one the effective ML algorithms that produces strong classifiers by combining weaker ones. AdaBoost sequentially applies a learning algorithm to the reweighted samples of the training data-set; it iteratively gives more weights to the misclassified example in the previous iteration. In the beginning, examples are assigned equal weights and then iteratively increase the weights for all the misclassified examples, on the other hand, we decrease the weights of the examples that are correctly classified. Models are produced by implementing a linear combination of all the models produced by the iterations conducted, finally, a strong classification model is obtained, it should be noted that AdaBoost is sensitive to both outliers and noisy data.

3.3 Logistic Regression

Logistic regression [37] is one of the probabilistic ML models that utilizes a logistic function to model binary dependent variables such as healthy/sick in its primary form.

It is a supervised learning algorithm that predicts the output of a categorical dependent variable. It gives probabilistic values between 0 and 1 and it is classified into the following three types:

Binomial: there are only two values for the dependent variables, such as 0 or 1.

Multinomial: there can be 3 or more possible dependent variables which are unordered, such as "triangle", "square", or "circle"

Ordinal: there can be 3 or more possible dependent variables which are ordered, such as "slow", "Medium", or "fast".

It uses sigmoid activation function to forecast the likelihood of a binary event occurring. The activation function aka logistic function, generates an "S" shaped curve that can be used to convert any real-valued integer to a number between 0 and 1. The output of this activation function becomes 1 when the curve reaches positive infinity, and 0 when the curve reaches negative infinity. If the output of the sigmoid is greater than 0.5, the output is 1 or True, otherwise, the output becomes 0 or False.

3.4 Decision Tree

Decision tree [38] is a supervised learning technique that is used to classify data. Utilizing decision trees aims at building a model that is capable of predicting target classes as stated in the observed training data, this is accomplished by learning simple decision rules. In decision trees, branches reflect observations about an item, while the leaves reflect the inferences about the item's target value. Decision trees comprise a root, internal and terminal nodes. A class label is assigned to each leaf node in the decision tree. The attribute test conditions in the non-terminal nodes are used to distinguish records with different characteristics. The following are the fundamental steps of decision tree classifiers:

- Step-1: Starting the decision tree with a root node, says S, that contains the whole dataset.
- Step-2: Getting the best attribute in the mentioned dataset.
- Step-3: Splitting the tree S into subsets that may contain candidate values for the best attributes. These best attributes are to build the decision tree.
- Step-4: Making new decision trees using the subsets of the dataset created in previous step.
- Step-5: Continue until getting leaf nodes where the nodes cannot be further classified.

3.5 Naïve Bayes

Naïve Bayes [39] is a probabilistic classifier based on Bayes rule, given an evidence E and a hypothesis H, then:
$$P(H|E) = P(H) \, P(E|H) \, / \, P(E) \qquad (2)$$
where $P(H|E)$ represents the belief about a hypothesis after obtaining E (called posterior), $P(H)$ is the belief about H

before observing E (called prior probability), P(E|H) is the likelihood of H (L(H|E)) given E is a measure of how well H explains E, and P(E) is a normalization constant to ensure P(H|E) = 1 for all the hypotheses.

3.6 Deep Neural Networks

Artificial Neural Network (ANNs) are inspired by the human's nervous system and are able to learn and to classify in many sophisticated and challenging tasks. Deep Learning (DL) is a new era of ANNs that is capable to achieve better performance in classification problems, their models represent complex structures that require large datasets for training to effectively achieve remarkable results and to support specialists in early detection, diagnosis and treatment of diseases such as BCs. CNN is one of the popular DL architectures that are used in many applications such as speech and natural language processing, moreover, effective CNN models called VGG16 are also able to achieve high accuracy on image classification tasks. As VGG16 is considered as one of the highest-quality architectures of CNN flavors, it is implemented to classify cancer images, VGG16 comes with 16 layers, it consists of 5 stacks, the first two stacks have two convolutional layers, each followed by ReLU and max-pool layers, the last three stacks have three convolutional layers, each followed by ReLU and max-pool layers, At the end, VGG16 has two fully connected layers followed by a soft-max layer as shown in Figure 1.
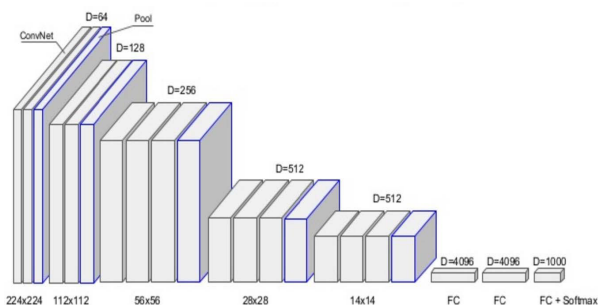

Fig. 1 VGG16 Architecture[2].

4. Results and Discussions

4.1 Data-Set

In this paper, the Wisconsin Diagnostic Breast Cancer (WDBC)[3] is used, it has 570 instances: Benign: 357, Malignant: 212), two classes: 37.19% malignant and 62.63%

benign) and 32 integer-valued attributes (see Figure 2). The five classifiers are trained to predicting cancers in the BC Wisconsin data-set, in which attribute clump thickness is used as evaluation class, in our experiments, ten attributes are taken from the data-set, these attributes shown in Table 1 noting that their scale varies from 1 to 10, however, class comes with 2 and 4 numeric values to represent benign and malignant tumors respectively.
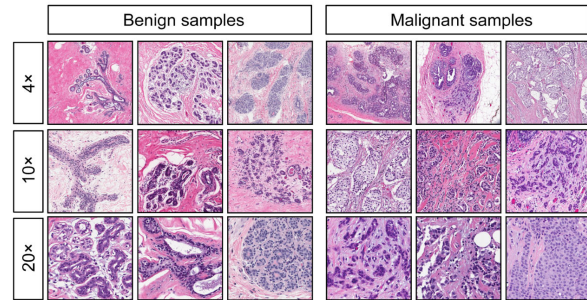

Fig. 2 Benign and malignant Samples for BCs[4].

Table 1: Attributes retrieved from Data-set

Clump thickness
Uniformity of cell size
Uniformity of cell shape
Marginal adhesion
Single epithelial cell size
Bare nuclei
Bland chromatin
Normal nucleoli
Mitoses
Class

4.2 Performance Measures

F-measure [25] is the weighted mean of precision (Pr) and recall (Re), where Pr is the ratio of true positives over all positives, on the other hand, Re is the ration of true positives over all samples that have to be identified as positive. Accuracy [25] is the correctly classified / total number of observations.

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[2] ML lecture slides of Professor A MESLEH
[3] https://archive.ics.uci.edu/ml/datasets/Breast+Cancer+Wisconsin+(Diagnostic)

[4] https://medium.com/analytics-vidhya/breast-cancer-diagnostic-dataset-eda-fa0de80f15bd

4.3 Results

In this paper, experiment runs are executed on an Intel Pentium (R) Lenovo notebook with 2.60 GHz i7- CPU and 16 GB RAM, running 64-bit Ubuntu 20.04.2.0 LTS, the classification algorithms are implemented using scikit-learn ML library. F-measure and accuracy values of the six classifiers are shown in Table 2. It is obvious that random forest achieved highest classification results, even slightly better than the DL algorithm, as the VGG16 need more training data to achieve higher accuracies.

Table 1: results achieved by the classifiers

Classifier Type	Performance	
	F-measure	Accuracy
VGG16	98.2	98.2
Random forest	99%	98.9%
AdaBoost	75%	83%
Logistic regression	97%	97.7%
Decision trees	75%	83%
Naïve Bayes	76%	74%

5. Conclusion

BCs are among the common malignant tumors of many women all over the globe, and it is most spread in elderly women, recently, it is also spread in youngers. As a result, it is always recommended to do more research that may help in early detecting BCs, moreover, it is obvious that many of the characteristics of this cancer are still to be explored. In this paper, five ML algorithm are used to detect BCs on the BCs Wisconsin data-set, results of random forest are the best as it achieved highest F-measure and accuracy scores, moreover, random forest achieved the testing process in less than one second, this indicates that random forest with this 99% accuracy will be able to help doctors to automatically identify whether their patients have malignant or benign tumors with high confidence. In the future, feature selection will be considered, moreover, additional sophisticated classifiers - other flavors of DL neural networks running on parallel platforms to accelerate the classification process to be applicable in real medical world, moreover, the detection may greatly enhance survival chances of the BC patients.

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