Mobile Application for Breast Cancer Diagnosis Using Morphological Associative Memories Implemented on a Cloud Platform

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Abstract*: *The astounding advances that have been observed in mobile device technologies and their underlying algorithms have prompted a worldwide surge in attention to their capabilities and potential for improving different human activities. The present work is framed by the academic cooperation process between Mexico and Saudi Arabia; it consists of the description of the design and development of a mobile information system aimed at performing diagnosis and verification of breast cancer using an application for mobile devices. The problem to be solved is represented as a binary classification problem between healthy patients and people that have been confirmed as control cases. The classification algorithm is a hybrid model, consisting of Morphological Associative Memories and the k-Nearest Neighbor classifier. The hybrid model improves upon the performance of its components. The proposed model was implemented on a cloud computing platform in order to optimize the response time for the diagnosis. A comparative study of our proposal and the state of the art shows that the proposed mobile information system has a high classification performance as well as a low false positive rate.

Keywords: mobile communications, morphological associative memories, early diagnosis of breast cancer, pattern classification.

I. INTRODUCTION

Breast cancer is one of today's biggest problems and it affects a huge part of the worldwide population. In 2016 only, 249,260 new cases were diagnosed, mainly in women, with a mortality rate of 36%. The last ten years have seen a rise of 0.3% of the incidence rate as well as a decline of 1.9% in deaths owing to the latest advances in early detection and treatment [1].

Today, the study of breast cancer is an active area of research, seeking paths to allow early detection [2], applying computational methods for evaluation and diagnosis [3, 4], as well as developing predictive algorithms based on pattern recognition [5-8].

The usual methods for detecting cancer usually use mammograms, with the disadvantage that the rate of detection of positive cases is low [8-11].

On the other hand, mobile devices have gained a great deal of popularity since they allow for innovation in a vast amount of fields, from online learning to disease diagnosis [12-15]; one specific example being e-health application, whose definition represents the union between health services and Internet technologies [16, 17].

A significant proportion of mobile applications require the consumption of Internet resources because high-power processing is not the forte of mobile devices. Due to this, they find support in cloud computing platforms for algorithm execution, limiting themselves to retrieving and presenting the results [18, 19]; turning the cloud into an useful tool for the healthcare field [20, 21].

In the frame of academic, scientific and technological cooperation between Mexico's National Polytechnic Institute and some Saudi universities, mobile information systems have been designed, developed and implemented among diverse application areas; specifically, those related to the sensitive topic of human health. The present paper describes a concrete result of this international cooperation: the design and development of a mobile application for breast cancer diagnosis using pattern recognition algorithms implemented on a cloud computing platform.

It is crucial to mention that the intent of the mobile information system is not to completely replace professional medical diagnosis, but to function as a supporting aid to medical experts when performing diagnosis and verification of a particular case; helping them to have a greater confidence in their diagnosis when performing a biopsy.

II. MATERIALS AND METHODS

This section consists of four parts. Subsection 2.1 describes the Web application that is integrated into the mobile information system proposed in this work; the different technologies employed in the implementation of the Web application are presented.

The content of subsection 2.2 is relevant in the context of this work, since this is where the hybrid classification system is described. This constitutes the part where the intelligent decision-making of the breast cancer diagnosis is made.

The backbone of this work, the mobile application, is presented in subsection 2.3; there, the underlying modern technologies of the mobile application are described. The application itself is the crux of the proposed mobile information system. Several screen captures from the mobile application in action are included.

Finally, the datasets used in this work are included in the last subsection.

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A. Web Application (Back-End)

One of the main problems with the data obtained in medical studies for breast cancer diagnosis is that the information is usually highly specific to one region of the world. It is for this reason that, to allow a certain flexibility in the use of the mobile application, an administration panel was implemented with which the classification algorithm can be trained and thus obtain results that are congruent to the particular characteristics of the patients in a specific region of the world.

Fig. 1 schematizes the architecture of the Web application implemented on the cloud computing platform Amazon AWS, making use of the services EC2 for the virtualization of the Apache Tomcat Server and MongoDB, and Amazon's S3 service for the massive storage of the datasets for the training of the system. Likewise, it can be seen that HTTP communication is performed via the AJAX Controller provided by PrimeFaces towards the business logic layer in the server, which is based on JSF, containing the pattern classification algorithm.

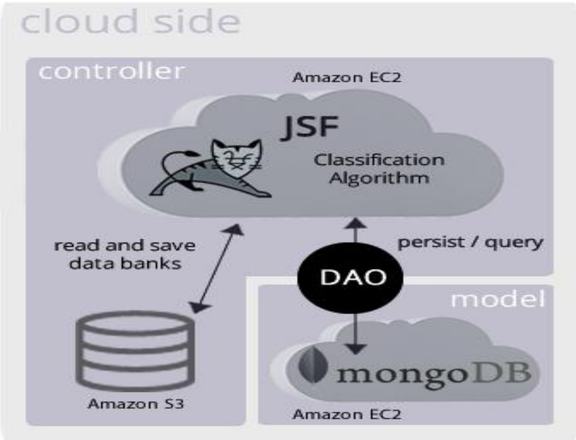

Fig. 1.Architecture of the Web application on the cloud.

B. Classification algorithm

Scientists in data science and in pattern recognition have discovered that intelligent classification of patterns can be applied to the diagnosis of diseases, where the classes are mainly healthy and sick patients. The features of the input patterns may be composed of the symptoms they present or of the results of laboratory studies.

The theoretical basis of the proposed hybrid classification and verification model presented in this paper consists of two main parts: on one hand, Morphological Associative Memories (MAM) [22], besides of the k-Nearest Neighbor (kNN) classifier [23]. MAM belong to the associative approach of machine learning, which has successful applications in various areas [24-47].

MAM are a pattern recall model developed by Ritter et al. in 1998. They may be operated in two dual modes: max and min. Max-type memories are very robust against dilative noise, while min-type MAM tolerate a great amount of erosive noise. One of the main advantages of MAM is that they allow real-valued components in the input patterns, such that no pre-processing of the data is needed beforehand. However, MAM are designed to work mainly as a pattern recall tool; that is, the output of the algorithm is a pattern similar to the input pattern, but with noise removed. Therefore, taking advantage of this property, a MAM is used as the first step of the hybrid model as a noise filter, which yields a cleaner pattern which is then presented to the well-known kNN classifier which obtains the final diagnosis.

Algorithm 1. Classification algorithm based on an auto-associative max-type MAM and kNN

<u>Training Phase</u>

The training phase consists of two stages:

1. Calculate the matrix $x^\mu \triangle (-x^\mu)^t$, where $(-x^\mu)^t = (-x^\mu_1, x^\mu_2, \ldots, x^\mu_n)$ and $\mu = 1,2,\ldots,p$
2. Apply the maximum operator $\vee$ to the p matrices calculated previously

$$M = \bigvee_{\mu=1}^{p}[x^\mu \triangle (-x^\mu)^t]$$

<u>Classification Phase</u>

Similar to the training phase, the classification phase consists of two stages:

1. Operate the associative memory M with an input pattern x^ω in order to obtain a recalled pattern:

$$\tilde{x} = M \triangle x^\omega$$

The i-th component of the recalled vector x is:

$$\tilde{x}_i = \bigwedge_{j=1}^{n}(m_{ij} + x^\omega_j)$$

2. Obtain the class of x^ω, using the pattern $\tilde{x}$ and the kNN classifier:

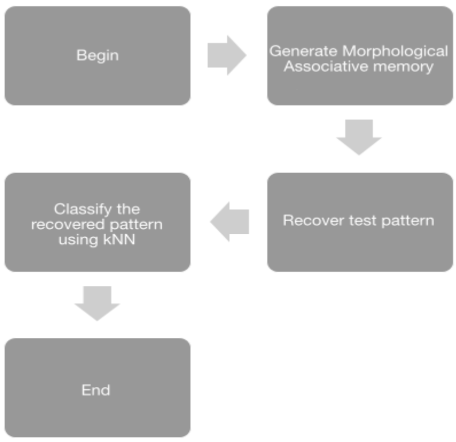

Fig. 2.Flowchart of the operation of the mNN algorithm

As can be observed in Algorithm 1, the proposed model is a hybrid between auto-associative morphological associative memories and the kNN classifier. The idea behind this model is to employ morphological memories as a filter that guards kNN against noisy patterns that can negatively impact its decision-making ability.

This way, the classification phase of the proposed model (hereafter called mNN) is shown in flowchart form in Fig. 2.

C. Mobile application (Front-End)

The mobile application was developed for Android and iOS devices using the SechaTouch platform, with the goal of avoiding the application store installation process found in those operating systems. Thus, the application can be executed using any web browser installed on the device. The communication with the Web application is carried out via Web services, allowing for the integration of the classification algorithm with the mobile application and thus reducing the amount of device resources consumed.

The algorithm execution-related workload resides directly in Amazon's cloud computing platform, while the mobile device functions as a dummy terminal.

Fig. 3 to Fig. 5 show three different mobile device screens, when the mobile information system about some interesting data is applied.

Fig. 3 screen allows the mobile device user to select a data file related to breast cancer (in this case it's an ARFF file), in order to execute the training phase of the proposed mobile information system.

The user has some facilities; for example, he/she can select the most interesting dataset according to him/her and set it as the default dataset, and he/she can also select or remove a specific file that best suits his/her needs.

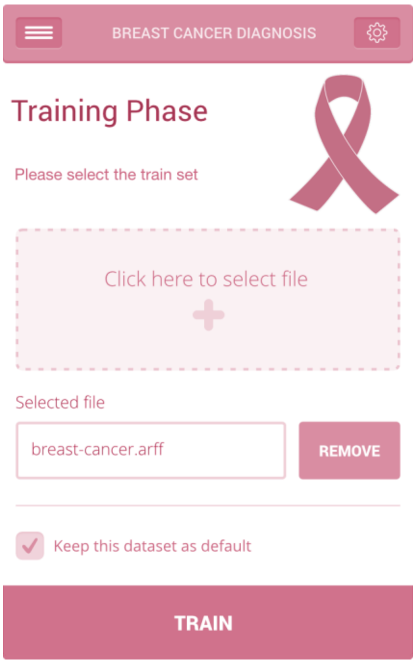

Fig. 3.Training phase.

The training phase of the mobile information system is very important because here is where the system learns which cases are diagnoses where breast cancer exists, and which data show the absence of this illness.

Fig. 4 screen shows the user the full performance of the proposed mobile information system; here is where the system decides if the patient has breast cancer or if she does not have it.

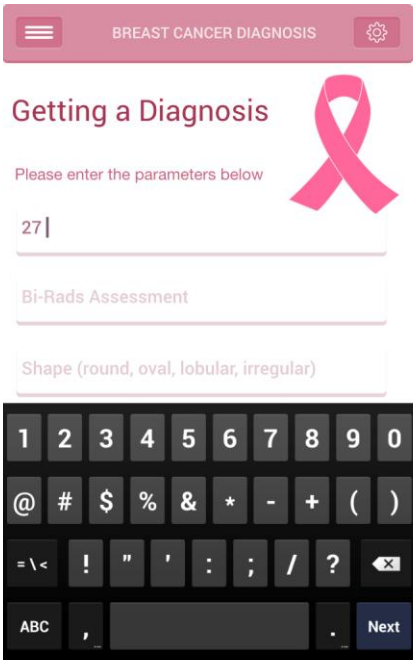

Fig. 4.Classification phase (diagnosis)

Finally, Fig. 5 screen is an example of the kind of results that the proposed mobile information system gives (in this case, unfortunately the tumor is malignant).

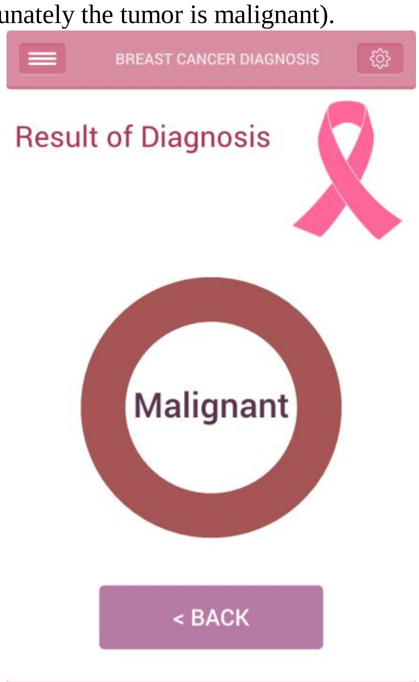

Fig. 5.Result of diagnosis.

D. Datasets

The datasets used for training and testing the mobile information system were selected from [48].

<u>Mammographic mass</u>

The patterns in this dataset contain features such as age, mass density and mammographic tumor shape. Using BI-RADS [49] can predict the severity of a tumor.

The data set contains 961, with 516 cases benign and 445 malignant.

The Radiology Institute of the University of Erlangen-Nuremberg created the patterns of this dataset.

BI-RADS is the acronym for Breast Imaging Report and Database System, a radiographic tool for quality assurance during mammogram reporting and interpretation [49].

Each instance is associated to a BI-RADS evaluation range, which goes from I (definitely benign) to 5 (high likelihood of being malignant).

Table 1 shows the attributes of the instances contained in the dataset.

Table- I: Mammographic mass data

Feature	Unit	Description
BI-RADS	Ordinal	1 - 5, not predictive
Age	Years	Patient's age
Shape	Nominal	Shape of the mass: 1 is rounded 2 is oval 3 is lobular 4 is irregular
Marg	Nominal	Mass margin: 1 is circumscribed 2 is microlobulated 3 is obscured 4 is ill-defined 5 is spiculated
Dens	Ordinal	Mass density: 1 is high 2 is iso 3 is low 4 is fat-containing
Severity	Boolean	Severity: 0 is benign 1 is malignant

When a dataset contains patterns with missing values in some attributes, it is necessary perform a pre-processing; that is the case.

Since this dataset presents missing values among the instances, a pre-processing of the data was performed in order impute by means

Table II shows the values obtained using the mean calculation for each attribute.

Table- II: Mean values per attribute

Feature	Mean
BI-RADS	4
Age	57
Shape	3
Marg	3
Dens	3

Wisconsin Breast Cancer

The dataset contains 699 cases of the University of Wisconsin. Each instance is associated to 9 attributes plus the class label; each one of them is inside an evaluation range from 1 to 10.

Table III shows the attributes for this dataset.

Table- III: Wisconsin Breast Cancer Data

Feature	Unit	Possible values
Clump Thick	Num	1 to 10
Cell Size Unif	Num	1 to 10
Cell Shape Unif	Num	1 to 10
Marg Adhesion	Num	1 to 10
Epithelial Cell Size	Num	1 to 10
Nuclei	Num	1 to 10
Chromatin	Num	1 to 10
Nucleoli	Num	1 to 10
Mitoses	Num	1 to 10
Class	Num	Class label (4=malignant, 2=benign)

III. RESEARCH METHODOLOGY

The development of the back-end of the mobile information system consisted of a Web application, implemented using several different technologies that collaborate to ensure the correct functioning of the system. These were:

- Amazon Web Services, used as a cloud host
- The server, a virtualized Apache Tomcat Server using JSF, which hosted the classification algorithm
- An HTTP communication controller in charge of transferring data to and from the server
- Amazon's S3 service, which stored the datasets an user uploads to tailor the system to a specific region's needs
- The EC2 service, used to virtualize the Apache Tomcat Server and MongoDB

Once all of these components were up and running, it was possible to train and test the proposed hybrid classification algorithm.

In order to perform comparisons against other classifiers, which were not implemented in our mobile system, the same datasets using for training our proposal were tested with the algorithms available in the data mining platform WEKA [50, 51]. All tests used 10-fold cross-validation as a performance measure.

To further analyze the results, two metrics were taken into account: the performance measure (proportion of correctly classified instances) and analysis of the ROC (Receiver Operating Characteristic) curves [52, 53]. (ROC), which are plotted on a bi-dimensional plane as the rate of tp against the rate of fp.

Finally, in order to have an interface with which the user could receive a diagnosis of new patients, a mobile front-end was needed. The development of the front-end of the application consisted of implementing the following key components:

- Graphical interface implemented using Sencha Touch
- Training dataset uploading tool and screen (Fig. 3)
- New diagnosis input screen (Fig. 4)
- Results screen (Fig. 5)
- Communicator that delivers input data to the Web service and retrieves the diagnosis information

This concluded the implementation of the proposed mobile information system; having all of the required components: a robust back-end in which all of the business logic operations are performed, an intelligent classification algorithm that is they key cog of the system, and an easy to use front-end that is user-friendly and allows for quick and simple training and operating of the diagnostic system.

IV. RESULT AND DISCUSSION

The relevance of the present proposal is evidenced during the operation of the mobile information system that makes the breast cancer diagnosis and verification.

During operation, the three main components of the mobile information system (Web application, classification algorithm and mobile application) are appropriately coordinated in order to act on patterns that reflect the attributes of a patient that may suffer from breast cancer.

While the correct functioning of the Web application and the mobile application do not depend on the data and its structure, the case of the classification algorithm, a crucial component of this mobile information system, is different: its correct functioning depends greatly on the kind and structure of the available data for the training phase of the hybrid classifier. It is crucial to have an accurate description of the attributes available as well as an appropriate encoding into patterns of a previously-determined size for the training phase to be carried out seamlessly.

Furthermore, it is also needed that the pattern that represents the state of health of a patient that is requesting a diagnosis possesses a similar structure to that of the training patterns; that is, the test patterns should be of the same type and structure than the training patterns.

The results, analysis and discussion presented herein correspond directly to the empirical data that consists of the patterns from the two datasets described in Section 2: Mammographic Mass and Wisconsin Breast Cancer.

Table IV include results which correspond to the performance measure and ROC curve analysis for the proposed mNN model alongside other well-known algorithms implemented in WEKA. For the ROC analysis, a positive instance was considered as one representing a malignant tumor; that is, when the patient would require a mammographic biopsy.

Table- IV: mNN results (Mammographic Mass dataset)

Algorithm	Performance (%)	RVP	RFP
mNN	76.3871	0.8028	0.2696
k-NN	79.3896	0.8031	0.2141
Euclidean	67.5691	0.7094	0.3534
NaiveBayes	82.3101	0.8610	0.209
BayesNet	82.5182	0.8470	0.1940
RandomTree	77.5234	0.7840	0.2330

Table V include results for the Wisconsin Breast Cancer dataset. The results correspond to the performance measure and ROC curve analysis for the proposed mNN model alongside other well-known algorithms implemented in WEKA. For the ROC analysis, a positive instance was considered as one representing a malignant tumor; that is, with class label 4.

Table- V: mNN results (Wisconsin Breast Cancer dataset)

Algorithm	Performance (%)	RVP	RFP
mNN	97.4202	0.9708	0.0241
k-NN	96.8773	0.9576	0.0249
Euclidean	96.1286	0.9333	0.0240
NaiveBayes	96.1373	0.9540	0.0460
BayesNet	97.1388	0.9670	0.0330
RandomTree	92.4177	0.954	0.046

It is important to mention that the above results were selected among a set of results from more than 60 algorithms available in the WEKA platform, among which stand out Support Vector Machines, Multilayer Perceptrons, and others. The tables above state the best results among all algorithms tested.

The social impact of this proposal is relevant in terms of the interpretation that emerges from the above results; for example, the mobile information system proposed in this paper is able to correctly predict the existence, or lack of it, of malignant tumors in more than 97 of each 100 patients on which the mobile information system is used to perform or verify a diagnosis.

These high performance scores for the proposed system allow us to foresee a fertile area for research and technological development with respect to the implications of this research to next generation mobile information systems.

The development of wireless technology is continuously advancing, and next generation mobile communication systems are the future of this field. To this end, we pretend to keep working on the design, implementation and operation of the proposed mobile information system in order to achieve all of the benefits that this new technological movement offers; among these, more energy-efficient and secure devices, ubiquitous, more dynamic and improved communication systems and protocols, and enhanced next-generation mobile operating systems.

V. CONCLUSION AND FUTURE SCOPE

In this paper, a method to look for a solution to the problem of breast cancer diagnosis is presented, using a mobile application that allows the user to obtain an almost instant diagnosis from almost anywhere in the world using intelligent pattern recognition algorithms and cloud computing.

Morphological associative memories, being a non-iterative algorithm, are considered a one-shot model, which gives advantages over the usual algorithms such as SVM and NN.

The developed Web system allows for the training of the intelligent algorithm with the purpose of tailoring the results depending on the characteristics of the patients in the region in which the system is being used.

Mobile devices nowadays are an accessible commodity for a large part of the population; thus, this kind of tools is useful for verifying a diagnosis made by a medical professional or clinical study. The application takes advantage of cloud resources to process data at a great speed and on-demand, without the need to install a dedicated data center.

Being the proposed system a mobile application, a desired next step would be to implement it natively for each of the target operating systems (iOS and Android).

With respect to the algorithm, it would be convenient to use other classification algorithms for the classification phase of the proposed hybrid system. Other kinds of classifiers could achieve even better results or quicker response times when combined with the MAM.

Finally, other medical datasets should be used and tested to evaluate the impact of this kind of mobile applications in helping reduce the need for costly biopsies.

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