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CSIMIDx: A Prototype for Cloud-Based Secure Intelligent System for Medical Image Classification

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Abstract: Breast cancer is commonly found among aged women and ranks second in women mortality all over the world as per World Health Organization (WHO). Here, we propose a novel method using cloud paradigm in diagnosing mammogram images for breast cancer with security. The transmission of patients' medical data in to the cloud infrastructure may bring about a few dangers as far as security and protection is concerned. The main focus is to quantify the performance and utilization of secure cloud-based intelligent medical diagnosis framework in the point of view of patients and experts. This proto type attains high sensitivity up to 99.09%, specificity up to 92.85% and accuracy of up to 98.4%. The performance of the CSIMIDx framework with respect to high users and low users is given as security and privacy of the prototype ($p = 0.87$), usefulness of the prototype ($p = 0.62$), ease of navigation ($p = 0.90$), user friendliness evaluation ($p = 0.97$) and overall satisfaction ($p = 0.33$).

Key words: Breast cancer, cloud security, digital watermarking, mammograms, intelligent system

INTRODUCTION

As of late patients are all that much inspired by thinking about their ailment and they need the most contemporary data (Silver, 2015). Analysts have exhibited that breast cancer patients are the most dynamic seekers of online social support contrasted with other patient group (Amante *et al*., 2015; Bhavani *et al*., 2015). Laugesen *et al*. (2015) observed that patients chose their web destinations which have solid and sound data. Cloud computing infrastructure serves to give the medical data in a successful and straight forward path without mediation. Moving patient information into the cloud framework implies that patient data is facilitated on the servers of the cloud administration supplier (Torre-Diez *et al*., 2015). It is fundamental that the privacy and security of patient information (Islam *et al*., 2015) deployed in cloud infrastructure must be ensured if a medical diagnosis framework is sent on the cloud and must be achieved by both the cloud administration suppliers and the social insurance suppliers, since facilitating of client information (Kruse *et al*., 2015) in the cloud environment obliges a precise methodology in overseeing security.

In this research, CSIMIDx web services are employed and installed in the cloud for the patients to diagnose their new image by ensuring security and privacy in the cloud infrastructure. It comprises of two main service models, i.e., training and test service models. They are positioned using Universal Discovery and Description Integration (UDDI) cloud server. It is highly constructive for experts, radiologists, researchers (both engineering and medical) and patients. The medical expert (owner of a query image) and the service provider (developer of CSIMIDx) additions their remarkable watermark into a new client image with wavelet transformation (Ganesan *et al*., 2014) and Rivest Shamir Adleman (RSA) encryption algorithm (Rivest *et al*., 1978) before diagnosis with CSIMIDx framework. This framework supports cross-platform application and makes easy access of CSIMIDx proto type. This study was directed with 250 client images and the outcome demonstrates high sensitivity (99.09%) and accuracy (98.4%).

MATERIALS AND METHODS

The CSIMIDx architecture: The proposed CSIMIDx system demonstrates to test the patient's mammogram image with security. It acquires visual features extricated from the client image with the expert suggestion for the classification of client image in the cloud environment. The CSIMIDx framework comprises of training and test models. Each training image is coupled with a set of key words or classes (key words are representative words specified by the expert for the classification of a medical image).

The CSIMIDx engineer is capable of training and testing the medical image while the client can just test

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their new mammogram image (in the predetermined configuration) by uploading on the web page and can get the diagnosis outcome from the CSIMIDx structure installed on the cloud in a safe way. In this examination, an incorporated progression of CSIMIDx training and test Web services structure is displayed to encourage the distributed mammogram image analysis which is shown in Fig. 1.

In training service model, the CSIMIDx model determines new information through representative association rules (intelligent rules) by invoking the accompanying web service models, specifically, image pre-processing (Adams and Bischof, 1994; Li *et al*., 2011), segmentation (Sun *et al*., 2009; Li *et al*., 2010; Bresson *et al*., 2006), visual feature extraction (Clausi and Deng, 2005; Zhu, 2012; Mukundan *et al*., 2001), feature selection and discretization (Liu and Yu, 2005; Senthilkumar *et al*., 2015) and representative association rule mining (Chu *et al*., 2010; Adnan and Alhajj, 2011). In the test service model, the clients invoke the test web services with their new image by utilizing the accompanying test web service models viz, image pre-processing, image segmentation, cloud security, visual feature extraction and representative association rule mining.

The proposed system encourages the sharing of resources and infrastructure and diminishment of time in knowing the classification analysis result with no mediation in the cloud base. The correspondence set up between the CSIMIDx web services and the cloud server is attained by Simple Object Access Protocol (SOAP). The CSIMIDx web service system was conversed in our preceding work (Bhavani *et al*., 2015). The readers are asked to advert for the vital system of diverse web service components.

CSIMIDx training web services: In training service model, the CSIMIDx framework determines new information through, representative association rules (intelligent rules) by invoking the accompanying web service models, specifically, image pre-processing (Adams and Bischof, 1994; Li *et al*., 2011), segmentation (Sun *et al*., 2009; Li *et al*., 2010; Bresson *et al*., 2006), visual feature extraction (Clausi and Deng, 2005;

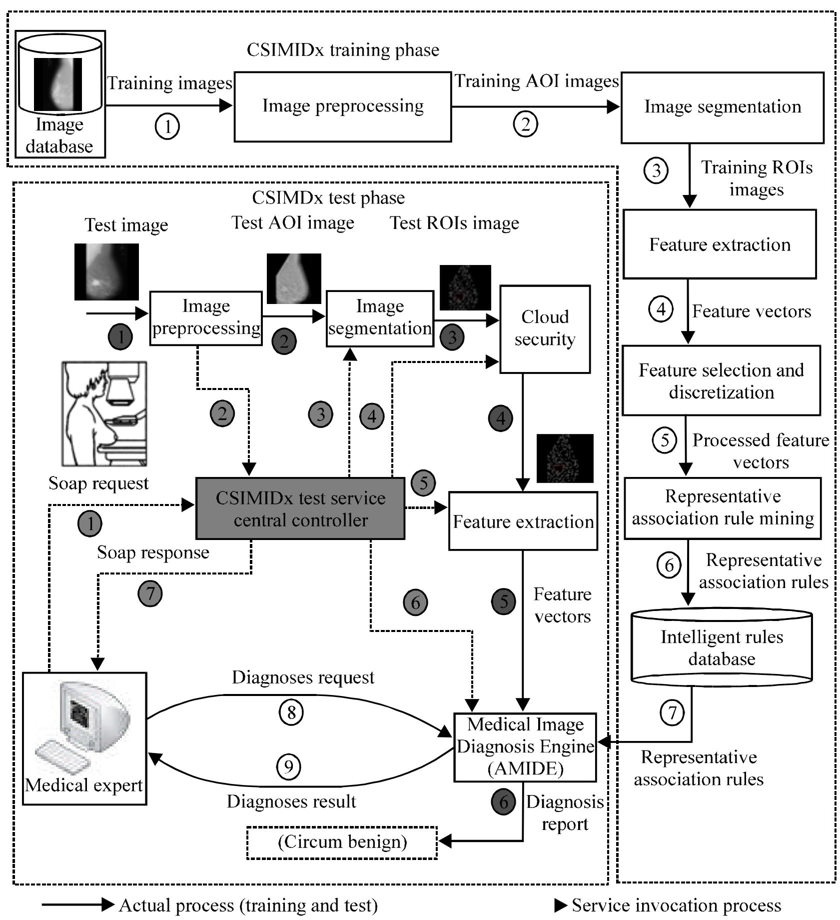

Fig. 1: Pipeline of CSIMIDx framework

Zhu, 2012; Mukundan *et al*., 2001), feature selection and discretization (Liu and Yu, 2005; Senthilkumar *et al*., 2015) and representative association rule mining (Chu *et al*., 2010; Adnan and Alhajj, 2011; Bhavani *et al*., 2015).The CC invokes the CSIMIDx training web services technique which mines new information as representative association rules to support the determination of the medical image in the cloud environment. The CSIMIDx training web services technique is described step by step.

The CC passes the training images to the CSIMIDx training image pre-processing web service model to uproot the undesirable regions (pectoral muscle) which biases the detection procedure. This methodology is implemented using Level Set Method (LSM) (Li *et al*., 2011) for the identification of breast border and Seeded Region Growing (SRG) (Adams and Bischof, 1994) algorithm to define an accurate area of interest (AOI). This model gives the AOI of the training image to the CC for image segmentation method.

The CC passes the training AOI images to the CSIMIDx training image segmentation web service model to recognize the Region Of Interest (ROI). The image segmentation is accomplished in two stages, edge detection to identify accurate region edge using DWT (Sun *et al*., 2009) and edge refinement with variational level set formulation method (Bresson *et al*., 2006) for additional refinement to get precise ROI in the image. The ROI image is given to the CC for visual feature extraction method.

The CC passes the ROI image to the visual feature extraction service model. The CSIMIDx strategy extricated 1092 dimensional visual sub band statistical and spectral texture features from each image. It incorporates 576 features by the Subband Statistical and Spectral Texture Feature (S^3TFe) based on wavelet transformation, 336 features by bivariate discrete orthogonal polynomials based texture feature which includes 112 features from Tchebichef-Krawtchouk Orthogonal Polynomials Texture Feature (TKOrPTFe), 112 features from Tchebichef-Hahn Orthogonal Polynomials Texture Feature (THOrPTFe), 112 features from Krawtchouk Tchebichef-Hahn Orthogonal Polynomials Texture Feature (KHOrPTFe) and 180 features by the Gradient Gray Level Co-occurrence Probabilities based Texture Feature ($G^2LCPTFe$). The visual feature extraction web service model results in the 1092 texture features to the CC for further feature selection and discretization.

The CC passes the 1092 texture feature vectors to the feature selection and discretization service model. The CSIMIDx strategy utilizes the NANO algorithm (Senthilkumar *et al*., 2015) and produces reliable features in the feature database. The feature selection and discretization web service model results in 120 consistent features to the central controller for mining the representative association rules.

The CC passes the 120 consistent features to the representative association rule mining service model. In this step, transaction representation of the training mammogram images are built using the key words of the training images and the processed feature vectors. Equation 1 shows the generation of the transaction representation of the training image:

$$\text{IMG1} = 2[0.9-17.9]4[48.75-52]\text{Benign mass} \quad (1)$$

Image 1 (IMG1) having the 2nd and 4th feature values (a measure of Sub-band Statistical and Spectral Texture Features (S^3TFe)) in the closed interval (0.9-17.9) and (48.75-52) are benign mass images. The transaction representations (training mammogram images) are submitted to the representative association rule mining model. It mines the representative association rules with bounded portion of the density frequency pattern tree (Chu *et al*., 2010) and density frequency pattern growth (Adnan and Alhajj, 2011) methods. Example for the mined representative association rule is given as:

$$2[0.9-17.9] \rightarrow \text{Benign mass}(0.08, 0.99) \quad (2)$$

This specifies that the images with the 2nd feature (a measure of Sub-band Statistical and Spectral Texture Features (S^3TFe)) in the closed interval [0.9-17.9] are benign mass images. The values 0.08 and 0.99 indicate support and confidence measures of the rule.

The greater part of the above characterized systems is proficient in a consecutive way. The CC passes the representative association rules as a SOAP response to the designer. The representative association rules are then facilitated in the cloud server to support the medical image diagnosis in a proficient way.

CSIMIDX test web services: In the test model, the administrator and clients invoked the CSIMIDx test web services with the new image. The CSIMIDx test web services technique analyze the new image (without the biopsy points of interest) by invoking the accompanying five web services. The central controller finishes, the test image from clients as a SOAP request to the CSIMIDx test web service model. The CSIMIDx test web services invoking methodology is as per the following: the CC passes the test image to the CSIMIDx test web service by invoking the image pre-processing web service model for the detection of AOI. The proposed pre-processing technique distinguishes the accurate AOI by removing the pectoral muscle in the mammogram image in light of LSM and SRG algorithm. The image pre-processing web services model replies as the AOI image to the central controller for further image segmentation method. This system makes utilization of these strategies (Adams and Bischof, 1994; Li *et al*., 2011).

The CC passes a test image to the image segmentation web service model. The proposed image segmentation technique distinguishes the precise ROI in view of wavelet transforms and LSM. The proposed image segmentation web services model replies and passes the ROI image to the central controller. This methodology makes use of these strategies (Sun *et al*., 2009; Li *et al*., 2010; Bresson *et al*., 2006).

The CC passes the test ROI image to the cloud security web service model. The proposed cloud security method is an image versatile and imperceptible two-party watermarking convention which performs digital watermarking taking into account wavelet transform (Ganesan *et al*., 2014) and RSA Encryption algorithm to the test ROI image (Rivest *et al*., 1978). The watermark embedding (Mukundan *et al*., 2001) comprise of disintegrating the test ROI image using DWT which produce four sub-groups (lower resolution approximation image (LL) as well as horizontal (HL), vertical (LH) and diagonal (HH) detail components) out of which LL (Lowest Level) has greatest vitality and it is chosen for watermark embedding. Since, the watermark embedded in this exploration is observable in nature or visible, it is inserted in the low frequency approximation component of the ROI image. The watermark of size (32×32) is inserted into LL band of the ROI image and the resultant image is called watermarked image. The watermark embedding process in the encryption domain is depicted beneath.

The watermark image (logo or trademark) WM_i is defined in terms of a set of independent real number $WM = \{Wm_1, Wm_2, ... Wm_m\}$ drawn from N (0, 1) is embedded by modifying the wavelet coefficients in the low frequency approximation component of the ROI image $\{x_1, x_2, ... x_m\}$ to give way modified coefficients $\{x'_1, x'_2, ... x'_m\}$. The watermarked image is obtained by:

$$x_i' = x_{LLi}\left(1+\alpha WM_i\right) \quad (3)$$

Where:

x'_1 = The watermarked image
x_{LLi} = The low frequency approximation of the original image
α = A scaling parameter

The proposed cloud security web services model reacts and passes the secured ROI image to the central controller. This system makes utilization of these procedures (Ganesan *et al*., 2014; Rivest *et al*., 1978).

The CC passes the secured test ROI image to DICOM server (ROI image database) then sent to the visual feature extraction method. The proposed VS^{3}TFe method extracts a sum of 1092 dimensional visual subband statistical and spectral orthogonal polynomials based texture features for each image and responds to the feature selection and discretization web service model. It responses these visual features to the central controller for further mining the representative association rules. This strategy makes utilization of these procedure (Clausi and Deng, 2005; Zhu, 2012; Mukundan *et al*., 2001; Liu and Yu, 2005).

The central controller passes the visual feature vectors are given to the Associative Medical Image Diagnosis Engine (AMIDE) algorithm (Chu *et al*., 2010; Adnan and Alhajj, 2011) which employs the representative association rules. The proposed AMIDE algorithm suggests the mixture of key words for the classification of client image.

All the above procedures are executed in a consecutive way. The central controller passes the findings of diagnosis (key word) as a SOAP response to the developer and the client.

RESULTS

Datasets discretion

BI-RADS datasets: The dataset BI-RADS (www.birads.at) comprises of 446 abnormal images and 26 normal images taken from mammograms, gathered from the Breast Imaging Reporting And Data System (BI-RADS) of the Department of Radiology, University of Vienna. The dataset is divided into two sets: the training set is made out of 316 images (67% of BI-RADS dataset) and the test set is made out of 156 images (33% of BI-RADS dataset).

MIAS dataset: The dataset scaled down MIAS (www.wiau.man.ac.uk/services/MIAS/MIASweb.html) utilized as a part of our examinations is taken from the mini-Mammographic Image Analysis Society (mini-MIAS). It comprises of 322 images and has a place with three major classifications: normal, benign and malignant. There are 208 normal images, 63 benign and 51 malignant which are considered abnormal. All the mammograms show a medio-lateral oblique view. An aggregate of 140 images of 63 benign, 51 malignant and 26 normal images are considered to train and test the proposed CSIMIDx framework. The dataset is partitioned into two sets: the training set made out of 93 images (67% of mini-MIAS dataset) and the test set made out of 47 images (33% of mini-MIAS dataset).

Client dataset: The present study incorporates screening mammograms interpreted by three accomplished radiologists at medical colleges and hospitals, Chennai, Tamil Nadu, India, between May 9, 2009 and April 30, 2015. Each of the three radiologists, two with 25 years and 22 years of clinical experience and the other with fellowship training in breast imaging and 8 years of clinical experience, amassed 5 months of clinical involvement with the CSIMIDx framework utilized as a part of this study before the patients were enlisted. This study was performed under an institutional audit board-approved convention.

Within the 6 year period of study, an aggregate of 16,166 asymptomatic women experienced screening mammography and CSIMIDx assessment were selected here. Standard screening methods were taken after and high-hazard patients between the age of 35 years and 40 years were confessed to experience screening.

A total of 5209 mammogram images of 5079 (97.5%) bilateral and 130 (2.5%) unilateral mammograms were obtained with a standard two-view evaluation of each breast performed by a mammography-certified radiology technologist. The mammograms were therefore, digitized and investigated by the CSIMIDx system. An aggregate of 5209 images of 1343 (25.8%) benign, 3740 (71.8%) malignant and 126 (2.4%) normal images were considered to train and test the proposed CSIMIDx framework. The dataset was partitioned into two sets: the training set made out of 3490 images (67% of client dataset) and the test set made out of 1719 images (33% of client dataset). All the images are used in the CSIMIDx research of sizes (16×16) to (256×256) with the grey values in the range of 0-255.

The patient's data were obtained from various hospitals and colleges in and around Chennai, Tamil Nadu were tested as independent variables in this study: age, education, annual income and breast cancer stage. The unit of analysis was the usage of CSIMIDx prototype by the clients and expert in this study. First, the classification accuracy of this model has been tabulated by comparing with other classification methods. Then, the descriptive statistics were tabulated to produce the usefulness of CSIMIDx prototype among low and high user group categories of the patients.

Here, a usability evaluation was performed to explore the effectiveness of the CSIMIDx framework by means of online questionnaires and interviews to assess the framework in terms of usefulness, user satisfaction, security and privacy of their data, user friendliness and interface quality of the evaluation constructs in achieving his/her specific goals (Shanahan *et al*., 2014; Kao *et al*., 2015).

The datasets 3899 (the 3781 abnormal and the 118 normal) images taken from 93 (the 76 abnormal and the 17 normal) cases in the mini-MIAS dataset, 316 (the 299 abnormal and the 17 normal) cases in the BI-RADS dataset and 3490 (the 3406 abnormal and the 84 normal) cases in the client dataset used to train the proposed CSIMIDx framework. The datasets 1922 (the 1862 abnormal and the 60 normal) images taken from 47 (the 38 abnormal and the 9 normal) cases in the mini-MIAS dataset, 156 (the 147 abnormal and the 9 normal) cases in the BI-RADS dataset and 1719 (the 1677 abnormal and the 42 normal) cases in the client dataset used to train the proposed CSIMIDx framework.

The classification accuracy of the CSIMIDx framework: Table 1 outlines that the classification accuracy of the CSIMIDx framework with mini-MIAS dataset compared using C4.5 (Quinlan, 1993) classification algorithm, IDEA (Ribeiro *et al*., 2009) and CIMIDx (Bhavani *et al*., 2015) methods. The diagnosis accuracy for both CSIMIDx and CIMIDx methods (95.74%) are higher than, the IDEA method (93.62%) and C4.5 classification algorithm (91.49%). The sensitivity is 94.74% for the CSIMIDx and IDEA methods and C4.5 algorithm whereas 97.37% for CIMIDx method. The specificity of the CSIMIDx method (100%) is greater than CIMIDx and IDEA methods (88.89%) and C4.5 algorithm (77.78%). The false positive rate is zero percent for CSIMIDx method whereas 11.11% for both CIMIDx and IDEA methods and 22.22% for C4.5 algorithm. The false negative rate is 5.26% for the CSIMIDx and IDEA methods and C4.5 algorithm whereas 2.63% for CIMIDx method. The results prove that the proposed CSIMIDx method explores the perceptual quality of the watermarked medical images and does not influence the diagnosis performance. Figure 2 shows the classification accuracy (percentage) of the proposed CSIMIDx framework with mini-MIAS dataset (Fig. 2).

Table 1: The classification accuracy of CSIMIDx framework for mini-MIAS dataset compared with C4.5 Classification algorithm, IDEA and CIMIDx methods (%)

		Methods		
Measurements	C4.5	IDEA	CIMIDx	CSIMIDx
Accuracy	91.49	93.62	95.74	95.74
Sensitivity	94.74	94.74	97.37	94.74
Specificity	77.78	88.89	88.89	100.00
False positive rate	22.22	11.11	11.11	0.00
False negative rate	5.26	5.26	2.63	5.26

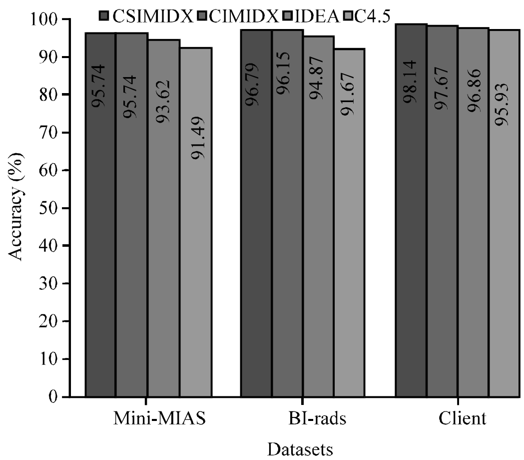

Fig. 2: The classification accuracy (percentage) of the proposed CSIMIDx framework compared with C4.5 (Quinlan, 1993) classification algorithm, IDEA (Ribeiro *et al*., 2009) and CIMIDx (Bhavani *et al*., 2015) methods

Table 2: The classification accuracy of CSIMIDx framework for BI-RADS dataset, compared with C4.5 classification algorithm, IDEA and CIMIDx methods (%)

	Methods			
Measurements	C4.5	IDEA	CIMIDx	CSIMIDx
Accuracy	91.670	94.870	96.150	96.790
Sensitivity	93.790	96.580	97.930	97.950
Specificity	63.640	70.000	72.730	80.000
False positive rate	36.360	30.000	27.270	20.000
False negative rate	6.210	3.420	2.070	2.050

Table 2 shows the classification accuracy of the CSIMIDx framework with BI-RADS dataset. The diagnosis accuracy of CSIMIDx method (96.79%) is slightly higher when compared to CIMIDx method (96.15%), higher than the IDEA method (94.87%) and C4.5 classification algorithm (91.67%). The sensitivity of the CSIMIDx (97.95%) is slightly greater than CIMIDx method (97.93%), IDEA method (96.58%) and C4.5 algorithm (93.79%). The specificity of CSIMIDx (80%) is higher than the CIMIDx method (72.73%), IDEA method (70%) and C4.5 algorithm (63.64%). The false positive rate for CSIMIDx method 20% is lesser than the CIMIDx method is 27.27%, IDEA method is 30% and C4.5 algorithm is 36.36%. The false negative rate is 2.05% for CSIMIDx method slightly smaller whereas 2.07% for CIMIDx method, 3.42% for IDEA method and 6.21% for C4.5 algorithm. The results prove that the cloud security method explores the perceptual quality of the watermarked medical images and does not influence the diagnosis performance. Figure 2 shows the classification accuracy of the proposed CSIMIDx framework with BI-RADS dataset.

Table 3: The classification accuracy (%) of CSIMIDx framework for client dataset, compared with C4.5 classification algorithm, IDEA and CIMIDx methods

	Methods			
Measurements	C4.5	IDEA	CIMIDx	CSIMIDx
Accuracy	95.930	96.860	97.670	98.140
Sensitivity	97.000	97.900	98.560	98.800
Specificity	61.540	64.810	68.630	75.000
False positive rate	38.460	35.190	31.370	25.000
False negative rate	3.000	2.100	1.440	1.200

Table 3 outlines that the classification accuracy of the CSIMIDx framework with client dataset. The diagnosis accuracy of CSIMIDx method (98.14%) is higher when compared to CIMIDx method (97.67%), IDEA method (96.86%) and C4.5 classification algorithm (95.93%). The sensitivity of the CSIMIDx method (98.8%) is slightly higher than CIMIDx method (98.56%), IDEA method (97.9%) and C4.5 algorithm (97%). The specificity of CSIMIDx method (75%) is higher when compared to CIMIDx method (68.63%), IDEA method (64.81%) and C4.5 algorithm (61.54%). The false positive rate is 25% for CSIMIDx method whereas 31.37% for CIMIDx method, 35.19% for IDEA method and 38.46% for C4.5 algorithm. The false negative rate for CSIMIDx method is 1.2%, CIMIDx method is 1.44%, IDEA method is 2.1% and C4.5 algorithm is 3%. The results prove that the proposed CSIMIDx method explores the perceptual quality of the watermarked medical images and does not influence the diagnosis performance. Figure 2 shows the classification accuracy of the proposed CSIMIDx framework with Client dataset.

Table 4 demonstrates the diagnosis accuracy of CSIMIDx framework with 250 patients in the diagnosis of mammogram images with high sensitivity (99.56%) and accuracy (98.4%) (246/250) (The classification accuracy for the malignant mass is 98.82% (168/170), 96.29% (52/54) for benign and 100% (26/26) for the normal category). The diagnosis rate of CSIMIDx framework is increased for the benign (mass and calcification) stages by 96.29% (52/54) compared with well-known methods (from up to 94.44% (51/54) both by CIMIDx and IDEA methods then C4.5 by 90.74% (49/54)). There is a noteworthy increment in the determination rate of malignant (mass and calcification) stages by 98.82% (from up to 98.82% (168/170) of CIMIDx, 97.65% (166/170) by IDEA and 95.88% (163/170) by C4.5). The diagnosis accuracy for CSIMIDx is 98.4% (246/250) whereas CIMIDx by 98% (245/250), IDEA method by 95.6% (239/250) and C4.5 by 92.8% (232/250) for the benign and malignant category. Almost 2% (4/250) was dismissed by both CSIMIDx and CIMIDx

Table 4: The classification accuracy of the proposed CSIMIDx cloud services model with 250 client test images during the development of CSIMIDx and compared with C4.5 classification algorithm, IDEA and CIMIDx methods (n = 250)[a]

	C4.5, n (%)		IDEA method, n(%)		CIMIDx method, n (%)		CSIMIDx method, n (%)	
Stages	Diagnosed	Missed	Diagnosed	Missed	Diagnosed	Missed	Diagnosed	Missed
Normal breast issue	20 (8)	6 (2.4)	22 (8.8)	4 (1.6)	26 (10.4)	0	26 (10.4)	0
Fibrocystic disease	14 (5.6)	1 (0.4)	14 (5.6)	1 (0.4)	14 (5.6)	1 (0.4)	14 (5.6)	1 (0.4)
Fibro adenoma	20 (8)	1 (0.4)	20 (8)	1 (0.4)	21 (8.4)	0	20 (8)	1 (0.4)
A typical ductal hyperplasia	10 (4)	2 (0.8)	11 (4.4)	1 (0.4)	11 (4.4)	1 (0.4)	12 (4.8)	0
Benign lesion,other	5 (2)	1 (0.4)	6 (2.4)	0	5 (2)	1 (0.4)	6 (2.4)	0
DCIS[b], grade I	23 (9.2)	2 (0.8)	24 (9.6)	1 (0.4)	24 (9.6)	1 (0.4)	25 (10)	0
DCIS grade II and III	39 (15.6)	2 (0.8)	40 (16)	1 (0.4)	41 (16.4)	0	40 (16)	1 (0.4)
IDC[c]	57 (22.8)	2 (0.8)	58 (23.2)	1 (0.4)	58 (23.2)	1 (0.4)	58 (23.2)	1 (0.4)
ILC[d]	25 (10)	1 (0.4)	26 (10.4)	0	26 (10.4)	0	26 (10.4)	0
ILC and IDC	12 (4.8)	0	11 (4.4)	1 (0.4)	12 (4.8)	0	12 (4.8)	0
Malignant lesion,others	7 (2.8)	0	7 (2.8)	0	7 (2.8)	0	7 (2.8)	0
Total	232 (92.8)	18 (7.2)	239 (95.6)	11 (4.4)	245 (98)	5 (2)	246 (98.4)	4 (1.6)

[a]Interviews conducted in various medical colleges and hospitals in Chennai, Tamil Nadu, India from May 2015 to December 2015, the secure cloud-based intelligent medical image diagnosis prototype was used for breast health issues; [b]DCIS: Ductal Carcinoma In Situ; [c]IDC: Invasive Ductal Cancer; [d]ILC: Invasive Lobular Cancer

Table 5: Characteristics of 250 women with breast cancer

Demographic variables	Category Mean (SD)/No. (%) (N = 169)	Use of CSIMIDx by patients Mean (SD)/# (%) (N = 81)	Use of CSIMIDx by experts	Significance (p)[a]
Age (years)		51.5 (42.74)	40.5 (23.33)	0.452
Time since, diagnosis (years)		51.5 (45.2)	40.5 (10.6)	0.119
Annual household income (INR)	<1,00,000	21 (12.4)		
	1,00,000-2,70,000	63 (37.3)		
	>2,70,000	85 (50.3)		
Education	Grades<12	24 (14.2)		
	Grades 13-15	59 (34.9)		
	Grades>15	86 (50.9)		
Stage (normal)	Normal breast issue	19 (11.2)	7 (8.6)	0.78
Benign	Fibrocystic disease	11 (6.5)	4 (4.9)	
	Fibroadenoma	19 (11.2)	2 (2.5)	
	A typical ductal hyperplasia	10 (5.9)	2 (2.5)	
	Benign lesion, other	4 (2.4)	2 (2.5)	
Malignant	DCISb, grade I	18 (10.7)	7 (8.6)	0.97
	DCIS grade II and III	23 (13.6)	18 (22.2)	
	IDCc	38 (22.5)	21 (25.9)	
	ILCd	15 (8.9)	11 (13.6)	
	ILC and IDC	7 (4.1)	5 (6.2)	
	Malignant lesion, others	5 (3)	2 (2.5)	

[a]p and t-tests; [b]DCIS: Ductal Carcinoma In Situ; [c]IDC: Invasive Ductal Cancer; [d]ILC: Invasive Lobular Cancer

whereas IDEA method by 4.4% (11/250) and C4.5 by 7.2% (18/250). Microsoft Excel spreadsheet was utilized for the examination of client information and measurable investigation was performed by statistical analysis tool-pak. The $p<0.05$ was found to be statistically significant.

The cloud-based self-intervention system's use is a boon for the women who want to test their image. More than 95% of our samples used for breast health issues. From the data obtained from 250 clients, it is analysed that the income and educational level were significant predictors for patients with the use of CSIMIDx. However, the income and education level may not reflect any changes in CSIMIDx of expert's usage. It is observed that age, length of diagnosis time and breast cancer stage were not the significant predictors of cloud based self-intervention.

Table 5 describes the characteristics of clients (patients) in the use of CSIMIDx for breast health. From the sample data collected from various hospitals and medical colleges, it is found that the mean age of the CSIMIDx users (patients) was 47.5 years and that of experts was 26 years. The average length of time since the diagnosis was found to be more significant than the age. In the CSIMIDx usage analysis for patients for the diagnosis of breast cancer, the users were more educated, more likely to be younger, middle aged group and it differed neither in the breast cancer stages nor in the length of time since their cancer diagnosis. The annual household income and education levels are not reflected

Table 6: Predictors of CSIMIDx use of 250 women with breast cancer

Stages	Categories	OR§	95% CI†	Significance (p)[a]
Age (years)		0.520	0.28-0.9400	0.03
Time since diagnosis (years)		0.480	0.27-0.8600	0.01
Annual household income (INR)	<1,00,000	1.000		
	1,00,000-2,70,000	2.360	0.61-9.1900	0.15
	>2,70,000	4.520	1.10-18.770	0.01
Education	Grades <12	0.914	0.12-6.5200	0.91
	Grades 13-15	0.711	0.13-3.5200	0.64
	Grades >15	1.289	0.41-4.0100	0.62
Stage (Normal)	Normal breast issue	0.780	0.09-6.2700	0.78
Benign	Fibrocystic disease	0.830	0.05-13.570	0.87
	Fibroadenoma	0.260	0.01-12.690	0.36
	A typical ductal hyperplasia	0.670	0.01-35.080	0.79
	Benign lesion, other	0.330	0.00-33.000	0.54
Malignant	DCISb, grade I	0.960	0.10-10.240	0.96
	DCIS grade II and III	3.810	0.55-28.990	0.11
	IDC[c]	0.300	0.07-1.3200	0.06
	ILC[d]	0.970	0.12-7.7400	0.97
	ILC and IDC	1.120	0.06-20.990	0.92
	Malignant lesion, others	1.500	0.02-129.12	0.81

[a]p and t-tests; [b]DCIS: Ductal Carcinoma In Situ; [c]IDC: Invasive Ductal Cancer; [d]ILC: Invasive Lobular Cancer

Table 7: Group characteristics (social and economic and the usefulness of the CSIMIDx prototype for the two user groups)

		Users (N = 169)		
Characteristics	Categories	Use of CSIMIDx by low user mean (SD)/No. (%) (N = 76)	Use of CSIMIDx by high user mean (SD)/No. (%) (N = 93)	Significance(p)[c]
Age (years)		38 (29.69)	46.5 (31.89)	0.81[a]
Time since diagnosis (years)		38 (33.94)	46.5 (30.40)	0.82[a]
Annual household income (INR)	<1,00,000	12 (15.8)	17 (18.3)	0.77[b]
	1,00,000-2,70,000	30 (39.5)	31 (33.3)	0.37[b]
	>2,70,000	34 (44.7)	45 (48.4)	0.82[b]
Education	Grade <12	11 (14.5)	16 (17.2)	0.77[b]
	Grade 13-15	28 (36.8)	30 (32.3)	0.45[b]
	Grade >15	37 (48.7)	47 (50.5)	0.80[b]
Security and privacy	Good	73 (96.1)	91 (97.8)	0.87[b]
	Average	3 (3.9)	2 (2.2)	0.71[b]
Interface quality	Good	72 (94.7)	91 (97.8)	0.90[b]
	Average	4 (5.3)	2 (2.2)	1.00[b]
Usefulness	Good	71 (93.4)	89 (95.7)	0.62[b]
	Average	5 (6.6)	4 (4.3)	0.29[b]
User friendliness	Good	70 (92.1)	88 (94.6)	0.97[b]
	Average	6 (7.9)	5 (5.4)	0.38[b]
Overall satisfaction	Good	74 (97.4)	90 (96.8)	0.33[b]
	Average	2 (2.6)	3 (3.2)	0.71[b]

[a]t-test; [b]Pearson Chi-Square test; [c]Interviews conducted in various medical colleges and hospitals in Chennai, Tamil Nadu, India from May 2015 to December 2015, regarding the secure cloud based intelligent medical image diagnosis prototype used for breast health issues the p values were calculated with t-tests for the means and the Pearson Chi-Square tests for the percentages

in the expert use of CSIMIDx in the diagnosis of medical images. The stages of cancer diagnosis are broadly classified as benign and malignant. The percentages of the sub categories of benign stages for CSIMIDx users (patients) are given as normal breast issue 11.2%, fibrocystic disease 6.5%, fibroadenoma 11.2%, a typical ductal hyperplasia 5.9%, benign lesion and others 2.4%. The percentages of the sub categories of malignant stages for CSIMIDx users (patients) were given as DCIS grade I 10.7%, DCIS grade II and III 13.6%, IDC 22.5%, ILC 8.9%, ILC and IDC 4.1% and malignant lesion, others 3%.

Table 6 shows the results of the logistic regression analysis for patients and experts in the diagnosis of medical images, using the CSIMIDx prototype. From our test samples obtained from clients at various hospitals, health centers and medical colleges, we found that, the age and time since, diagnosis have significance value by 0.03 and 0.01, respectively. The annual household income for the category 1,00,000-2,70,000 was significant by 0.15, compared with the other income level categories. In education, the grade 12 was significant by 0.91. In the benign stage, the category fibrocystic disease was significant by 0.87 and in the malignant stage, the category ILC was significant by 0.97. The overall significance value P is obtained from the Odds Ratio (OR) and Confidence Interval (CI).

Table 7 shows the usefulness of CSIMIDx prototype among two user group categories (low user and high user) based on the comparison of the intended versus observed frequency and activity; 76 low users and 93 high users. The data perceived for security and privacy of information with CSIMIDx prototype was higher among the high users (good category) 97.8% (91/93) compared to low users 96.1% (73/76) with a significance of $p = 0.87$.

The follow-up of CSIMIDx usage with interface quality found to be higher in high users (good category) 97.8% (91/93) compared to low users 94.7% (72/76) with a significance of $p = 0.89$. The survey on CSIMIDx's usefulness were collected as useful was higher among the high users (good category) 95.7% (89/93) compared to low users 93.4% (71/76) with a significance of $p = 0.62$. The review on CSIMIDx prototype's user friendliness was higher among the high users (N = 88, percentage = 94.6) compared to low users 92.1% (70/76) with a significance of $p = 0.97$.

Finally, analysis about the overall satisfaction of the CSIMIDx prototype was higher among the high users 98.11% (52/76) compared to low users 95.46% (42/76) with a significance of $p = 0.31$. The overall significance value p is based on the t-test and the Pearson chi-square test.

DISCUSSION

Principal findings: The prime intent of the CSIMIDx technology is to facilitate the experts and financially, weak patients to invoke the CSIMIDx prototype-based mammogram image diagnosis anywhere across the world. It attains high sensitivity (99.55%) and accuracy (98.4%) (246/250) (The classification accuracy 98.82% (168/170) in the malignant mass, 96.29% (52/54) in the benign and 100% (26/26) in the normal category).

The diagnosis rate of CSIMIDx prototype is improved for the benign (mass and calcification) stages by 96.29% compared with the other methods (94.44% of CSIMIDx, IDEA method and 90.74% by C4.5). Also, there is a significant increase in the diagnosis rate of malignant (mass and calcification) stages by 99% (from 96.61% of the IDEA method and 87.28% by the C4.5).

The CSIMIDx alone diagnosed 98.21% (220/22) of benign and malignant stages whereas CIMIDx by 97.76% (219/224), IDEA method by 96.87% (217/224) and C4.5 by 94.64% (212/224). The 1.6% (4/250) was dismissed by the CSIMIDx whereas CIMIDx by 2% (5/250), IDEA method dismissed 4.4% (11/250) and C4.5 7.2% (18/250) which is apparent from Table 5.

The characteristics of CSIMIDx usage patients and experts have been obtained using online questionnaire for breast health. With the sample of 250 women screened during the study period, 21.6% (54/250) were diagnosed under the category of benign, 68% (170/250) under malignant category and 10.4% (26/250) under normal category. It is clear from Table 5, that the malignant stage of diagnosis was significant by >0.97 than the benign stage.

The predictors of CSIMIDx (250 women with breast cancer) attained the results based on logistic regression analysis. It is evident that the income and education levels remained significant in the diagnosis of the medical image. The income level between 1,00,000-2,70,000 have higher significance than people with income range >2,70,000. Women with college education (i.e., grades 13-15) have higher significance than those with high school level (Grade <12). The usage of CSIMIDx prototype is not linked with the patients' age, duration of the diagnosis and breast cancer stages. It is obvious from Table 6 that the model was significant with $\chi_1^2 = 0.36$ and $p = 0.55$.

In this analysis study, the user (low and high) groups were differed only in the usage statistics. As per the analysis, high users provided the self-help information more often and reported more consistently on the social and economic forums compared to low users. In addition, no specific socio-demographic, medical or personal characteristic that distinguishes the user groups and supports our hypothesis. It can be seen that, the CSIMIDx prototype was highly useful with the significance of $p = 0.77$.

The refinement of the CSIMIDx framework is based on the patient information from the questionnaire in Appendix I.

CONCLUSION

The proposed CSIMIDx model is a productive and valuable tool for the restorative, mainstream researchers and patients to handle their medical images with the related analysis in the cloud environment. This study acknowledged in the location of more growths amid screening and diagnosing with an expanded sensitivity up to 99.09%, specificity up to 92.85% and accuracy up to 98.4%. This study has demonstrated that patients over the world can get to this model with less cost and it has been a profitable asset for their needs guaranteeing security and protection. With the behaviour of this review and comprehension of patients' utilization and data looking for CSIMIDx has the capacity to effectively fulfil their prerequisites with considerably few resources.

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APPENDIX I

Intelligent Internet Medical Research Group (IIMRG), Information and Communication Engineering Research, Anna University, Chennai, Tamil Nadu, India

Dear Participant:
The reason for this survey is to assess Cloud Based System Support Secure Intelligent Medical Image Diagnosis (CSIMIDx) structure from your viewpoint. Kindly answer all the questions. All data gave in this poll is secret and just for exploration purposes. In the event that you have any enquiries with respect to this survey, you can get in touch with us at senthil@cs.annauniv.edu and rv_bhavani@yahoo.com.

Question	Answer
Q1: Category of your age group (circle one)	ABCD
A. 30-40 B. 40-50 C. 50-60 D. 60-70	
In the event that no, you now outfit your age_____	
Q2: Do you utilize the Internet (circle one)	YES NO
If no, you have now wrapped up	
If yes, proceed beneath	
Internet access (circle as many as relevant)	
A. Home B. Work C. Internet Café D. Friend	ABCD
How frequently do you utilize the Internet for your personal health care?	ABCD
A. Weekly B. Monthly C. Half yearly D. Yearly	
Q4 Do you use the World Wide Web (circle one)	YES NO
If yes, do you use it for information regarding breast health/women's health issues?	YES NO
If yes, estimated current number of hours weekly.	
If yes, estimated number of hours weekly before surgery_____	
Q5 Do you use e-mail (circle one)	YES NO
If yes, do you use it for information regarding breast health/women's health issues?	YES NO
If yes, estimated current number of messages weekly__	
If yes, estimated number of messages weekly before surgery___	
Q6 Categorize your annual income (INR) (Circle one)	ABC
A.<_1,00,000 B. 1,00,000-2,70,000 C. 2,70,000	
Q7 Does the CSIMIDx prototype provide ease of navigation?	YES NO
Q8 Does the CSIMIDx model guarantee security and protection in keeping up understandings close to home data?	YES NO
Q9 Do you feel that the secure cloud based medical diagnosis is really useful for women and society?	YES NO
Q10 Is the secure cloud based medical diagnosis framework user friendly?	YES NO
Q11 Does the CSIMIDx client get general fulfilment?	YES NO
Q12 Are you intrigued by self-analysis about breast health/women's health issues if the cloud based medical diagnosis system facility provided in the Internet before consulting a physician?	YES NO
Q13 Are you interested to discuss your breast health/women's health issues in the Internet blogs, after testing from the secure cloud based medical diagnosis system?	YES NO
Q14 Do you think that Internet blogs creates considerable measure of mindfulness for the breast health/women's health issues	YES NO
Q15 Do you feel that utilization of CSIMIDx for breast health/women's health issues can considerably spare time and money?	YES NO
Name of the Participant	
Signature of the Participant	

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