

A review of the dedicated studies to breast cancer diagnosis by thermal imaging in the fields of medical and artificial intelligence sciences.

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Abstract

Introduction: Body temperature is a natural criteria for the diagnosis of diseases. Thermal imaging (thermography) applies infrared method which is fast, non-invasive, non-contact and flexible to monitor the temperature of the human body.

Materials and methods: This paper investigates highly diversified studies implemented before and after the year 2000 and it emphasizes mostly on the newly published articles including: performance and evaluation of thermal imaging, the various aspects of imaging as well as the available technology in this field and its disadvantages in the diagnosis of breast cancer.

Result: Thermal imaging has been adopted by researchers in the fields of medicine and biomedical engineering for the diagnosis of breast cancer. These days, thermal imaging method has not been established as an applicative method for screening or diagnosing purposes in academic centers. But there are different centers that adopt this method for the diagnosis and examining purposes.

Conclusions: Thermal imaging is an effective method which is highly facilitative for breast cancer screening (due to the low cost and without harms), also its impact will increase by combining other methods such as a mammogram and sonography. However, it has not been widely recognised as an accepted method for determining the types of tumours (benign and malignant) and diseases of breast tissue.

Keywords: Breast cancer, Thermal imaging, Artificial intelligence.

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Introduction

Breast cancer is the most common cancer in women and one of the leading of death among them. The high and increasing incidence of the disease and its difficult treatment specifically in advanced stages imposes hard situations for different countries' health systems [1]. Historically, temperature is a very good health indicator [2,3]. Since 400BC, temperature is used as clinical diagnosis criteria [4]. Humans are warm-blooded animals, in other words their body produces heat and hold body temperature steady, which may be different from the surrounding temperature [5]. The body of warm-blooded animals can be divided to two parts: inner core and around. The core temperature is maintained within a narrow range of about 33°C to 42°C. The inner core temperature regulation is essential for normal body function. Several degree changes in internal core temperature are considered as a sign of probable diseases. The ability to hold body core temperature steady is known as thermoregulation [6]. Thermometers were developed from the 17th century onwards [7]. George Martin regularly

had looked daily temperature changes in healthy people by using thermometers [8]. Carl Wundelich in 1868 for the first time, studied temperature of fever sufferers and healthy subjects and stated that temperature is a scientific criteria of disease. He showed that the normal body temperature is between 36.3°C to 37.5°C and the temperatures out of this range can be considered as a disease sign [9]. Discovery of infrared light by William Herschel in 1800 and recording the first thermal images by his son John Herschel opened new dimensions in the field of temperature measurement [10]. Hardy in 1934 provided the physiological role of infrared emission from the human body and proposed that human skin can be considered as a black body radiator. He studied diagnostic tools in medical science using infrared thermography surveys. Using of this technology, for the first time, has been reported on the specific conditions in 1960, due to the unavailability of equipment quality and the lack of knowledge [11]. All objects with a temperature above absolute zero emits electromagnetic waves, which are known as infrared radiation or thermal radiation [12,13]. Human skin epidermis is

the outer layer of epithelial cells that is placed on the middle membrane and it is a layer of dense connective tissue (Figure 1). Epidermis is formed by separate layers. The cells have been formed in the deep layers and with indirect distribution pushed the old cells to the surface and caused peeling or flaking. Thereafter, the cytoplasm changes to sulfur rich keratin proteins and eventually they die to protect the outer layer of cells. Thickness of epidermis is approximately constant. Yet dermis thickness is variable from 1 mm on the eyelids and genitals to more than 5 mm in the posterior trunk [5].



Figure 1. Epidermis consists of keratinized stratum corneum and a base layer, which interfaces with the middle membrane, the middle membrane of connective tissue includes blood vessels [4]. The exposure of dark skin tones with a range of exposure between 2 and 14 μm (Table 1), is more or less than 0.98 ± 0.01 [14,15]. So, in this area of the wavelengths, the human skin acts as a black physical body and because of the absorption coefficient of 2.5 to 3.1 mm at a wavelength of between 2/2 and 5 microns thermal radiations come from the surface of the outer skin [15].

Table1. The exposure of human skin with different skin colors.

Tissue	Exposure
Black skin (3-12 μm)	0.98 ± 0.01
White skin (3-14 μm)	0.97 ± 0.02
Bronze skin (3-14 μm)	0.97 ± 0.02

Steketee confirms that there is no difference between radiation ability of black, white or bronze skin, whether it was measured *in vivo* or *in vitro* so, an infrared thermography is a record of the temperature distribution of the outer layer of the skin. The surface temperature of human skin is usually around 300 K and has a maximum radiation at a wavelength of 10 microns. Radiation at a wavelength of 10 μm absorbs strongly by glass and can only be focused by lenses made of special materials such as germanium and identified by specifically micro machined materials such as silicon. Planck function decreases exponentially with temperature so the skin has a very low radiated power, sometimes it is six times lower than the power of the sun. Such small levels of radiation areas; need very sensitive detectors and for reducing the noise, early cameras were cooled to liquid nitrogen temperature. High wavelength and low power radiation makes a significant engineering challenge in the thermal imaging of human skin. Skin surface temperature determined by the rate of heat exchanging between the body and surrounding. The temperature more or less is kept constant and acts as a heat sink. Heat is transferred to the skin by blood flow through blood vessels and therefore by heat

conduction to the surface of the skin, skin temperature drops between $0.2^\circ\text{C} \sim 0.5^\circ\text{C}/\text{mm}$ [15], however, it may be more nearly a malignant tumor. The skin heat is balanced by heat loss to the surrounding by means of thermal radiation heat loss to the surrounding, thermal conductivity, respiration, natural convection, forced convection, blood evaporation that takes out the latent heat of vaporization of blood 583 Cal/g in 25°C . Thermal equilibrium of the human body with its surroundings can be seen in figure 2.

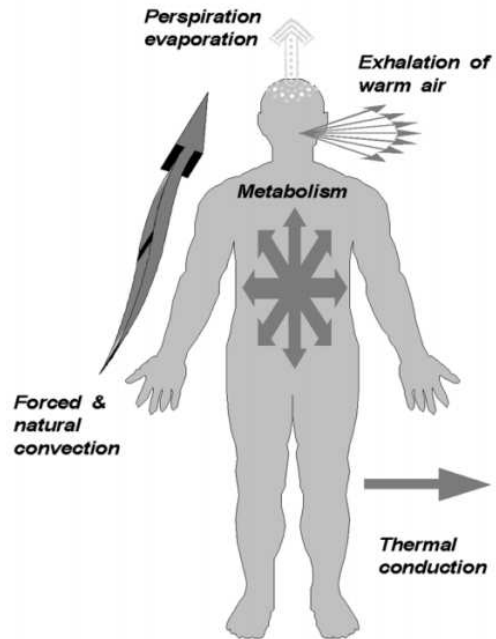


Figure 2. Skin temperature is determined by balancing the heat generated during metabolism and heat dissipation during heat conduction, forced convection, natural, sweating and exhaling. The two last mechanisms are the most important ones. However, a disabled person can sweat trickle at a rate of 3 ml/h and an active person loses fluid to 1 L.

Physical principles of thermal imaging

All objects at any temperature above absolute zero, spontaneously emits electromagnetic radiation, this phenomenon is called natural radiation or heat radiation. The radiant power of a surface is the total energy that flows from the surface to the surrounding. The radiant power of a black body E_{bv} polar radiation energy, is a line in frequency spacing of ν to $\nu+d\nu$ in watts per steradian per square meter surface per Hz. By definition, a man with black skin, absorbs the while radiation and according to Planck's law (1), shines in a continuous spectrum.

$$E_{bv}d\nu = \frac{h\nu^3}{c^2 \left(\exp\left(\frac{h\nu}{kT}\right) - 1 \right)} d\nu \quad (1)$$

h is Planck's constant, c the speed of light, k is Boltzmann's constant and T is the absolute temperature. Law can also be

explained in terms of distance wavelength. Planck energy distribution function has a defined maximum at a frequency that is a function of temperature and at high frequency rate will rise and at low frequency rate will be less. Planck function integration on all frequencies, leading to the Stefan-Boltzmann law for radiation power of a black body (E_b).

$$E_b = \sigma T^4 \quad (2)$$

Where σ is the Stefan-Boltzmann constant. Radiation power of a black body dropped exponentially with temperature and according to Vienna law, by decreasing-temperature, wavelength of the maximum radiant power goes to longer wavelengths.

$$\lambda_{\max} T = 0.002898 \quad (3)$$

λ_{\max} is the maximum radiated power wavelength (m) at temperature T (in K). α_v (Absorption coefficient) is defined as the failure of radiation absorbed per time unit in a thin layer of a thickness unit. For each body in thermal equilibrium, the energy released should be balanced by the energy absorbed from the surroundings. Kirchhoff's law states that for every united medium of thermal equilibrium, the diffusion and absorption coefficient at any spectral region is radiated power of the body to the radiation power of a black body, this connection serves to identify the publication ϵ_v of a body.

$$\alpha_v = \frac{E_v}{E_{bv}} = \epsilon_v \quad (4)$$

A bio-heat equation penny (16) is used to determine the amount of heat emitted by the surface of cancer cells and surrounding blood flow.

$$p_t c_t \frac{\partial T}{\partial t} + W_b C_b (T - T_a) = K \frac{\partial^2 T}{\partial x^2} \quad (5)$$

That p_t is density, c_t is specific heat tissue, T is tissue temperature, t is time, W_b is the blood Fusion ratio, c_b is specific heat of blood, T_a is arterial blood temperature, k is the thermal conductivity of tissue and x the distance from the surface of the skin. Watmough et al. [14] calculated that the radiation at the wavelength of λ from a material with a reflective index n_λ is changing by angle \emptyset :

$$\epsilon_{\emptyset\lambda} =$$

$$1 - 0.5 \left(\frac{\beta - \cos \emptyset}{\beta + \cos \emptyset} \right)^2 \left(1 + \left(\frac{\cos \emptyset - \sin^2 \emptyset}{\cos \emptyset + \sin^2 \emptyset} \right)^2 \right) \quad (6)$$

$$\beta = (n_\lambda^2 \sin^2 \emptyset)^2 \quad (7)$$

For wider range of view, thermal radiation from the surrounding, is reflected from the skin and affects the errors at ΔT , which is proportional with the difference between the temperature of the patient's skin TS and setting T0 and the deviation of radiation (or absorption coefficient), which implies that the thermograms obtained infrared wavelengths in the region of 2% to 14 micrometers, which is close to single exposure, uncertainty ΔT temperature will be small. In most cases, the body angle is less than $\pi/4$ but the skin surface

temperature that is shown on the angles must be carefully beveled.

Thermography in medicine

Abnormal thermal patterns can be easily detected by thermal imaging. The results of thermal measurement in general compared with other clinical findings to assess the possible correlation. Although the method is non-specific and environment can affect its results, but there are several reasons which have caused thermal imaging, wide acceptance among the medical community. First of all, thermal imaging is non-contact, non-invasive method and can be used from far way. Because of the short time for taking pictures, it's possible to simultaneously monitor a large area of the population. Interpretation of thermo gram's colors is easy and fast. In addition, this method only records natural radiation from the surface of the skin and there is no trace of harmful rays, so is suitable for long-term and repeating use. Finally thermography is a fast method which enables to monitor and observe the dynamic changes in temperature. Due to these advantages, thermography as a replaced Diagnostic tool is effective. Table 2 shows the temperature difference between the two sides (between the left and right) for several parts of the body in healthy people [16,17].

Table 2. The temperature difference between the two sides (between the left and right) for several parts of the body in healthy people.

Organs	The average difference in temperature (C)
Forehead	0.21
Palm	0.23
cheeks	0.18
Abdomen	0.018
Chest	0.14
Neck (posterior)	0.15
Waist	0.25
The trunk	0.17
Arm (biceps)	0.13
Thigh (anterior)	0.11
Thigh (posterior)	0.15
Foot (back)	0.30
Finger (middle)	0.38
Toe (middle)	0.50

Analysis Method

This article is an attempt to analysis the performance and functionality of thermal cameras and advantages and disadvantages of thermal imaging in the diagnosis of various diseases. In addition, two fields of study will be investigated, which include laboratory and medical field and the field is

engineering research and thermal image processing. All studies in the two time period before 2005 and after 2005 to 2015 were studied.

Thermography in the diagnosis of breast cancer

Thermography has a series of unique features. One of these features is the ability for early detection of cancer by identifying early signs of cancer, ten years earlier than other methods such as mammography [18,19]. Another unique feature of thermography is its ability to valuation methods of cancer treatment [20]. Predict the future state of the patient is also one of the thermography's features [21]. It has been shown that 44% of patients with abnormal thermogram, about 5 years after thermography, have been diagnosed with breast cancer. Thermography also showed that there is 24% probability survival in 3 years after diagnose for the patient with an advanced cancer level, when this probability for cancers at earlier levels are close to 80% [22]. The sensitivity of mammography in younger people or patient with dense breast tissue will be reduced. Although thermography is independence to the age of the patient and the density of breast tissue [23,24]. In 70% of cases, thermography can detect symptoms of breast cancer 1 year earlier than mammography [18]. The size of undetectable tumors by mammography is about 1.66 cm while limiting size in thermography is decrease to 1.28 cm [21].

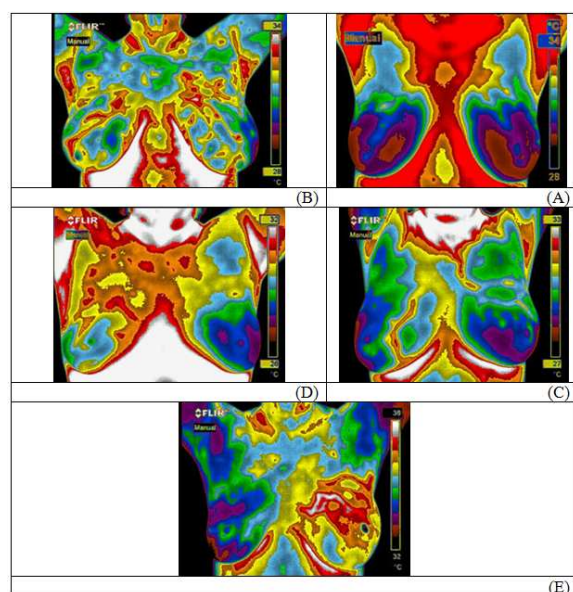


Figure 3. Thermal images classification based on: (A) TH1- normal uniform non-vascular, (B) TH2- vascular ordinary uniform, (C) TH3- vague (questionable), (D) TH4- abnormal, (E) TH5-extremely abnormal.

As a detector for risk of breast cancer in future, an abnormal thermogram in compare to a normal thermogram can demonstrate risk of breast cancer 22 times. Also the abnormal thermogram is 10 times more important and influential than first family member history of the disease [25]. Thermal

images analysis can be grouped according to Thermobiology in Five main groups: TH1- normal uniform non-vascular, TH2- vascular ordinary uniform, TH3- vague (questionable), TH4- abnormal, TH5-extremely abnormal, sample divide classified images are shown in Figure 3 [26].

Thermography as a diagnostic method

Studies based on existing technologies can be analyzed in both pre and post-2005. In the years before 2005, the 5 study, reported the accuracy of thermography as a diagnostic method in 9887 Lady with signs, symptoms or abnormal mammogram [27-31]. Average median or average age was 51 years during the study. Diagnostic studies have been carried out sooner than the time of the screening. Average rate quality of these studies are poor-fair. The main factors that influence the quality of this method (thermography) in comparison of other methods and reduces its quality is lack of specialized knowledge that required to read the results of thermography and intention for "the other method are" the CBE, a mammography and biopsy. The average sensitivity of thermography itself in 5 diagnostic studies was 59% (range 25-97). When cases with less than the poor (weak) quality rate deleted average sensitivity decrease to 31% (range 25-47% in 2 articles) [27,32]. The highest sensitivity (95% and 97%) obtained in the test that patients with suspicious mammograms had chosen [29,30]. In these studies, pair's specificity/sensitivity represents that when the sensitivity of the thermography is remarkably high (unlike most of the articles or against the average estimated) specificity is very low (12% and 14%) [29,30]. These statistics indicate that thermography even in clinical trials with large sample sizes, has limited ability to discriminate between cancer and existence of changes. 5 diagnostic articles also report results for CBE in direct comparison with thermography, the mean sensitivity of CBE was 61% (range 51-86) [32-36]. In 3 articles out of these 5 articles CBE is more sensitive than thermography [32,34,36]. Two paper reported Thermography sensitivity based on tumors size [34,37]. These results have shown less sensitivity in tumor T1 (26-37%) compared with large tumors (T2-4) over 82%. Average positive- false rate of thermography in diagnostic was 29% (range 8-86%). Average positive- false rate in both screening methods (average 31%) and diagnostic procedures (29%) in averages indicate that thermography will have a false-positive rate of about every 3 Lady. According to approach and ability of Thermography, it can be used in to assess the effect of hormone receptor status (both estrogen and progesterone) in breast cancer, and then use the result of thermography [38]. This study has been done with in cooperation of 75 women with a mean age of 64 years and advanced breast cancer that has been proven through biopsy. System evaluation Results of thermography, and the maximum, minimum and average temperature deviation of the tumor areas, all breast with tumor, normal breast and tumor areas in healthy breast have been identified. Thermography findings were compared with various status of the hormone receptor. Studies on hormone receptors results same as thermography; the cancer tissue has a higher temperature than healthy tissue. The study also demonstrate that among patients with different

hormonal receptor status (positive or negative receptors), there is no significant statistical difference. However, these studies have shown that negative hormone receptor tumors are warmer tumors, show more invasive behavior, they lost control of the endocrine glands and have a shorter life. Tumors with positive hormone receptor are cooler and show less invasive behavior. This information was not understood through thermography. Base on the results of this study through all patients with advanced breast cancer, 77% had positive receptor and 23% had negative receptor of estrogen also 60% had positive receptor and 40% had negative receptor of progesterone. Offering new models of thermal cameras and the use of modern technology for increase the accuracy and identification of tumors help for diagnosis such as three-dimensional thermal imaging method that evaluate in the article [39] that the obtained values of sensitivity and specificity in this article are 90.9% and 72.5% .

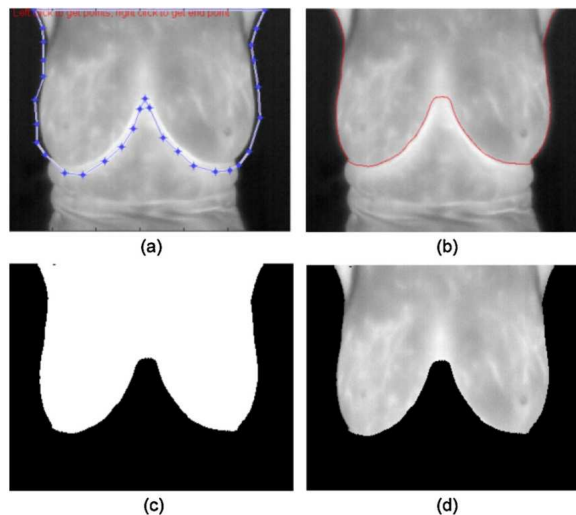


Figure 4. (a) primary contour, (b) evolved contour, (c) dividing the mask (D) division of breast tissue.

Thermography as a screening method

4 articles have reported the accuracy of thermography screening in 60802 ladies [40-43]. Information related to the age of the patients is incomplete. 3 of these articles Have been carried out in the 1960 to 1970 (2 of these articles are part of BCDDP programs) But these articles have been published in our desired period. The quality average rate of these articles has been fair-good. Mid-sensitive thermography has been only 47% (range: 25-70%) and the highest sensitivity in the study (nearly 40,000 Lady) has been (70%); However, this sensitivity should be checked in the context of Cancer Detection Rate (CDR) of 1.8/1000 images for periodic prevalence of screening. The least sensitivity of the BCP Michigan project during the daily screening was 25% (50% in the period of prevalence) [40]. Two studies reported their results for CBE; Haberman et al. achieved 70% sensitivity (more than CBE “58%”) in their experiment. Against Gohanet et al. (study of higher quality), achieved 44% sensitivity in thermography and

revealed that thermography sensitivity lower than the sensitivity of CBE (47%) and mammography (68%) [41]. During all tests, the combination of thermography and CBE results directed to the average sensitivity of 79% (range: 67-79%) [41,42]. CDR for thermograph has been offered a report in one of the 4 screening and screening number was 5.3/1000 [43]. The average rate of positive-false for thermography has been 31% (range: 21-38%) in thermography. In use of neural networks; combinations of such network scan be used [44] by using a combination of MLP and SOM neural networks, abnormal areas was isolated, then the cancer has been detected .The proposed method was performed on 50 patients that showed a 88% sensitivity.

Artificial intelligence in thermography

Preliminary studies on the use of computers for processing medical images were conducted in 1960s. In those years the tendency toward using computers instead of physicians was immense, as a result, the PC Diagnostic is promising however, those computers were in progress and they were in initial levels of processing ability. In addition, modern image processing techniques didn't exist, even digital images were very rare; However, there was an extreme hope for recognition by computers. These issues caused the computer's failure for recognizing the abnormalities [45]. In spite of the initial failure in the 1980's scientists began to use computers to help physicians in order to highlight the abnormal areas and also provide a second opinion beside doctor's diagnosis. This approach toward using computers is called Computer Assisted Diagnosis (CAD) and it is accepted all around the World [45]. CAD didn't attempt to replace physicians with computer but it helped physicians to diagnose better and more reliable. In recent years, due to advances in image processing techniques as well as CAD, Sensitivity and Specificity in thermography has been able to achieve more than mammography [46-48]. One of the first things to do in the field of CAD in thermography has been done by Negin et al. in 1977, they named their system Computerized Breast Thermographic Interpreter (CBTI). While design is based on linear discriminant and used computers were so simple that even didn't have a screen, and process performance needed 5 minutes to make decisions between abnormal and normal conditions; they could reach average accuracy of 79 % that was an amazing result with that time technology [49]. Even in 2002, with images taken from the camera of the second generation and the use of recurrent neural networks, the percentage of accuracy was a challenge [50]. With production and development of neural networks or ANN and also introducing systems based on fuzzy logic or FL and as well as the high quality of the thermograms as a result of the second generation of cameras, thermography systems (CAD) draw attention of many researchers. Many outstanding CAD systems in thermography have been made during the years of 1977 to 2015; which the review of this article are discussed. This study discuss about extraction features from thermography images and diagnosis of cancer with the help of thermography images.

Extraction Features

Currently, the methods for extracting feature from breast's thermograms are based on the following [51]:

- Geometrical construction
- Eigen value
- Transformation of wavelet energy
- Analysis of the Eigen values based on the picture's moment
- Analysis of the Eigen values based on the development of unique value scale

The aim of feature extraction in these pictures is the isolation of the abnormal and suspected area from the healthy tissue. The breast area should be separated to extract the features of thermal images. In articles such as: use of Hough method for separating region [52,53], use of edge and contour filters [54,55] as shown in figure 4, is discussed.

Also to detect abnormal area of breast cancer in thermal imaging authors in [56] have used lyapunov exponent modeling. By using this model we can comment on differentiate between malignant and benign patterns. The breast cancer tissue features and the use of moments were evaluated in [57], that 3/83% accuracy has been achieved. Entropy, variance and covariance of image are the moments which are used. The results states that rotational thermography has great potential as a screening tool to detect breast cancer. Abnormal breast conditions can be discovered by using curved interpretation of the features and characteristics of thermography images which is discussed in the article [58]. Thermography has been taken of 22 women (11 women with breast cancer confirmed by biopsy with a mean age of 42 and 11 female healthy volunteers with an average age of 37). The thermograms are beginning to turn gray, and the desired state (abnormal areas) were identified. The desirable areas by using the curves in the form of discrete are decomposed then the breast profile is analyzed and classified in domain curve. This system has classified normal and abnormal thermograms with 90.91% precision, 81.82% sensitivity and 100% expertise. Finally, it can be stated that the curves are based on the structural characteristics can improve the efficiency of spontaneous detection of anomalies in breast thermograms.

Artificial neural networks

The neural networks are bio-physiological models of human's brain which is modeling the functional processes of human's brain. The main part of each artificial neural network is it's element processor. Neural networks gather these element processors with different methods to answer their different numerical needs. In [59], writers benefited combinational artificial neural networks and genetic algorithm model to extrapolate the best first properties in software diagnosis of breast cancer from thermal images. Moreover, in their study, they used fuzzy model for increasing the accuracy [60]. In 1965, fuzzy logic was presented by professor Lotfizadeh from university of California in Berkeley. This logic is based on humanistic etiology, thus the programming language is so

simple and understandable. However, at the beginning, the usage of this logic was for solving the controlled system problems; but it found its place in artificial intelligence and image processing quickly. Etehadtavakol et al. used "C-means" fuzzy model for separating and classification of thermal regions into parts [61]. The diagnosis power of thermography in breast cancer was evaluated by using classification of Bayesian networks [62]. The result of the article shows that the thermography is a complementary method for diagnosis.

CAD's role in thermography

However, the results of each approach are different from others, but all of them confirm the effectiveness of CAD system in thermography. The worst outcome of CAD system was caused by the use of BP-ANN that had 61.54% accuracy, which was even worse than its result in the twenty-two years ago. The system had an appropriate sensitivity (68.97%) but specificity was below 40%, which reduced the accuracy [50] further progress was achieved when the BP-ANN was replaced with RBFN. Nonlinear features of RBFN caused sensitivity and specificity and then the accuracy of CAD system to increase considerably. The value of sensitivity 81.2%, specificity 88.2% and thus amount of accuracy became 80.95%. Now the CAD system's function based on RBFN is comparable with mammography, which its accuracy is about 80% [46] some researchers have adapted the fuzzy logic to analyze the thermo grams. As mentioned, one of the most important features of fuzzy logic is use of humanistic etiology method. This would help physicians while using this system to reach such degree of confidence that why system concluded or diagnosed on this way. CAD based on fuzzy logic can achieve an accuracy of about 79.53%, which almost equals to accuracy of mammography and CAD method based on RBFN [47] but the reason of non-using of this approach is that the number of existing rule in fuzzy logic is very high and over 2500 rules, resulting in difficult mathematical calculations and occupation of a lot of memory space. "Genetic Algorithm" is used to reduce the number of rules used in fuzzy logic. "Genetic Algorithm" or "GA" was presented by "John Holland" in 1955, for the first time. This algorithm has been defined by using Darwin's "evaluation theory". This algorithm considers each individual rule as part of a population and then creates a new rule by combination of different rules, which is called "mutation". Then, all of the rules were studied and evaluated according to their ability to solve the problem. As the system is designed to solve; each rule is checked and according to its ability to solve system's problem, a number is assigned to it, which is called "fitness". Then, the mutation process is repeated again and the new rules are implanted and each new rule is given "fitness". The repetition of process depends on optional criteria that have being reached to desired size and amount. The optional criteria can be time, number of mutations, best solution and etc. finally, the rules which have the best "fitness" number are chosen as new rules. This process can include a long period of time but it decreases the number of rules, considerably. A new "hybrid" system based on fuzzy logic is formed by using this genetic algorithm [63], which

could reach increased accuracy of 80.98%. It means that by decreasing 250% of number of required rules, system's accuracy is increased about 1%, which mentions the effectiveness of genetic algorithm in decreasing rules in fuzzy logic. It is likely that the greatest progress is achieved when etiology a feature of fuzzy logic is mixed with ANN's training features. What is yielded is called Complementary Learning

Fuzzy Neural Network (CLFNN), which has the ability of both positive and negative learning. This means that the system has a person's ability to learn, and then fuzzy logic rules is just similar to human's conclusions that can mention both positive and negative reasons for his conclusions. In conclusion, the use of artificial intelligence systems is given in table 3.

Table 3. Comparison between the derived results from different artificial intelligence methods in detecting breast cancer from thermal image [63-68].

Article	Property	Classifier	Function	
[63]	Cross co-occurrence texture features	fuzzy logic	Accuracy	80%
[64]	DWT features	neural networks	Accuracy	86/6%
[65]	Co-occurrence texture features	supportive vector machine	Accuracy	88/1%
			sensitivity	85/71%
			specificity	90/48%
[66]	Co-occurrence texture features	returning neural networks	Accuracy	85/19%
			sensitivity	88/89%
			specificity	77/78%
[67]	HOS features	neural networks	sensitivity	92%
			specificity	88%
		supportive vector machine	sensitivity	76%
			Specificity	84%
[68]	Curvelet based Co-occurrence texture features	supportive vector machine	sensitivity	85/7%
			specificity	86/5%

Restrictions of thermography

Just like mammography, Thermography has some restrictions, which restrict the ability of this method in diagnosis abnormal states of breast tissue. Since thermography is a thermal imaging of skin's surface, it cannot detect a region or tumor; indeed, abnormal states found by thermography cannot be presented as a biopsy surgery region. The interpretation of thermography images depends on the ability of detecting regions with high temperature, especially regions with low metabolic function, or cold tumor, which is too difficult. From a study in 2003, which is about function of thermography, it was found that all of the false-negative results of thermography have been related on tumors on micro size; Which suggests that thermography is not as good as mammography in diagnosis of these abnormal states.

Discussion and conclusion

Thermography doesn't provide information about morphological structures of breast but it can show functional temperature data and condition of breast tissue's vessels. It is supposed that the functional alteration is created before starting structural alteration caused by sickness or cancer. It is also known that the physiological alterations are created before

pathological alterations and researches support the role of thermography in early diagnosis of abnormal state of breast, which can create cancer. Since the recent decade of 20th century, 1970, there have been a lot of studies about the efficiency of this method. If abnormal thermo grams suggest the abnormal function causing breast cancer, thus it can be provide a chance for early intervention and improve the abnormal function. Nowadays, none of the current methods can forecast breast cancer for 100%. The only certain diagnostic method is biopsy. In past 30 years, there have been a lot of studies showing that thermography has such sensitivity in diagnosis of "Ville Marie" breast cancers while other methods cannot detect them. The sensitivity of thermography in breast studies is just 83%. However, by combination with mammography it would be increase to 95%. As a result, thermography was never evaluated in accidental controlled studies. The sensitivity of thermography is low (47% for screening and 59% for diagnosis) and this is considerably lower than the sensitivity of mammography. The CDR in this method is unacceptably low and the positive-false rate in comparison with standard screening is too high. This study never supports using of thermography as a screening method that can replace mammography, in cancer evaluation in women. This study emphasizes that thermography shouldn't

use for first time diagnosis. Considering the progress of this technology and increasing the patient's requests for a screening method with low price and no ionization can be a potential for choosing thermography as a breast imaging method. This technology needs accurate clinical evaluation and it is unlikely that thermography can be a part of breast screening, detecting and etc., in future.

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