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Detection of Breast Cancer using Artificial Neural Network

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Abstract— *Breast cancer is one of leading reasons and the second common cause of death among women all over the world. The simplified diagnosis of breast cancer is one of the significant, real world problems that has been faced in the field of medical science. Machine learning is gaining importance in diagnosis of abnormalities as it is a quick simple way for detection of diseases. In this work, we seek to explore the artificial intelligence techniques and machine learning approach to detect breast cancer. The method is applied to the Wisconsin Breast Cancer Dataset collected form the open source. The dataset consists of nine attributes that are used to train the network. The network used in the work is back-propagation. The simulation is done in Matlab software. The network classifies the input data into the two classes of cancer (benign or malignant) as result. The machine learning algorithm of back-propagation seems to be an efficient terminology for the diagnosis of breast cancer.*

Index Terms— *Machine learning, Artificial neural network, Back-propagation network, Wisconsin Breast Cancer Database, Matlab.*

I. INTRODUCTION

Breast cancer is one of leading reasons and the second common cause of death among women all over the world [1]. According to a WHO report of 2018, it is approximated that 627,000 women died due to breast cancer which is 15% of the total cancer related death worldwide [2]. Since 2006, the rate of breast cancer has increased every year, and is two to six times higher in Asian women [3]. Breast cancer is a virulent tumor that is formed when the cells changes in number or type. This change can occur due to abrupt growth or division of cells. This can result in destruction of healthy cells that are near to the lump in the body. According to the study, last few decades holds a record of a steady rise in the mortality rates due to breast cancer all around the world [4]. It is quite necessary to detect the cancer at an early stage as the healing rate increases rapidly if it is detected at its initial stage. It is noticed by a report that survival of ten years of a patient in stage 0 and 1 is approximately 98% and that in stage 3 is nearly 65%. The major criteria for a testing system should have great accuracy, precision, specificity, and sensitivity [1]. The major point-of-care equipments are required for early detection of breast cancer [5]. WHO runs programs for

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helping women educate so that they are able to recognize the early symptoms of breast cancer [6]. Early detection of cancer is of great significance.

Early-stage cancer detection could reduce breast cancer death rates significantly in the long-term. The most vital point for the best prediction analysis is to detect cancer cells at an early-stage. Researchers have studied various diagnostic approaches such as mammography, computerized tomography scanning, magnetic resonance imaging, ultrasound and biopsy. The techniques listed are the most widely used methods for diagnosis purpose but still holds some disadvantages. They are expensive, time-consuming and do not give reliable results with women having dense breasts. Developing a highly sensitive and rapid early-stage breast cancer diagnostic method is an urgent need for the healthcare sector. In the current times, researchers are more concerned of developing biosensors that have the ability to detect breast tumours by applying particular biomarkers [7,8].

The major concern of the diagnostic of breast cancer is that it lacks the presence of early signs which ultimately results in detection of disease at the late stage. The inadequacy of education about the disease and the less frequent clinical breast examinations contributes the late detection of the disease. The alleviation process automatically increases if the malignant tumour is detected at an early stage. Therefore, it is quite necessary to diagnose the disease as early as possible. The properly organised clinical breast examinations should be encouraged amongst women of all ages in order to decrease the mortality rates caused due to the disease [4].

There is an immediate need for a cost-effective, reliable and efficient sensor that can help the medical professionals in detection of breast tumour in the early stage [7]. There are various techniques for the diagnosis of early breast cancer. Out of all the existing methodologies used for the detection of breast cancer, machine learning has emerged out as the most trending methods for diagnosis. Machine learning approach is used in various medical sectors as explained in fig 1. The main difference between conventional approaches and machine learning approach is that in machine learning, the designed model learns from dataset fed into the system as input rather than learning form the program. To complete a particular task, examples are fed into the model as inputs. The digitized slides used in pathology are transformed into the labels and features. For the purpose of learning, algorithms are used from which the system performs mapping for creating a model. This designed model has the ability to generalize the data so that the task can be performed more efficiently. This process is called supervised machine learning [8]. Artificial Neural Networks (ANNs) work by these algorithms that are based on the functions of interpretation of nonlinear data same as that of the human brain. ANNs consists of small units known as neurons. These neurons are layered into multiple folds between the input and the output multiple layers between the input of data and the output of results. The artificial neural network works in the similar manner as the biological neural network performs. The patterns between the neurons determine the future outputs. The network observes and learns from the behavior of the model which is known as back-propagation [9]. There is no specific bright line between conventional models and the machine learning models [10]. However, the models of machine learning approach are much more sophisticated to learn even the complex data such as medical images, medical notes and the data collected by monitoring sensors of patients [8].

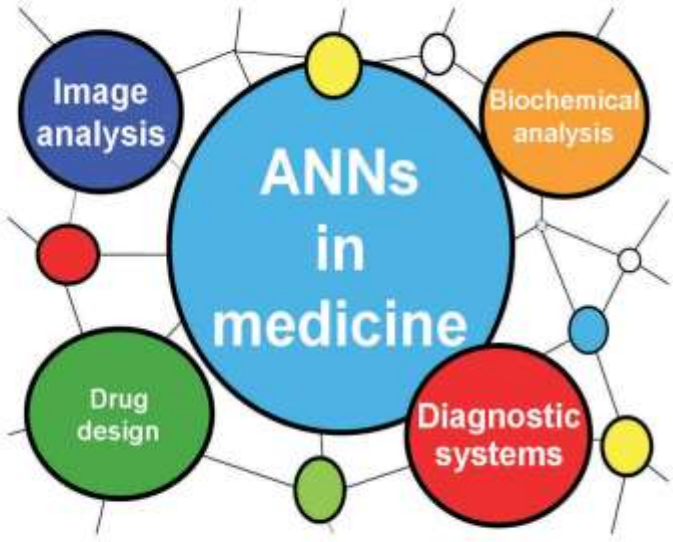

Fig. 1 Applications of ANN in healthcare

A. Conventional Methods

The breast cancer screening (BSC) is the most traditional technique which detects the abnormal genes in the body even if the early signs are not present. It is an easy way to diagnose the early signs of breast tumour in women [7]. Screening of breast cancer at an early stage plays a major role in improving the outcomes of the treatment of the disease. Therefore, it becomes significant to analyse the traditional as well as new methods developed for detection of breast cancer so there is a large scope for survival of the patients. There are several tests available for screening of breast cancer such as self-breast examinations, mammography, magnetic resonance imaging technique and sonography. Mammography is still the widely applicable technique for the early detection of breast cancer amongst all other methods. It is believed that the results of mammography are quite accurate when performed on the postmenopausal women. In the X-ray mammography screening, radiologists examine two X-rays taken of each breast from different angles (mammograms) for abnormalities associated with malignant tumors. Studies have proved that regular mammography screening, when associated with proper treatment, can detect breast cancer at an earlier stage and can eventually decrease the mortality rate due to breast cancer. However, there are some disadvantages associated with the mammography technique. Studies have shown that regular mammography screening can decrease the number of deaths caused by breast cancer by about 25%–30% between the ages of 50 and 70 in women but is less reliable in women aged between 40 and 49. Screening mammography cannot decrease the mortality rates from breast cancer because it does not detect all cancers, including some that are detected by physical exam. According to the reports, 15% percent of breast cancers may produce false results by mammography screening. In addition, it is very difficult to produce consistent mammograms of good quality in technical terms. The interpretation of the test data varies from person to person and is quite subjective and interpretation is subjective. Mammograms face difficulty in producing accurate results while dealing with dense breast tissue especially in young females. The dense tissue interferes in the detection process of the tumors and has the ability to produce false positive or false negative [11].

The American Cancer Society recommend breast MRI combined with a mammogram on a yearly basis [27]. Recent studies have shown that MRI technique is a better alternative to the mammography technique as it does not expose the patients to the radiation which is harmful for human body. MRI is proved to operate perfectly on pre-menopausal and post-menopausal women. Breast MRI are used to examine the abnormal cell growth very closely. Breast MRI utilizes radio waves and magnetic field to vary the positions of protons of hydrogen nuclei and using this produces a cross-sectional image. However, MRI has some disadvantages such as low specificity, very expensive and it is not has no standard to compare with. The National Institute of Biomedical Imaging and Bioengineering that the scan time of the process of breast MRI can be reduced by using a flexible screen printed MRI coils [28]. The sensitivity of the breast MRI is very high even while dealing with the invasive cancer detection [12, 13]. Breast Self-Examinations (BSE) is a primary conventional method for cancer screening. Clinical Breast Examination has a specificity and sensitivity ranging upto 97.11% and 57.14% [14]. It is quite helpful for the detection of any breast abnormality but the results are uncertain in the case of BSE. A mammogram is a test involving an X-ray which is used for the detection of any examination for evaluation and detection of the breast abnormalities. The advanced X-ray machines are much faster and are ready to use, therefore, it is considered as the hand-on method for the early detection. However, there are various drawbacks including short dynamic range, and unclear imaging. It becomes quite tedious task to detect small tumour present in the breast or in the patients having implants [15]. The American Cancer Society suggests to the women with high risks, to undergo breast MRI and mammography on a yearly basis [16].

Digital medical image recognition (DMIR) is considered as a major part of artificial intelligence. DMIR techniques aims in extracting the data form medical test images to help the doctors in detection of various diseases. DMIR uses various techniques associated with image processing such as classification, detection, and segmentation. DMIR is associated with various imaging techniques such as CT scan, MRI, digital mammography [29]. Depending on the type of breast tissue, breast mass appears different in a mammogram. While it appears as solid block in dense breast, it appears as a round pie structure in a fatty breast. The mass may be alone or with microcalcifications [30]. Breast ultrasound generally referred to as sonography uses sound waves for the detection of breast tumour. Breast ultrasound is a technique for the breast tissue examination using high frequency ultrasonic waves that pass through the breast. After the diagnosis of lump by mammography (palpative examination) breast ultrasound is performed. Ultrasonography is really helpful in diagnosis of cysts and benign tumours of breast, especially in the cases of young females in which the glandular tissue is still developing. This helps in differentiating between liquid filled cysts, complex cysts made of tissue plus liquid and a solid tumour. The most important usage of USG is to diagnose palpable masses in women under 35 and in those where it is not palpable in mammography [4].

A device is made to move on the breast skin that acts a transducer. The echoes generated by sound waves are reflected back by the skin are recorded and gets displayed on the screen attached [12]. These echoes are converted into images that are used for diagnosis [17]. It records the blood flow and also signifies the mechanical properties of the tissue. It is widely used as it has shown improvement in the quality of image [18]. A single instrument consists of the characteristics of mammography and ultrasound that can improve the scanning quality and efficiency of the diagnosis [19].

Enzyme-linked immunosorbent assay (ELISA) has been used in the detection and quantification of peptides, proteins, hormones, antigens, antibodies etc., in different fields like clinical diagnoses, food safety and environmental monitoring. ELISA is a very simple, reliable, and sensitive tool for analysis of rapid screening compared to other detection techniques like gas chromatography, mass spectrometry and liquid chromatography. Components of conventional ELISA are (i) antigen, (ii) antibodies formed against that antigen, (iii) an enzyme label, and (iv) a chromogenic substrate, that gives a specific colour on reaction with the enzyme label. The four major types of ELISA are direct, indirect, sandwich, and competitive assays. In direct ELISA, complexes are formed between the analyte to be tested which is adhered on a well plate and an enzyme labelled primary antibody. After the antigen is immobilized and not incubated with the antigen specific antibody, an agent (typically Bovine Serum Albumin) is added to the well plate to saturate available sites so that to prevent any nonspecific antibody binding. This helps in maximizing the signal-to-noise ratio. As soon as the complex is formed between the antigen and the antibody, the enzyme reacts to the chromogenic substrate which results to give a visible colorimetric output that is measured by a UV−vis spectrophotometer [31].

Electrical impedance scanning (EIS), also known as electrical impedance tomography (EIT) determine various electrical properties of breast tissue and produces an equivalent image. It is used for detecting the non-palpable lesions. The cell membrane is primarily capacitive but displays conductivity in its semipermeable function. EIS measures the conductance at very low frequencies (<1000 Hz) and capacitance at high frequencies. These electrical properties affect the impedance value. Mostly, the EIS system works on higher frequencies as the impedance of the electrode affects the constant behaviour of the input current. The electrical properties of the malignant and normal tissues vary, but their corresponding values overlap at a particular point. The electrical impedance cycles can be performed using the Siemens TransScan TS2000 and TS2000ED (EarlyDetection). The current is fed into the breast and determining corresponding voltages produced at the electrodes that are placed on the breast skin. The measurements are observed and analysed with the help of a computer algorithm. There are various advantages of using an EIS for the detection of abnormalities in growth of cells such as it is expensive, non-invasive and adds no risks. The cycles generally take about 15 minutes in total and cause less discomfort. It can be operated in vivo or in vitro, but in vitro measurements must be done as soon as the tissue dies [13]. EIS produces reliable results even with dense breasts tissues unlike mammography. It has the ability to detect small lesions which other techniques are unable of detecting. The method produces outcomes as images having poor SNR and resolution less than that of CT and MRI. Recent reports states that EIS can detect abnormalities and can objectifies which patient is prone to develop a malignant cells in the future [32]. EIT can be utilized to increase the specificity which consequently results in reliable results and less false outcomes. It is important to receive an affordable and easy way to interpret detection instead of biopsies. The main principle of the process of detection using the EIS approach depends on the small amount of current through electrode surface and recording the corresponding voltage signal over particular frequencies. The process of simulation and recording the signal allows the determination of the impedance at the surface of the electrode. The conductance of malignant tumours varies from the conductance of the benign tissue. It is nearly 35 microSiemens/mm for a normal healthy breast tissue and 3-4 times higher for carcinoma at 1 kHz [33]. The impedance difference is more effective at higher frequencies approximately 1 MHz [34].

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B. Machine Learning for Diagnosis of Breast Cancer

A machine-learning model can observe and learn from the patterns of reports of many patients. This feature helps the doctors in forecasting the future outcomes at a reliable level [8]. An ANN is a mathematical representation of the human neural network architecture, signifying the learning and analysing ability. ANNs are highly applicable in research fields as they have the ability to model non-linear systems that are quite complex in nature. A. Khatija et al. reported a study of breast cancer data classification using artificial neural network. They prepared an algorithm to train the network by multi-layer perceptron approach [20]. Naushad et al. developed an ANN-based model which analyzes the interaction of genes, nutrients, and demographic indicators to anticipate the chances of an individual of developing breast cancer. This model proved to be very precise having accuracy of 94.2% and determined variables that enhances the risk of breast cancer, such as folate deficiency and estrogen exposure [21]. V. Bhateja et al. proposed the approach of evaluating edge detection algorithms for mammographic calcifications. In their work they performed the work by using MIAS database with different category of background tissues [22]. An ANN developed by He et al. was proposed to diagnose breast cancer at a sufficient level was modeled after the producer-scrounger model of animal searching behavior [23]. S. Paramkusham et al. performed image processing techniques for the detection of breast cancer using MATLAB and Labview [24].

II. METHODOLOGY

The methodology of the proposed work from the processing of raw data from WBCD to the analysis of performance of the prepared network is shown in fig 2.

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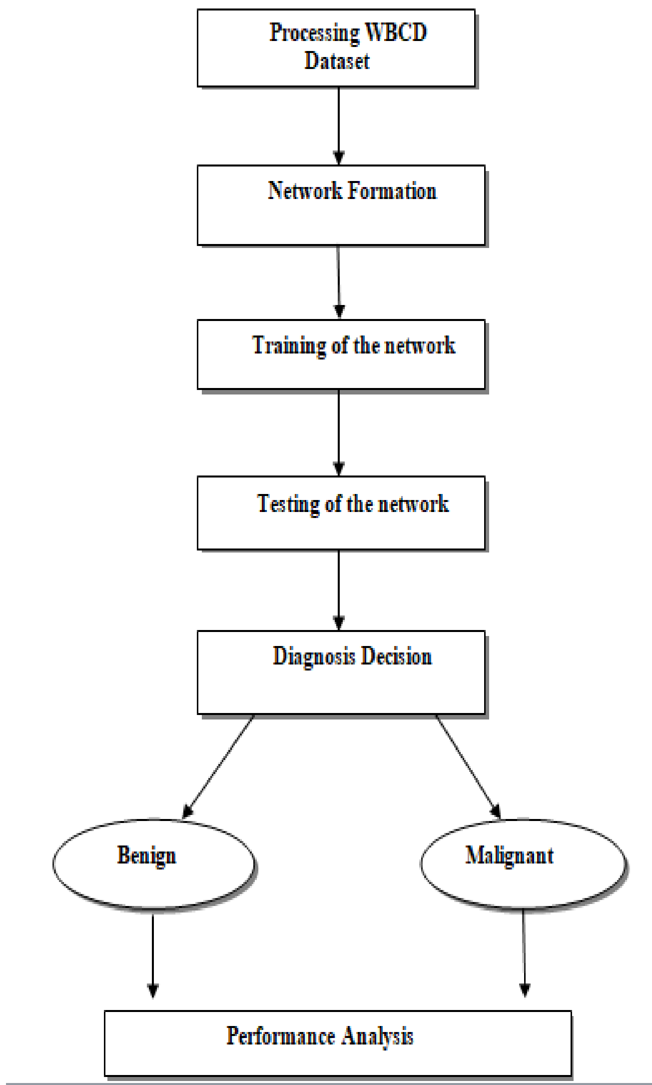

Fig.2. Methodology of work

The dataset used in the work to train the algorithm is Wisconsin Breast Cancer Database obtained from the open source [25]. The algorithm used to train the system for the detection of breast cancer is backpropagation algorithm. The dataset was trained on the MATLAB software.

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Table 1. Summary of Wisconsin Breast Cancer Dataset.

Attributes	Possible Values
Clump Thickness	Integer 1-10
Uniformity of cell size	Integer 1-10
Uniformity of cell shape	Integer 1-10
Marginal Adhesion	Integer 1-10
Size of single epithelial cell	Integer 1-10
Bare Nuclei	Integer 1-10
Bland Chromatin	Integer 1-10
Normal nucleoli	Integer 1-10
Mitoses	Integer 1-10
Class	Benign(2) / Malignant(4)

III. EXPERIMENTS PERFORMED

A. Processing of Data

The processing was performed on the raw breast cancer data to scale the features and parameters. Standardization of datasets is a common requirement for many machine learning estimators. The raw data is aligned into a form that can be used as dataset to train the system.

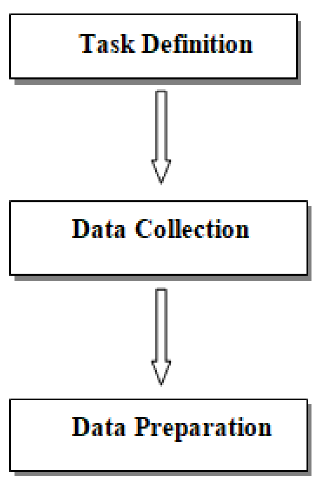

Fig.3. Data Processing of ten dataset

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B. Formation of the network

The network is formed using the neural network toolbox in MATLAB. The network follows the backpropagation algorithm. There were two layers in the network containing 10 neurons. The input is fed into the hidden layers which passes the values to the output. The output which the network passes is referred as the actual output. The error is calculated by the difference between target output and the actual output. This error is given back to the hidden layers so the network trains the data accurately and avoids the previous error.

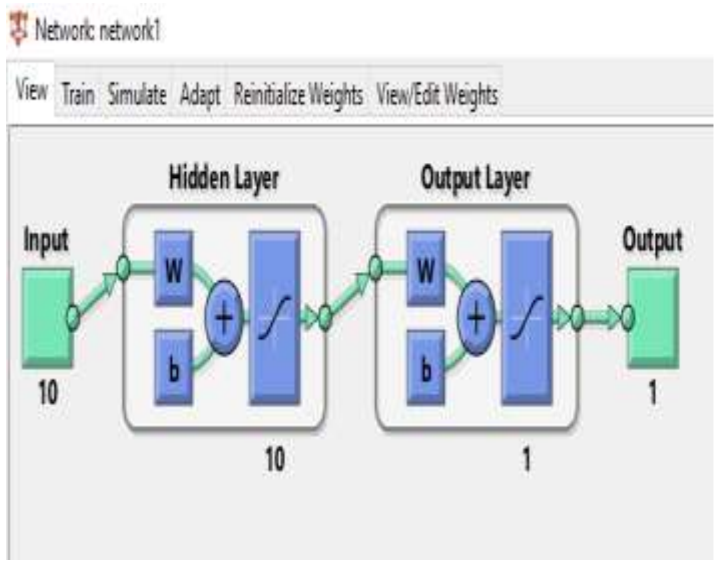
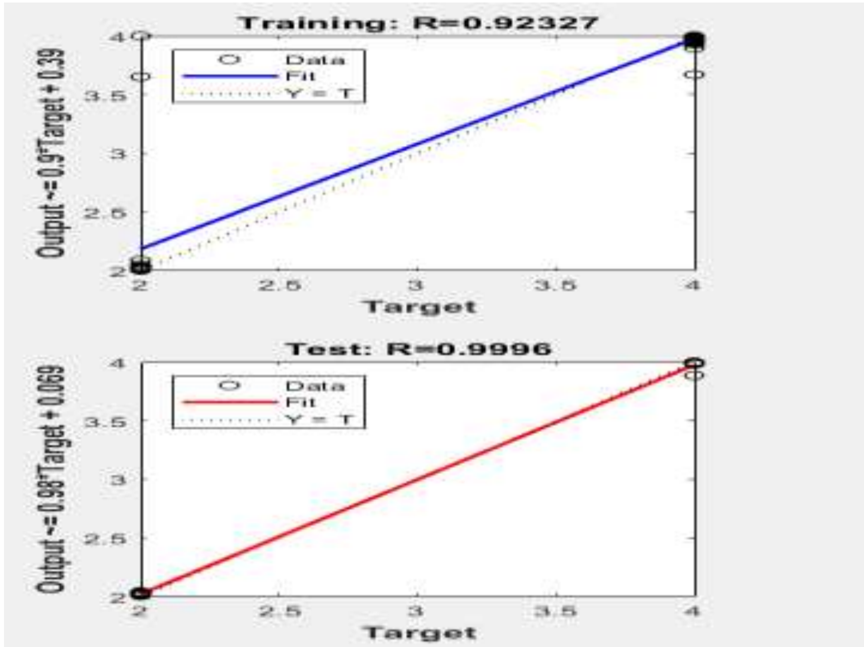


Fig.4. Back-propagation Network

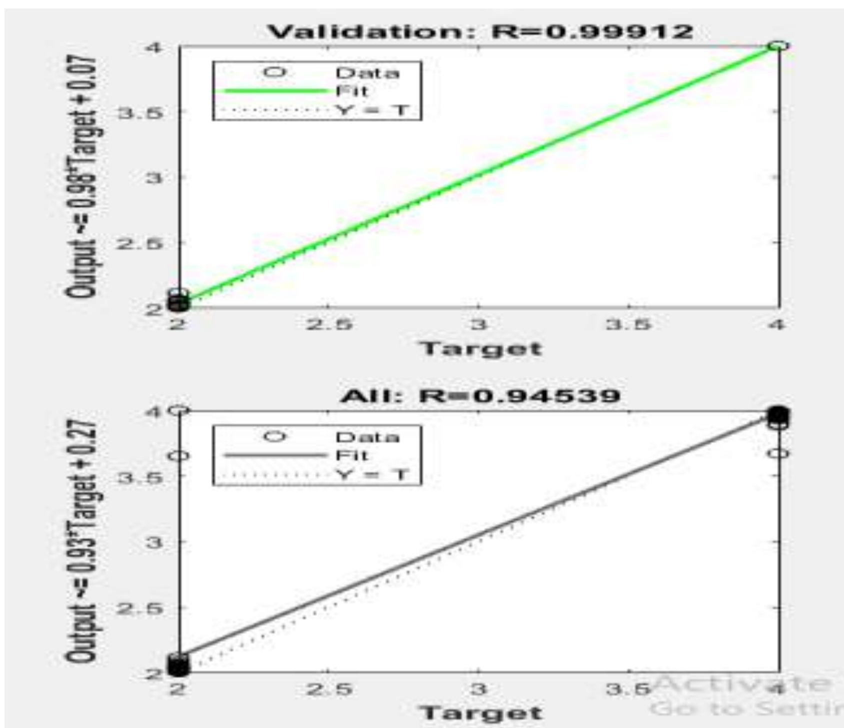
C. Training the network

The algorithm that is used for training the network having input as the dataset is back-propagation. The back-propagation network, also called multi-layer feed-forward neural network or multi-layer perceptron is the most widely used algorithm. The BPN is based on the supervised machine learning approach, i.e. the network operates the model based on input dataset with known outputs. The architecture of the BPN is a layered feed forward neural network, where the non-linear units are layered successively in successively and the flow of data is unidirectional i.e., from input layer to output layer, through the hidden layers [26].

The network is trained several times to get the best validation result. The dotted line represents the target output whereas, the blue, green and red lines signifies the fit of training, validation and test data.



(a)



(b)

Fig. 5. (a) Receiver operator characteristic of training set and test set;

(b) Receiver operator characteristic of validation set.

D. Testing of the network

The network is trained several times to obtain the best result closest to the target output. To check the sensitivity of the designed network, it is important to test the network. A dataset with 25 inputs were fed into the network to detect the presence of breast cancer. The test is performed to calculate the sensitivity of the backpropagation network. The network is used to forecast the outcomes for the validation dataset. The validation dataset performs the evaluation of a network fit on the training dataset while tuning the network's parameters. Validation datasets can be used for optimization by stopping it early. This easy procedure is much more complicated while using it as the validation dataset errors may vary during training.

Finally, the test dataset is a dataset used to provide an unbiased evaluation of a final model fit on the training dataset. If the data in the test dataset has never been used in training (for example in cross-validation), the test dataset is also called a holdout dataset.

Table 2. Target output and Actual output of test dataset

Serial Number	Target Output (Test)	Actual Output (Test)
1.	2	2.8362
2.	2	2.9450
3.	2	3.0258
4.	4	2.9207
5.	2	2.5023
6.	4	3.6873
7.	4	3.5609
8.	2	2.9002
9.	2	2.9155
10.	4	3.4821
11.	2	2.7579
12.	4	3.4075
13.	4	2.0603
14.	2	2.7091
15.	2	3.1560
16.	4	3.5280
17.	2	2.9149
18.	2	2.9210
19.	4	3.7660
20.	2	3.3818
21.	2	2.5884
22.	4	3.4968
23.	4	3.5295
24.	2	2.8464
25.	2	2.7288

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IV. RESULTS AND DISCUSSION

In this study, we applied the Wisconsin Breast Cancer dataset to validate the designed models. The network can be used for the diagnosis of breast cancer in patients. The network is trained many times to obtain the best performance of the network. The performance of the network is represented in table 2 and by the graph shown in fig 6.

The blue curve in the graph represents the test performance of the back-propagation network, green curve signifies the validation performance and the red curve represents the testing performance of the network designed.

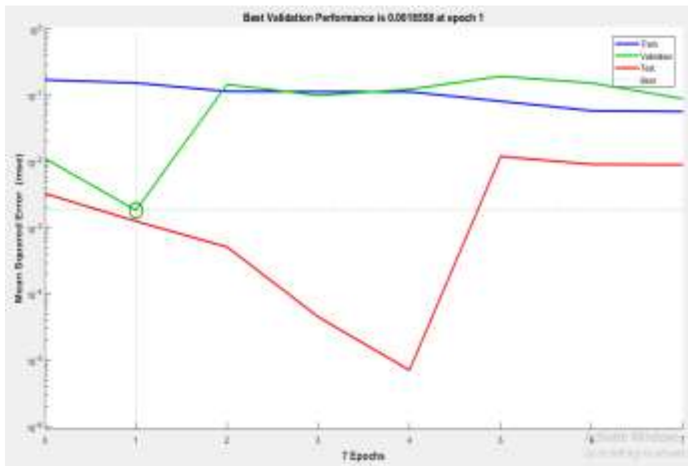

Fig.6. Performance of the network

The confusion matrix consisted of the number of actual positive and negative cases. The next class consisted of true positive and true negative cases. The final class constituted of the false positive and false negative cases.

The results of the network are illustrated using the sensitivity and specificity. The sensitivity of the network can be calculated by equation (1). The specificity of the network can be illustrated by equation (2).

Table 3. Confusion matrix for two class classifier

		Predicted Class	
		Positive	Negative
Actual Class	Positive	True Positive(TP)	False Negative(FN)
	Negative	False Positive(FP)	True Negative(TN)

$$\text{Sensitivity} = TP / (TP+FN) \qquad (1)$$

$$\text{Specificity} = TN / (TN+FP) \qquad (2)$$

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The number of true positive cases is 8, whereas, the number of false negatives is 2. The number of true negative cases is 14 and the number of false positive cases is 3 as represented in table 3.

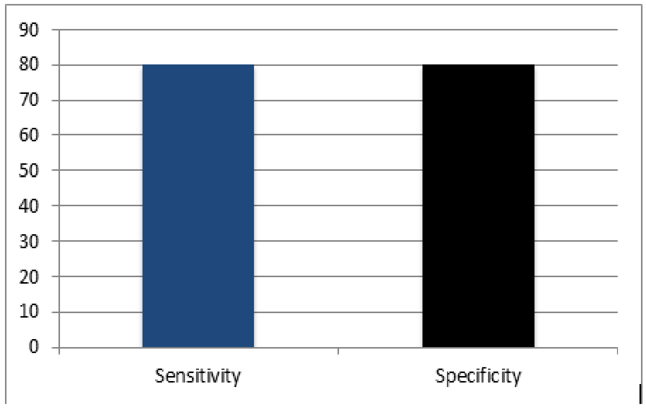

Fig.7. Sensitivity and Specificity Chart

V. CONCLUSION

It can be seen that machine learning is a simplified and quick approach to diagnose abnormalities in patients through a given dataset. Many configurations of the network were trained several times and tested against the Wisconsin Breast Cancer database. The results show the ability of the neural networks to classify the applied input into either of the two classes (benign or malignant). The sensitivity and specificity of the network with 100 input data and 25 testing data was found to be 80%. The sensitivity of the neural network can be increased by providing a large dataset to the network. Based on these results we can state that the range of effectiveness of diagnosis of the back-propagation neural network is high. The results clearly show the strong ability of the classificatory models of neural networks to show better performance. The experiments performed in this paper are limited to the use a single database with a limited attributes for Breast Cancer. Based on the above trends, different models may be built and experimented for effective disease diagnosis. Classification becomes very difficult when the inter-class separation is low into the feature space. This requires good attributes for better separation that may be easily classified. Working on better attributes and methods of diagnosis may highly increase the accuracy diagnosis.

REFERENCES

1. Adam B. Nover, Shami Jagtap, Waqas Anjum, Hakki Yegingil, Wan Y. Shih, Wei-Heng Shih, Ari D. Brooks; "Modern Breast Cancer Detection: A Technological Review"; International Journal of Biomedical Imaging; December 2009.
2. WHO Breast Cancer Report 2018; https://www.who.int/cancer/prevention/diagnosis-screening/breast-cancer/en/

3. Kim, Soogeun, Kim, Tae, Lee, Soo Hyun, Kim, Wansun, Bang, Ayoung, Moon, Sang, Song, Jeongyoon, Shin, Jae-Ho, Yu, Jae, Choi, Samjin; "Label-Free Surface-Enhanced Raman Spectroscopy Biosensor for On-Site Breast Cancer Detection Using Human Tears"; ACS Applied Materials & Interfaces; 2020.

4. Milosevic M, Jankovic D, Milenkovic A, Stojanov D., "Early diagnosis and detection of breast cancer. Technology and Health Care", Official Journal of the European Society for Engineering and Medicine; 2018.

5. Ali, Md Azahar, Mondal, Kunal, Jiao, Yueyi, Oren, Seval, Xu, Zhen, Sharma IITK, Ashutosh. Dong, Liang;; "Microfluidic Immuno-Biochip for Detection of Breast Cancer Biomarkers Using Hierarchical Composite of Porous Graphene and Titanium Dioxide Nanofibers"; ACS Applied Materials & Interfaces; 2016.

6. Ain, Khusnul, Wibowo, Ricky, Soelistiono, Soegianto; "Modeling of electrical impedance tomography to detect breast cancer by finite volume methods"; Journal of Physics: Conference Series; 2017.

7. S.K. Bandyopadhyay, S. Banerjee, I.K. Maitra; "Digital imaging in pathology towards detection and analysis of human breast cancer"; International conference on computational, intelligence, communication systems andnetworks (CICSYN), Liverpool, United Kingdom, pp. 295–300; 2010.

8. Rajkomar A, Dean J, Kohane I. Machine Learning in Medicine. *N Engl J Med*. 2019;380(14):1347-1358. doi:10.1056/NEJMra1814259.

9. Steiner, Margaret C.. "Solving cancer: The use of artificial neural networks in cancer diagnosis and treatment." *Journal of Young Investigators* 33 (2017).

10. Beam AL, Kohane IS. Big data and machine learning in health care. JAMA 2018; 319: 1317-8.

11. https://en.wikipedia.org/wiki/Breast_cancer_screening. 2016.

12. Jaglan, Poonam , Dass, Rajeshwar, Duhan, Manoj; "Breast Cancer Detection Techniques: Issues and Challenges"; Journal of The Institution of Engineers (India): Series B; 2019.

13. Nover, A.B., Jagtap, S., Anjum, W., Yegingil, H., Shih, W.Y., Shih, W., & Brooks, A.D., "Modern Breast Cancer Detection: A Technological Review"; *International Journal of Biomedical Imaging; pp.*2137 – 2150; 2009.

14. T. Ratanachaikanont; " Clinical breast examination and its relevance to diagnosis of palpable breast lesion"; J. Med Assoc. Thai; pp. 505–507; 2005.

15. B. Cunitz et. al.; " Improved detection of kidney stones using an optimized doppler imaging sequence"; IEEE International Ultrasonic Symposium Proceedings, pp. 452–456; 2014.

16. Pandya, Hardik & Park, Kihan & Chen, Wenjin & Chekmareva, Marina & Foran, David & Desai, Jaydev; "Simultaneous MEMS-based electro-mechanical phenotyping of breast cancer. Lab on a Chip"; 15. 3695-3706. 10.1039/C5LC00491H; 2015.

17. A. Kapur, P.L. Carson, J. Eberhard, M.M. Goodsitt, K. Thomenius, M. Lokhandwalla; "Combination of digital mammography with semi-automated 3D breast ultrasound" Technol. Cancer Res. Treat. 3(4); pp.325–334; 2004.

18. P.K. Saini, M. Singh; " Brain tumor detection in medical imaging using matlab."; Int. Res. J. Eng. Technol. 02(02); pp.91–196; 2015.

19. B. Cunitz et. al.; " Improved detection of kidney stones using an optimized doppler imaging sequence"; IEEE International Ultrasonic Symposium Proceedings, pp. 452–456; 2014.

20. Amato, Filippo & López-Rodríguez, Alberto & Peña-Méndez, Eladia & Vaňhara, Petr & Hampl, Aleš & Havel, Josef. (2013). Artificial neural networks in medical diagnosis. J Appl Biomed. 11. 47-58.10.2478/v10136-012-0031-x.

21. Naushad, S.M, Ramaiah, M.J, Pavithrakumari, M, Jayapriya J, Hussain, T, Alrokayan, S.AKutala, V.K; "Artificial neural network-based exploration of gene-nutrient interactions in folate and xenobiotic metabolic pathways that modulate suspectibility to breast cancer". *Gene*, *580*(2), 159-168. doi:10.1016/j.gene.2016.01.023.

22. Bhateja, Vikrant & Devi, Swapna & Urooj, Shabana. (2013). An Evaluation of Edge Detection Algorithms for Mammographic Calcifications. 10.1007/978-81-322-1000-9_46.

23. He, S., Wu, Q., & Saunders, J. (2009). Breast cancer diagnosis using an artificial neural network trained by group search optimizer. Transactions of the Institute of Measurement and Control, 31(6), 517-531. doi:10.1177/0142331208094239.

24. Paramkusham, Spandana & Rao, Kunda & Rao, B. (2013). Early stage detection of breast cancer using novel image processing techniques, Matlab and Labview implementation. 2013,15th International Conference on Advanced Computing Technologies, ICACT 2013. 1-5. 10.1109/ICACT.2013.6710511.

25.https://archive.ics.uci.edu/ml/datasets/breast+cancer+wisconsin+(original)

26. Mishra, BK & Singh, S. & Bhala, S.. (2011). Breast cancer diagnosis using back-propagation algorithm. 470-473. 10.1145/1980022.1980123.

27. F.E.Z.A. El-Gamal et al; "Current trends in medical image registration and fusion. Egypt. Inform. J. 17, pp. 99–124 ; 2015.

28. Joseph R. Corea et al., Screen-printed flexible MRI receive coils. Nat. Commun. 7, 10839. (2016).

29. Dheeb AA.; "Thesis of Embedded feature selection methods based on support vector machine for histopathology grading"; Malaysia: Universiti Kebangsaan; 2017.

30. Ashwaq Q, Siti Norul Huda SA, Shahnorbanun S, Rizuana IH, Fuad I; "An accurate rejection model for false positive reduction of mass localisation in mammogram"; Pertanika Journal of Science and Technology; 25(S):pp.49-62; 2017.

31. Gao Yuan, Zhou Yingzhu, Chandrawati Rona; "Metal and Metal Oxide Nanoparticles to Enhance the Performance of Enzyme-Linked Immunosorbent Assay (ELISA)" 10.1021/acsanm.9b02003; 2020.

32. A. Stojadinovic, A. Nissan, C. D. Shriver, et al., "Electrical impedance scanning as a new breast cancer risk stratification tool for young women," Journal of Surgical Oncology, vol.97, no. 2, pp. 112–120, 2008.

33. B. Sholz and R. Anderson, "On Electrical Impedance Scanning- Principles and Simulations," vol. 68, no. 1, pp.35-44, 2000.

34. Campisi, Matthew & Barbre, Curtis & Chola, Aditya & Cunningham, Gisselle & Woods, Virginia & Viventi, Jonathan. (2014). Breast cancer detection using high-density flexible electrode arrays and electrical impedance tomography. 2014 36th Annual International Conference of the IEEE Engineering in Medicine and Biology Society, EMBC 2014. 2014.