ISSN: 2278 – 909X
International Journal of Advanced Research in Electronics and Communication Engineering (IJARECE)
Volume 5, Issue 3, March 2016

DETECTION OF BREAST CANCER USING CONTINUOUS WAVELET TRANSFORM AND SUPPORT VECTOR MACHINE

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***Abstract*: Breast cancer is the leading cause of non-preventable cancer death among women. A typical mammogram is an intensity X-ray image with gray levels showing levels of contrast inside the breast that which characterize normal tissue and different calcifications and masses. Analyzing an X-ray mammogram is challenging because of the similarities of cancer growth with other tissue growth. Therefore, it poses inaccuracy in identifying the presence of breast cancer. Nowadays, detection of calcifications in mammograms has received much attention from researchers and public health practitioners. In this paper, we propose a novel technique that uses continuous wavelet transform (ID - CWT) as feature selection technique and support vector machine (SVM) as classifier. Our experimental result achieved excellent classification accuracy (100%) and compared with the other technique (ID - CWT and Fuzzy-C-mean clustering).**

Keywords :Continuous Wavelet Transform (CWT), Fuzzy C-Means(FCM), Support Vector Machine (SVM)

I.INTRODUCTION

Breast cancer is the second leading cause of cancer deaths for women and is found as one in eight women in the United States. It is the disease in which cells in the tissues of the Breast become abnormal divide without order or control. The abnormal cells form too much tissues of the breast become abnormal instantaneously. These abnormal tissues form too much tissue and become tumor. According to WHO report, nearly two million women are diagnosed with breast cancer every year worldwide. The disease can be treated if it is discovered so early enough. The effective detection of breast cancer in earlier stage increases the survival rate. The appropriate method for early detection of pre-cancerous symptoms is screening mammography, which has to be conducted as a regular test for women. All the techniques that are used till date detects breast cancer only at later stages. Even if detected at early stage, it may not be accurate and may also provide false results. Hence it will be very difficult to cure the cancer completely. This motivated us to refer several papers based on breast cancer detection that too in earlier stages and initiate a technique that accurately detects breast cancer in its early stage.

II.LITERATURE SURVEY

Jinshan Tang et al [1] examined that CAD is an important tool for early detection of Breast cancer. It provides an overview of recent advances in CAD systems and related techniques. It describes some basic concepts related to breast cancer detection and diagnosis. It is also reviewed many key CAD techniques for breast cancer detection. Heng-Da Cheng et al [2] proposed a novel approach using fuzzy logic to detect micro calcifications in digitized mammograms with densities. This approach consists of five major steps including image fuzzification, image enhancement, irrelevant breast structure removal, segmentation and image reconstruction. Further improvement of this approach can be achieved by using higher resolution images, more powerful contrast enhancement algorithm, and neural networks. G. Lemaur et al [3] proposed new wavelets with a higher Sobolev regularity compared with the classical wavelets, assuming the same support width. Contrary to the classical smoothness or moment regularity of a wavelet, the Sobolev regularity refers to the fractional derivatives of the signal and to its singular spectrum such as a more sophisticated structure. Karthikeyan Ganesan et al [4] discussed a literature to shoe that the accuracy of cancer detection has indeed improved with introduction of CAD based diagnostic procedures. Here the best results are obtained are around 90% which is not sufficient enough for implementation in clinical trails. But there is still a long way to go for implementation of the same in a clinical setting. Maria Rizzi et al [5] employ two systems and compares them for automatic detection of micro calcification clusters in mammographic images. The implemented techniques adopt a three layer ANN and an SVM with a Gaussian RBF kernel function as classifier. To make the system performance independent from the adopted image quality, the DDSM and MIAS databases are used for the training phase and the test phase, respectively. Cheng-Hong Yang et al [6] presented an Improved Genetic Algorithm to determine that multiple Single Nucleotide Polymorphism (SNP) are exclusively used in association studies to investigate polygenic diseases and cancer. In nature, genes can be damaged or modified in various ways and this damage can lead to an increased risk of disease and cancer. It is thus important to obtain informative SNP patterns from the SNPs located in the relevant genes and pathways. Ahmed B. Ashraf et al [7] reported a methodological framework for a multichannel extension of Markov Random Fields (MRFs) for breast tumor segmentation from MRI images. It has also presented a method to search for optimal MRF that satisfies conditional independence conditions by employing pairwise conditional mutual information. Liyang Wei et al [8] proposed an RVM technique for detection of micro calcification clusters in digital mammograms. RVM classifier is trained through supervised learning to determine at each location in a mammogram whether micro calcification is present or not. Its experimental results show that RVM technique maintains best detection accuracy. This makes RVM more feasible for real-time processing of micro calcification clusters in mammograms. Issam EI-Naqa et al [9] has investigated the use of SVM for the detection of micro calcifications in digital mammograms. It has proposed that an SVM classifier can be trained through supervised learning to test at every location in the mammogram whether micro calcification is present or not. The SVM classifier achieves low generalization error when applied to classify samples that were not included in training. Yasmeen Mourice George et al [10] developed a fully automated method for the segmentation of cell nuclei in breast images. Through this work it has effectively overcome the problem related to the detection of nuclei locations. It has also eliminated the false positive nuclei markers which result in the efficient segmentation of nuclei boundaries. Arianna Mencattini et al [11] addressed problem of enhancement and denoising of mammographic images. A new algorithm based on the dyadic wavelet transform has been presented. The main advantage of this method, with respect to other methodologies proposed in the literature, is its adaptability to the different nature of diagnostic relevant features in the image under analysis, permitting the use of the same core algorithm for both micro calcifications and mass detection. The improving quality of the processed images has been considered by radiologists as a true significant aid for the early detection of breast cancer. Jacob Levman et al [12] proposed the use of SVM as a classification mechanism for delineating malignant and benign lesions from dynamic contrast-enhanced magnetic resonance images (DCE-MRI) of the Breast. The Support Vector Machine has also been demonstrated as offering significant flexibility in the design of a Computer aided diagnostic system for DCE-MRI of the breast. But more research is needed to fully implement the SVM technique in a clinically acceptable manner that is not constrained with respect to the Magnetic Resonance acquisition protocol. Liyang Wei et al [13] developed an RVM technique for detection of MC Clusters in digital Mammograms. In this approach, an RVM classifier was trained through supervised learning to determine at each location in a mammogram whether an MC is present or not. Mohammad Sameti et al [14] discussed the differences between the regions that subsequently becomes a malignant mass and other normal areas of the mammogram images taken in the last screening examination prior to the detection of a mass. The system then calculates the features for this region and classifies the region as Normal or Abnormal. The region will be flagged if the system classifies it as abnormal. It can be further improved by automatically examining the whole mammogram, region by region and determining whether it is normal or abnormal. Song yang Yu et al [15] proposed the research and development of a CAD system for the automatic identification of micro calcification clusters in digitized mammogram films. This system consists of two main steps; in the first step potential micro calcification pixels are segmented out and labeled into potential individual micro calcification objects and in the second step these objects are classified as true or false.

III.EXISTING WORK

Wavelet transform is an ideal tool to analyze image containing different structures. It discriminates among several spatial orientations and decomposes images into different scale orientations providing a method for space scale representation. CWT is used to divide a continuous time function into wavelets. Many authors have developed different techniques to detect clustered calcifications by applying discrete wavelet transform but this method is limited to regular regions because of construction of wavelet functions and bases. CWT performs over each line of images and it can also be applied over irregular areas. In the CWT, the analyzing function is a wavelet, ψ. The CWT compares the signal to be shifted and compressed or stretched versions of a wavelet. Stretching or compressing a function is collectively referred to as dilation or scaling and corresponds to the physical notion of scale. By comparing the signal to the wavelet at various scales and positions, you obtain a function of two variables. The two-dimensional representation of a one-dimensional signal is redundant. If the wavelet is complex-valued, the CWT is a complex-valued function of scale and position. If the signal is real-valued, the CWT is a real-valued function of scale and position. For a scale parameter, a>0, and position, b, the CWT is

$$W_f=S(a,b)=\frac{1}{\sqrt{a}}\int_{-\infty}^{\infty} f(t)\,\overline{\varphi\left(\frac{t-b}{a}\right)}\,dt \qquad \text{---(1)}$$

Fuzzy-*C* Means Clustering

The minimization of the *c*-means functional represents a nonlinear optimization problem that can be solved by using a variety of methods, including iteration method. The most popular method is a simple Picard iteration through the first-order conditions for stationary points known as the Fuzzy C-Means (FCM) algorithm. The stationary points of the objective function can be found by adjoining the constraint to *J* by means of Lagrange multipliers. Before using the FCM algorithm, the following parameters must be specified: the number of clusters, *c*, the 'fuzziness' exponent, *m*, the termination tolerance and the norm-inducing matrix, A. In the FCM approach, instead, the same given datum does not belong exclusively to a well-defined cluster, but it can be placed in a middle way. In this case, the membership function follows a smoother line to indicate that every datum may belong to several clusters with different values of the membership coefficient.

IV.PROPOSED WORK

A. Support Vector Machine Classifier

Support Vector Machines (SVM) is a relatively new learning method used for binary classification. The basic idea is to find a hyper plane which separates the dimensional data perfectly into its two classes. Overall, SVM is intuitive, theoretically well- founded, and have shown to be practically successful. SVM have also been extended to solve regression tasks where the system is trained to output a binary value 0 or 1 classification. An SVM classifies data by finding the best hyper plane that separates all data points of one class from those of the other class. The best hyper plane for an SVM means the one with the largest margin between the two classes. Margin means the maximal width of the slab parallel to the hyper plane that has no interior data points. The support vectors are the data points that are closest to the separating hyper plane; these points are on the boundary of the slab.

B. Block Diagram Of Proposed Technique

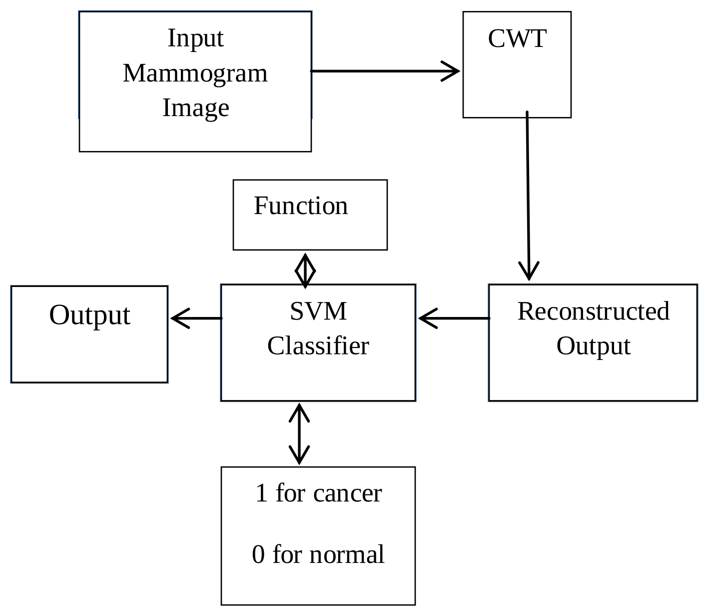

Fig 1.Block diagram of proposed system

The block diagram explains in detail about the detection of breast cancer which increases the efficiency by using Support Vector Machine as a classifier. Since SVM is used as a classifier, the given input image is exactly examined and detected whether the MC is present or absent i.e., 0 or 1.

C .Kernel Function

Some binary classification problems do not have a simple hyper plane as a useful separating criterion. For those problems, there is a variant of the mathematical approach that retains nearly all the simplicity of an SVM separating hyper plane. It is nothing but a kernel function.

The mathematical approach using kernels relies on the computational method of hyper planes. All the calculations for hyper plane classification use nothing more than dot products. Therefore, nonlinear kernels can use identical calculations and solution algorithms, and obtain classifiers that are nonlinear.

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V.EXPERIMENTAL RESULTS AND DISCUSSION

A.CWT Along With Fuzzy C Means

The output of CWT is processed under the principle of Fuzzy C Means and performs several iterations. The resulted output is as follows.

Fig .2 Input Mammogram Image

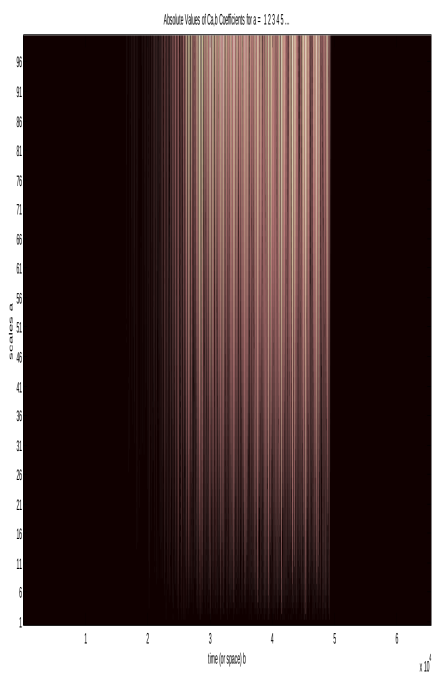

Fig 3.Output of Continuous Wavelet Transform

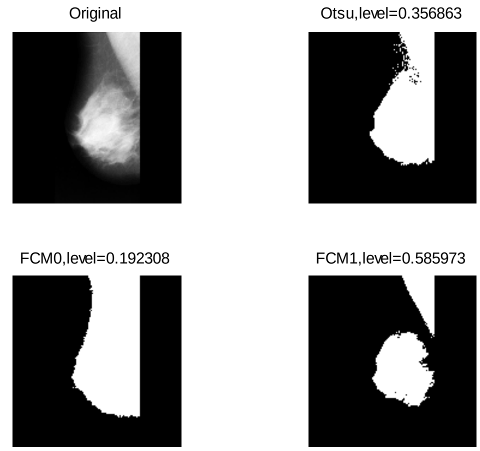

Fig 4.Fuzzy with Continuous Wavelet Transform

Since combination of continuous wavelet transform and Fuzzy c means provides less accurate output i.e., it cannot be assured that the image is cancerous or not. Hence Fuzzy c means is replaced by Support Vector Machine classifier. Here the breast cancer is detected using Continuous wavelet transform and fed to Support Vector Machine.

B. Support Vector Machine.

The SVM detects the image and the output is obtained in terms of graph. The graph is plotted between intensity of the image and number of iterations.

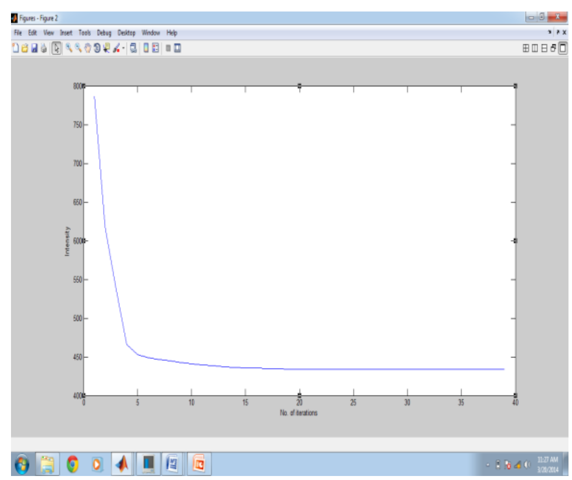

Fig 5.Support Vector Machine Output for normal Image

In a support Vector Machine Output for a normal image of the breast the intensity will always tends to be exponentially decreasing for first few iterations and remains constant thereafter based on the coefficient value. The constant propagation indicates that no further iteration is possible.

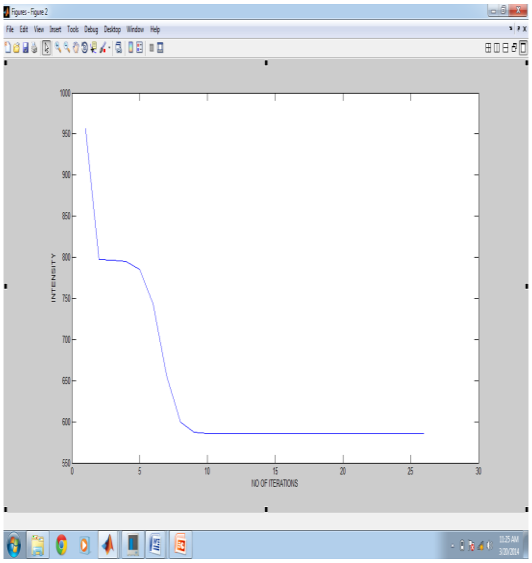

Fig 6.Support Vector Machine Output for cancer Image

In a support Vector Machine output for a cancerous image, there will be sudden up and down variation in the intensity due to change in the coefficient value. This bulged part represents the cancer affected area. Hence abnormality in the graph identifies the input image to be cancerous.

VI.CONCLUSION

In this paper, a technique which detects the breast cancer in its early stage by using Continuous Wavelet Transform and Support Vector Machine is presented. Support Vector Machine is a binary classifier which evaluates the input mammogram image and detects whether the given image is cancerous or not. The accuracy gets better because of the binary output 0 or 1. The performance has been compared by the simulation results of the existing algorithm and its importance for real time applications has been identified.

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