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Research paper

Multi Intelligent Fuzzy Integration (Mifi) Support Vector Machines for the Mammogram Classification

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Abstract

Breast cancer is the most important problem across the globe in which the 80% of the women are suffering without knowing the causes and effects of the cancer cells. Mammogram Image is the most powerful tool for the diagnosis of the Breast cancer. The analysis of this mammogram images proves to be more vital in terms of diagnosis but the accuracy level still needs improvisation. Several intelligent techniques are suggested for the detection of Micro calcification in mammogram images. The new technique MIFI-SVM has been proposed which integrates the GLCM features along with the Fuzzy Support Vector Machines. ROI Segmentation using Saliency maps has been used for the proposed algorithm and feature is extracted using GLCM and fed to Fuzzy Support Vector Machines The MIAS datasets has been used for testing the proposed algorithm and accuracy, sensitivity has been measured which proves to be better when compared to other Multi-level SVM's, C-SVM and Neural Networks.

***Keywords**: GLCM, Extreme Fuzzy Support Vector Machines,MIFI,Saliency Maps, Micro calcification, ROI Segmentation.*

1. Introduction

Recently, Mammogram Analysis has drawn the greater research light due to the advent of the many classifiers. Several Classifiers are proposed for the classification of malignant in the Images. SVM is one such Classifier which classifies based on the location of the data points on hyper plane. The principle of operation of SVM is explained as follows

The theory of support vector machines (SVMs) is a new classification technique and has drawn much attention on this topic in recently. The theory of SVM is based on the idea of structural risk minimization (SRM) . In many applications, SVM has been shown to provide higher performance than traditional learning machines and has been introduced as powerful tools for solving classification problems.

An SVM first maps the input points into a high-dimensional feature space and finds a separating hyperplane that maximizes the margin between two classes in this space. Maximizing the margin is a quadratic programming (QP) problem and can be solved from its dual problem by introducing Lagrangian multipliers.

Without any knowledge of the mapping, the SVM finds the optimal hyperplane by using the dot product functions in feature space that are called *kernels*. The solution of the optimal hyperplane can be written as a combination of a few input points that are called *support vectors*. There are more and more applications using the SVM techniques. However, in many applications, some input points may not be exactly assigned to one of these two classes.

Some are more important to be fully assigned to one class so that SVM can separate these points more correctly. Some data points corrupted by noises are less meaningful and the machine should better to discard them. SVM lacks this kind of ability. In this paper, we apply a fuzzy membership to each input point of SVM and reformulate SVM into fuzzy SVM (FSVM) such that different input points can make different contributions to the learning of decision surface. The proposed method enhances the SVM in reducing the effect of outliers and noises in data points.

The proposed Algorithm MIFI-SVM has been formulated by using the above mentioned concept with the integration of the Gray level Co occurence Matrix with the Saliency ROI (Region of Interest) techniques. The different features are extracted from the segmented Mammogram Images and feed to the proposed classifier to detect the abnormalities such as Malignant or Benign in the images. The classifier produces the better accuracy and methodology has been explained in the preceding sections.

The paper is organized in such manner such that as Section-I consists of related works. The Section-II consists of the proposed algorithms The Section –III Consists of the performance evaluation along with the experimental setup and finally conclusion.

2. Related Works

Fadi Abu-Amara and Ikhlas Abdel-Qader [2] introduced a new system called computer aided detection (CAD) for images of mammogram to detect and classify the images. This system uses three modules namely dimensionality reduction module that uses the principal of component analysis, a feature extraction module that uses independent component analysis, and a feature subset selection module that utilize rough set model. In this system fuzzy classifier is to identify the images as normal and abnormal images. So this classifier is comes under the rough set model because it is used to reduce the inconsistency data effect. Finally their outcome shows that their system has accuracy 84.03% and percentage of recall is 87.28%

B. Surendiran and A. Vadivel[3] proposed two classifier approach namely ADA-NN and ADA-RBFN are proposed to classify the masses which are present in the mammograms. To extract the shape and margin features from the masses these classifiers are used. When compared to other single statistical and NN classifiers their proposed classifier gives higher rate of classification that is 91.56 %. The classification accuracy is compared using the basic features like area, ESD, perimeter, SD. Finally they found difficulty in their experiment because of lobular and irregular masses.

Amal AlQoud and M. Arfan Jaffar[4] introduced a breast cancer detection system using mammogram. This cancer detection system has three phases and they are preprocessing of image, features extraction of image, and classification. Gabor filters with Local Binary Patterns are used to extract the texture features and for classification. For the mass detection, the discrete wavelet transform (DWT) is used in the Gabor filters. After that LBF are extracted from each filter in the system. The outcome features are robust due to invariant and scale variant. Authors also use neural network schemes for high tolerance classifier and they can also use to classify the image patterns

M. Arfan Jaffar [5] proposed Computer Aided Diagnosis system has been introduced for breast cancer detection. This system has three different tasks to identify the breast cancer. The first task involves breast segmentation using combination of bilateral filter, log transformation, adaptive active contour and entropy. The second task is image enhancement and that has been done by using Partitioned Iterated Function System. Finally authors used ensemble classifier AdaBoost for the feature extraction is done and they are classified using mammograms and compared to other models of classifiers. Their outcomes shows that the proposed system achieves accuracy of 96.74% and sensitivity of 98.34% .

R.NITHYA, B.SANTHI [6] introduced mammogram CAD system for normal and abnormal breast detection is introduced. For the feature selection process there is simple and effective algorithm that is Maximum Difference Feature Selection (MDFS) proposed. The proposed system uses this algorithm to classify normal and abnormal patterns of breast image. This method simply eliminates the irrelevant features of the images and hence gives higher accuracy. The random selection method outperforms 98% accuracy.

Ping Zhang, Kuldeep Kumar, and Brijesh Verma[7] proposed a hybrid system which is the combination of both human extracted features and computer extracted features using mammogram. When compared with the neural and single statistical classifiers the hybrid system produces best results. Hybrid system produces the classification rate of 91.3% and it produces 0.962 area value under the curve of ROC. This shows that the hybrid features produces great classification of mass patterns in the mammograms.

Ankita Satyendra Singh, M. M. Pawar [8] proposed the system to avoid False Negative Rate (FNR) problem in Computer Aided Diagnosis System a new system is developed in CAD. This system mainly focuses identification of breast masses using feature extraction. The input images are first pre-processed in first stage and segmented in the second stage and further it can be subjected into feature extraction, selection and these are finally classified. For texture feature extraction the MIAS data base is considered in which 60 images are taken into account out of 322 images. There are 22 features are extracted and they are used for feature classification. This is done by PNN classifier. Finally their outcome obtained sensitivity of 100%, Specificity of 100%, Accuracy of 100%.

Jinchang Ren, DongWang, JianminJiang[9] proposed the improved neural classifier is introduced. In mammograms for classification of benign and malignant MCCs optimized decision making and balanced learning are introduced. The experiment uses DDSM database for the feature extraction in which 748 samples are extracted. The classification accuracy has been significantly improved by balanced learning method and 10% gain can be achieved for ANN in terms of A_z measurements. Optimized decision making gives improved results and balanced training will results only 54% of additional computational load.

R. Swiniarski Hun Ki Lim[10] studied various hybrid methods for selection of image features, extraction, classifiers for breast cancer recognition in area of mammograms. Rough sets, PCA, ICA methods also studied. Authors designed and tested three classifier methods and they are classifier based on rough set, neural network based on Learning Vector Quantization, error back propagation neural network. They also provided comparative study for various data sets, in which rough sets rule-based classifier produces best performance with better level of accuracy when compared with the other classifiers. Rough set and rule based classification will produce improved solution in mammogram recognition for the detection of breast cancer.

S Murali and P Sathees Kumar[11] proposed a Trace transform function method and it's framing a new functional method. The overlapping of images is done easily with the help of fuzzy logic techniques. These are all the methods presented in this paper and it can could assist the medical staff and improve the accuracy of detection. This method significantly reduces the computational cost of image analysis in the mammogram applications. The features extracted from the trace function and it can be coupled with the GLSM classifier that produces higher accuracy of 95% when compared with the other classifiers

3. Mifi-Svm Classifier – an Insight Working Methodology

MIFI-SVM Classifier works on the principle of saliency based texture extractions which are then fed to the single layer feed forward learning classifier and predictive layers for the diagnosis and prediction of the diseases. The working mechanisms of the proposed algorithm which is given as follows as

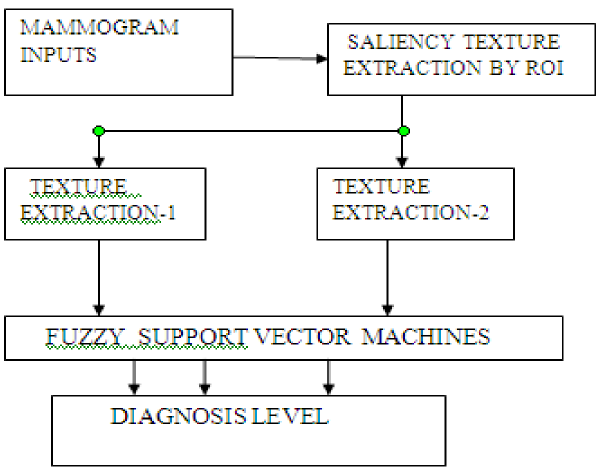


Fig: Shows the Working methodology for the MIFI-SVM Classifier for Mammogram Detection Methods.

4. Saliency Segmentation

Segmentation is the process of segmenting the images into the different sizes of the pixels and textures for which the several segmentation techniques were proposed. We incorporate the new methodology of Segmentation called Intelligent Saliency Segmentation which involves the decomposition of a given image into compact, perceptually homogeneous elements in which the unnecessary details will be subtracted. Based on this layer of abstraction of Images, unique contrast and the spatial distribution of these elements are calculated. From calculation and computation obtained pixel-accurate saliency maps which uniformly covers the objects of interest and consistently separates fore- and background are obtained .The complete contrast and saliency estimation can be formulated in a unique way by using high- dimensional Gaussian filters. This Saliency maps Segmentation increases the accuracy in segmenting the distinct objects such as the growth of malignant in the Mammogram Images. The various steps of the Saliency maps are shown in Fig 2

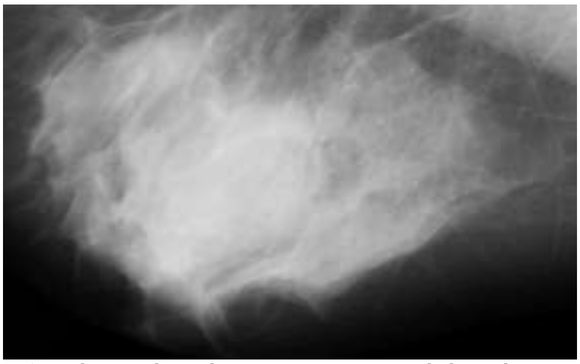


Fig1: Shows Enhanced Mammogram Image with the Malignant

Fig2: Saliency Segmentation of the Distinct Malignant in the Mammogram Image

5. Texture Extraction and Analysis

The obtained Saliency maps which shows the distinct objects in an unified manners are now used for the extraction of the various parameters for the textures by using the GLCM principles.

5.1 GLCM (Gray Level Co -Occurence Matrix)

GLCM has defined by Haralick is two –dimensional histogram images of gray levels for the pair of pixels which are separated by a spatial fixed relationship. GLCM of the Image is computed by the displacement vector d which depends on the radius R and orientation.

In this proposed texture calculation radius R is taken as 2 and Orientation angles are taken from 0 .45,90 and 135 . After selecting the suitable R and Orientation factor, no of gray levels G are computed without sacrificing the more computation time. These gray levels are more important in extraction and the no of levels are decides the accuracy of the textures*)*

In the Proposed Algorithms, GLCM calculates the G for the radius R and Orientation from 0,45,90 and 135. To determine the texture features, selected statistics are applied to each GLCM by iterating through the entire matrix. The textural features are based on statistics which summarized in the table I represents the relative frequency distribution which describes how often one gray tone will appear in a specified spatial relationship to another gray tone on the image.

The different features are calculated for the different mammogram images taken from the MIAS datasets which are as follows

Table: Representation of GCLM Statistics for the different Mammogram Malignant Images.

Sl. No	Image Datasets	Image_1	Image_2	Image_3	Image_4	Image_5
01	Energy	2.3691 e-01	2.7234 e-01	1.935e-01	1.530e-01	3.5079e -01
02	Contrast	3.56e-02	1.57e-01	3.921e-0	1.491e-01	6.083e-02
03	Auto Correlation	1.855e +02	1.759e +01	1.921e+01	2.25e+01	1.406e+01
04	Variance	9.737e-01	8.894e-01	3.923e-01	5.895e+01	6.083e-02
05	Sum of Average	5.854e +00	6.624e +00	7.3718e +00	8.511e+00	5.7703e +00
06	Cluster Prominence	6.304e +02	9.883e-01	9.377e+02	5.7143e +02	[9.081e +02
07	Entropy	1.874e +00	1.918e +00	2.120e+00	2.197e+00	1.6157e +00
08	Homogeneity	9.676e-01	9.574e-01	9.498e-01	9.441e-00	9.7049e -01
09	Maximum probability	4.579e-01	4.8765 e-01	3.484e-01	2.4342e -00	5.659e-01
10	Sum of sqaures	1.322e +01	1.768e +01	1.922e+01	2.264e+00	1.409e+01

6. Fuzzy Support Vector Machines

6.1 Need for the System

SVM is the most powerful tool for solving the classification problem but if the training data belongs to one or more classes then SVM treats all the datas uniformly which may lead to the inaccurate measurement. In the real world application, training datas are considered to be more important for the classification.

6.2 Fuzzy Incorporation

For the meaningful data classification, Fuzzy membership has been incorporated along with the SVM machines. The intelligent rule sets has been defined for the best classification of the data. In MIFI-SVM, classifies the features extracted with the intelligent rule systems and detects whether it is normal or abnormal.

6.3 Mifi-Svm –an Overall Working Mechanism

Step 1 : Enhance Mammogram Image
Step 2 : Segment the Distinct ROI using the Saliency Maps
Step 3 : Apply the GLCM for the Different Feature Extraction
Step 4 : Initialize the MIFI-SVM
Step 5 : Optimize the SVM by Kuhan-Tucker Conditions
Step 6 : Apply Fuzzy Intelligent Rule Sets for the Classification.

Step 7 : Detection Process.

6.4 MIFI-SVM Rule Engine

if(E_{ther_n} < $(ENERGY)_{nn}$ < E_{ther_nn}
AND
if C_{ther_n} < $(CONTRAST)_n$ < C_{ther_nn}
AND
if C_{ther_n} < $(CORRELATION)_{nn}$ < C_{ther_on}
AND
V_{ther_n} < $(VARIANCE)_{nn}$ < V_{ther_nn} …………..)
{ ABNORMALITY FOUND
}
Else
{
NORMAL
}

Where E_{ther_n} , C_{ther_n} C_{ther_n} V_{ther_n} are Lower bound Fuzzy thresholds used for the classifications and E_{ther_nn} , C_{ther_nn} , C_{ther_on} V_{ther_nn} are Upper Bound Fuzzy threshold for the classification.

7. Mammogram Datasets

The mammogram datasets are downloaded from the Mammogram Image Analysis Society(MIAS) which contains the original 322 images (161 pairs) at 50 micron resolution in "Portable Gray Map" (PGM) format and associated truth data. The above mentioned datasets has been used for training and classification for the 'n=100 'iterations for calculating and evaluating the below mentioned parameters.

7.1 Perfromance Evaluation

7.2 Accuracy Measurement

The accuracy of the detection is determined by the expression which is given below
ACCURACY : [(T.R)/(T.N)] x100
Where T.R = No of detected results T.N - Total Number of Iterations.
The accuracy level has been calculated for the different datasets which are taken as NORMAL, Beg and malignant. The accuracy level has been calculated for the two different cases which is mentioned above.

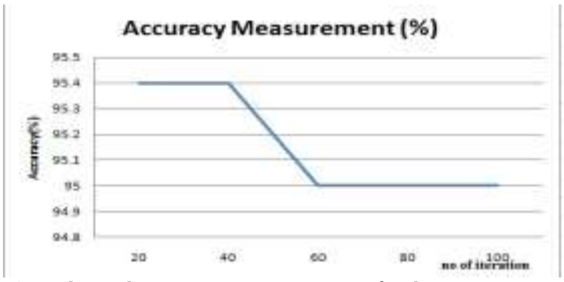


Fig3: Shows the Accuracy Measurement for the Iterations n=100 using Normal Mammogram Images.

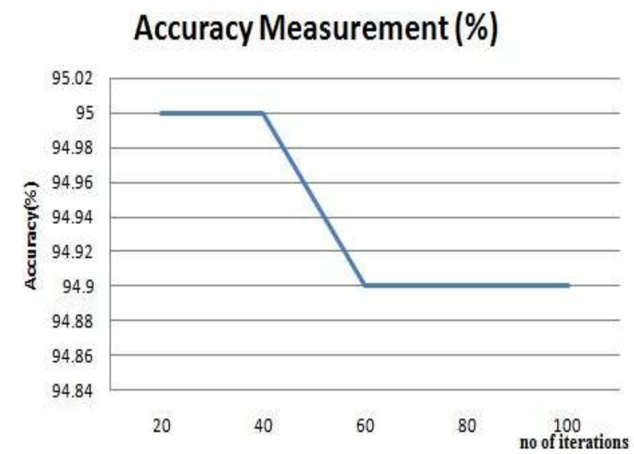


Fig4: Shows the Accuracy Measurement for the Iterations n=100 using Benign /Malignant Mammogram Images.

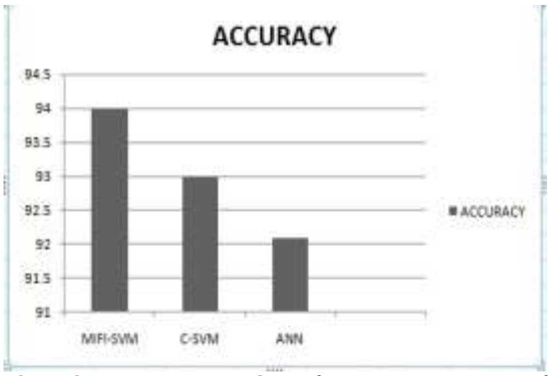


Fig5: Shows the Comparative Analysis of Accuracy Measurement for the different classifiers using Normal Mammogram Images.

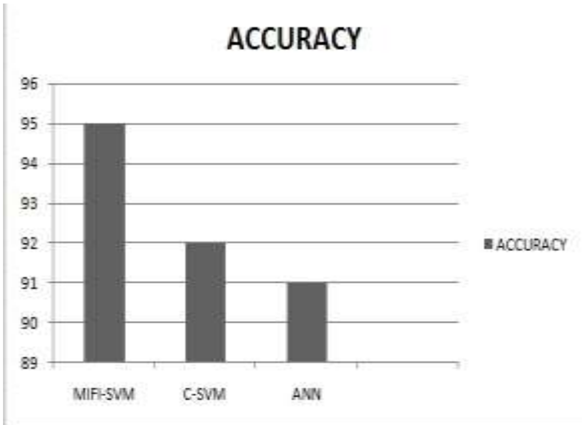


Fig6: Shows the Comparative Analysis of Accuracy Measurement for the different classifiers using Malignant Mammogram Images.

Above Fig 3,4,5,6 shows the accuracy measurement of the different images after training the proposed MIFI-SVM Classifier. The Classifier is fed for 100 iterations and the accuracy is measured. It is found as the no of iteration increases, accuracy level of the proposed classifier is maintained at 95% when the other classifiers are gradually decreases as the no of iterations increases.

7.3 Sensitivity Calculation :

The Sensitivity has been calculated based on the expression which is given by
Sensitivity : No of true values detected/No of Total iteration

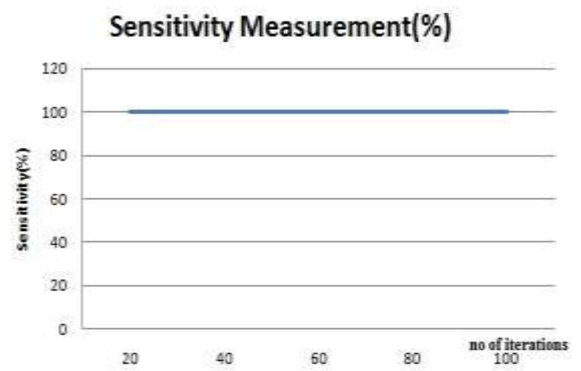


Fig 7: Shows the Comparative Analysis of the Sensitivity of the Proposed Algorithm with that of the Other Classifiers.

From the above Fig 7, clearly states that the Proposed MIFI-SVM Classifier has more Sensitivity 100% to which the even the micro growth rate of the cancer cells can be determined.

8. Overall Comparison Analysis

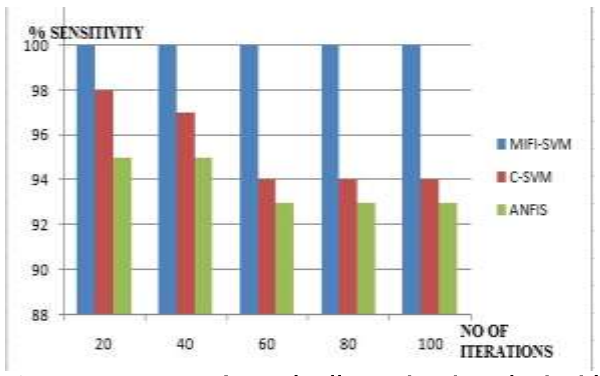


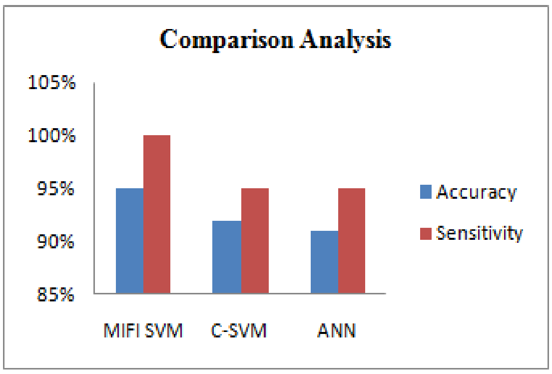
Fig 8: Comparative Analysis of Different Algorithms for the different Sensitivity measured at the different iterations.

The sensitivity is maintained at 100% when no of iterations increases. It is compared with the C_SVM and ANFIS whose sensitivity gradually decreases as the no of iteration of experimentation increases.

8.1 Comparison Analysis

In this paper the proposed method is efficient method in Accuracy and Sensitivity. The following table shows comparison with proposed system and C-SVM, ANN.

Parameter	Method		
	MIFI SVM	C-SVM	ANN
Accuracy	95%	92%	91%
Sensitivity	100%	95%	95%



9. Conclusion

MIFI-SVM –the integration of Saliency Segmentation with the GLCM features along with the Extreme Fuzzy Learning Machines proves to be more efficient in terms of the accuracy and sensitivity measurement. It outperforms other SVN and neural based classifiers by the higher peaks of different and but still requires more insight for o prediction ratio measurement, architectures for the real time diagnosis of the breast cancers.

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