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Enhanced Breast Cancer Classification with Automatic Thresholding Using Support Vector Machine and Harris Corner Detection

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ENHANCED BREAST CANCER CLASSIFICATION WITH AUTOMATIC THRESHOLDING USING SUPPORT VECTOR MACHINE AND HARRIS CORNER DETECTION

BY

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This thesis is approved as a creditable and independent investigation by a candidate for the Master of Science in Computer Science degree and is acceptable for meeting the thesis requirements for this degree. Acceptance of this thesis does not imply the conclusions reached by candidates are necessarily the conclusions of the major department.

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ABBREVIATIONS

MRI	Magnetic Resonance Imaging
SVM	Support Vector Machine
CAD	Computer Aided System
ANN	Artificial Neural Network
HCD	Harris Corner Detection
MMT	Mobile Microwave Tomography
PPV	Positive Predicted Value

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ABSTRACT

ENHANCED BREAST CANCER CLASSIFICATION WITH AUTOMATIC THRESHOLDING USING SUPPORT VECTOR MACHINE AND HARRIS CORNER DETECTION

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Image classification and extracting the characteristics of a tumor are the powerful tools in medical science. In case of breast cancer medical treatment, the breast cancer classification methods can be used to classify input images as benign and malignant classes for better diagnoses and earlier detection with breast tumors. However, classification process can be challenging because of the existence of noise in the images, and complicated structures of the image. Manual classification of the images is time-consuming, and need to be done only by medical experts. Hence using an automated medical image classification tool is useful and necessary. In addition, having a better training data set directly affect the quality of classification process. In this paper, a method is proposed based on supervised learning and automatic thresholding for both generating better training data set, and more accurate classification of the mammogram images into benign/malignant classes. The procedure consists of pre-processing, removing noise, elimination of unwanted objects, features extraction, and classification. A Support Vector Machine (SVM) is used as the supervised model in two phases which are testing and training. Intensity value, auto-correlation matrix value of detected corners,

and, energy, are three extracted features used to train the SVM. Experimental results show this method classify images with more accuracy and less execution time compared to the existing method.

1. INTRODUCTION

Cancer is among the leading causes of mortality worldwide with approximately 14 million new cases and 8.2 million cancer deaths in 2012 and the number of new cases was expected to rise by 70% over the next two decades [1]. The American Cancer Society estimated about 231,840 new breast cancer cases for women in 2015, in 2016 it was 249,260 new breast cancer cases and 40,890 deaths, and for 2017 the estimation is 225180 new breast cancer cases and 41,070 deaths [2][3], thus it is important to have more studies and research about it, a summary of the estimations from 2012 to 2017 is shown in figure 1.

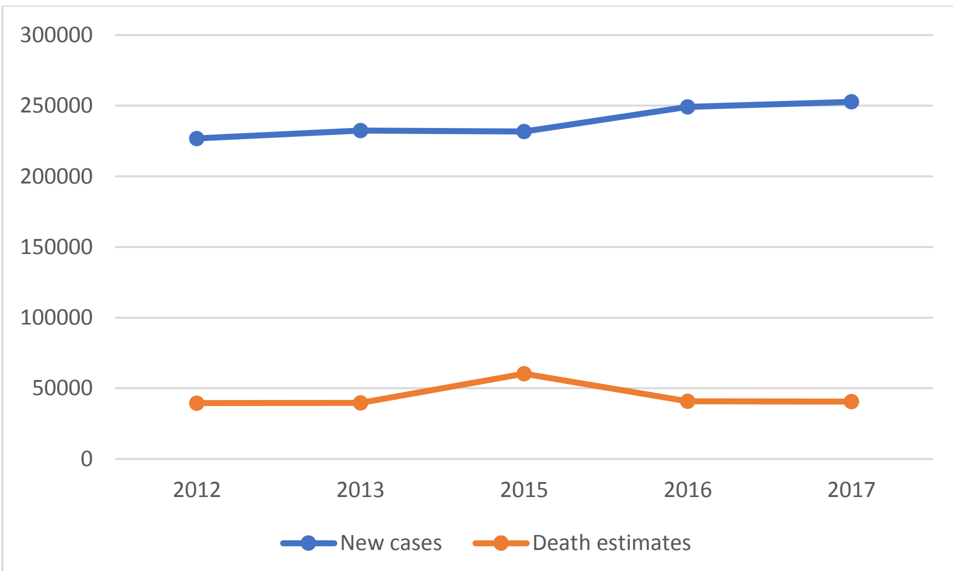


Figure 1. A summary of breast cancer new cases and death estimates from 2012 to 2017

As it can be seen from figure 1 the number new cases have been increased, but the number of death estimates has been decreased, one of the reasons is the improvements in medical imaging and Computer Aided Diagnosis (CAD) systems. Diagnoses of abnormality of the breast has improved using medical imaging, such as mammography, Magnetic Resonance Imaging (MRI), phantom imaging etc., thus usage of medical images is an inevitable part of the treatment process for both early and further diagnoses. Medical experts analyze the images to have a better understanding of the patient status and exact location of the tumors. These medical images help doctors and medical experts for medical treatments and analysis [4].

Detection of the abnormality in breast tissue is challenging in early detection stage because of uncertainty in the location of the tumor. The reason is that healthy and unhealthy part of the body have different intensity values and they are overlaid [5]. Existence of noise can also decrease the quality of the image and increase computational time [6]. Excessive need for examination and large number of medical images to be processed is another reason that make this process challenging [7]. Finding the correct area of the tumor would be difficult process, even for medical experts, especially if it must be done manually. Thus, using an efficient and reliable automated method for classification and segmentation of the image can be led to better accuracy in detection of the region of interest (ROI), less time spent for using the CAD system, and better presentation of the result.

In MR imaging, some abnormalities might be selected as cancerous because it is highly sensitive [8]. Although Mammogram images may have long execution time, they still can be used for early detection of the tumors in breasts along with other tools such as machine learning techniques with adequate number of input images. Machine learning techniques can be used for classification, these techniques are based on study of patterns, so they can make predictions based on their knowledge [9]. There are many approaches for machine learning, some common used approaches are Support Vector Machine

(SVM), similarity measurement, Artificial Neural Network (ANN), genetic algorithms and many more. An artificial neural network is a computational system for processing information as an effort for stimulation of the real case problem, which has a set of elements called neurons, in which they are interconnected in a multi-layer model [10]. ANN is one of the common supervised learning techniques, which can be also used for classification, but greater computational burden, proneness to overfitting, and not having enough training input data are some of its drawbacks [11]. In [8] ANN was used in a smartphone based method to extract breast tumors information from Mobile Microwave Tomography (MMT) raw data sets, but in their study they have used 30 images for both training and testing phases which seems insufficient. SVM is another supervised learning technique which classifies labeled data into two distinct classes [12]. In [13] SVM was used with two input features for training phase and manual thresholding to classify mammogram images into benign/malignant classes, using 5 different test data sets, in which three of them were generated by themselves and the other two were used from some existing methods, out of all of their data sets, only one data set showed better performance. Additionally, the reported execution time is not efficient. To achieve better result, pre-processing along with automatic thresholding are used in this study. SVM was also used in [14] which the authors used Fuzzy Multiple-parameter SVM to tune up each training data points by assigning suitable weight, matching to its feature, and adopts multiple parameters as a classifier for SVM. For evaluating the method, they used total 100 mammogram images (50 benign and 50 malignant). Although their method showed some improvements in classification of abnormalities in breast mammogram images, but for better evaluation the method, their proposed scheme must be tested using more many test cases. Results of this paper is compared with the proposed methods in [13] and [14] in section 4, result and discussion. In this study SVM was used as the supervised classifier along with automatic thresholding for better classification of the mammogram images into two classes of malignant/benign with higher accuracy. To extract features for training the SVM classifier, enhanced Harris Corner Detecting (HCD) along with intensity values of the pre-processed image was used from [13], In addition energy of the pre-processed image was added to the set of features. Energy of an image can be calculated using the average of squared values of all of the pixels, energy can be defined as the order of permittivity of the data [15]. Entropy was another feature used in [8] as an input features, but it was not used it this study because as it resulted in reduction of the accuracy of the classification. Thus, it can be said that having more input features is not always a good idea, the goal is to increase the number of features until the accuracy of the system reduces to it cause the system to have a long execution time. All the images went through pre-processing for both training and testing phase, this will provide more reliable input data sets and reduces the execution time. To improve the existing method for classification of mammogram images into benign/malignant classes, this study focuses for both generating better training images for the SVM classifier and better classification of the mammogram images. In, addition, more test cases were used in this study compared to the number of test cases used in existing methods proposed in [13] and [14]. In [13] totally 200 breast mammogram images (100 benign, 100 malignant) were used for evaluation of the proposed method, and in [14] totally 100 breast mammogram images (50 benign, 50 malignant) were used for evaluation of the proposed method. But in this study totally 600 breast mammogram images (300 benign, 300 malignant) images were used for evaluation of the proposed method, in order to better evaluation of the accuracy of the algorithm and test the performance of the proposed method under more complicated cases.

The paper is organized as follows. Section 2 is a literature review. Section 3 describes the existing method. Section 4 explains the overall process and proposed algorithm, which includes image acquisition, feature extraction, automatic thresholding, and machine learning. Experimental result and comparison with existing method are shown in section 5. Then in section 6 conclusion is discussed.

2. LITERATURE REVIEW

Feature extraction is important in terms of defining the classification systems [16]. A feature is a function of one or more measurements, in which each of the measurements specifies some quantifiable property of an object. Each feature quantifies some significant characteristics of the object [17] [18].

Most image processing algorithms include some common steps as shown in

Figure 2. The first step is preprocessing of the digitized images to remove artifacts such as patient information and reduce noise and improve quality of the image, thus features can be extracted easier. Feature extraction is the next step which is based on finding unique properties of an image to represent the image in terms of vector elements. All the important information from the image is extracted in this step. After the features are extracted, next step is to classify the images based on the extracted features. In order to have a more accurate prediction of the medical images with less execution time, the number of extracted features is limited [16]. In this study only three features are extracted as with adding more features accuracy of the classification was reduced and the computational time was increased.

Figure 2. Common steps in image processing algorithms

Features extracted from the images can be classified into two main categories: general features and domain-specific features. General features can be defined as application-independent features, such as color, texture and shape. General features include pixel-level features, local features and global features. [18].

In this paper, the focus is on based color features as the input images are gray-scale mammogram images. The features are intensity value of the pre-processed gray-scale image of the detected corner by HCD, Intensity values of the auto-correlation matrix by HCD, and energy of the image.

3. EXISITING METHOD

3.1. Support Vector Machines (SVM)

Support vector machines are well-studied and wieldy used in machine learning as a learning model. It is used to find patterns in the data and classify the input based on analyzing the data [19][20][21][22].

For better explanation of the SVM an example is shown in two-dimensional feature space in figure 3. As it was mentioned in SVM there are two different phases; testing and training. X_1 and X_2 axis will be features as described earlier. For the training phase, we train the algorithm by introducing the labeled data to the model.

To introduce our input data (benign and malignant images) to SVM for training phase, we need to label the data. Thus, let's assume that class 1 represented by red circles are malignant cases/images, and class 2 represented by green circles are benign cases/images.

Figure 3. Two-dimensional feature environment and class definition

In real case, we introduce the data to the algorithm with digits or a range of digits, for this study +1 was used for malignant and -1 for benign images. After the classes are defined and the labels are assigned to the training data, SVM reads input images one by one and plot them in the two-dimensional feature environment, an example can be seen in figure 4.

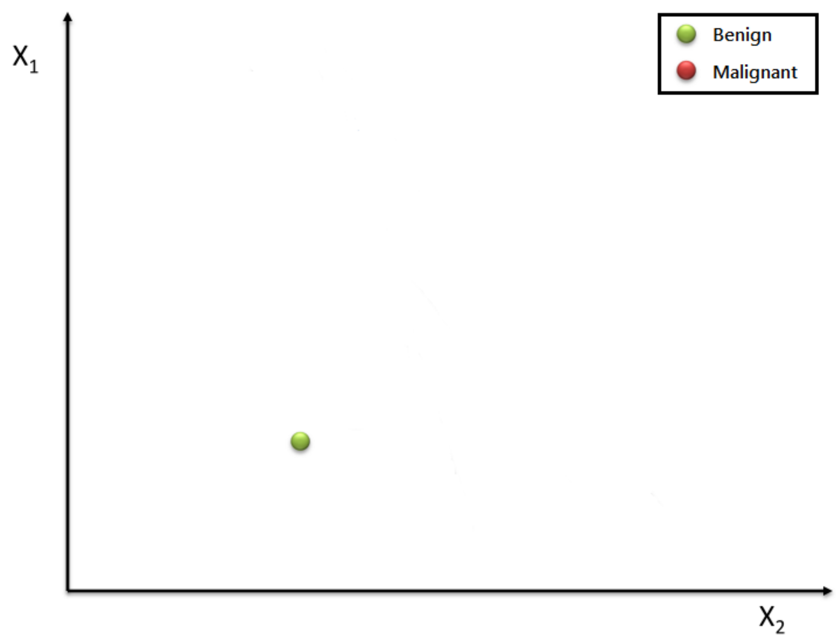


Figure 4. An example of reading training images by SVM in training phase

The image in figure 4 was a benign case and shown with a green circle, SVM continue reading training images until all the input images are red, figure 5 and figure 6.

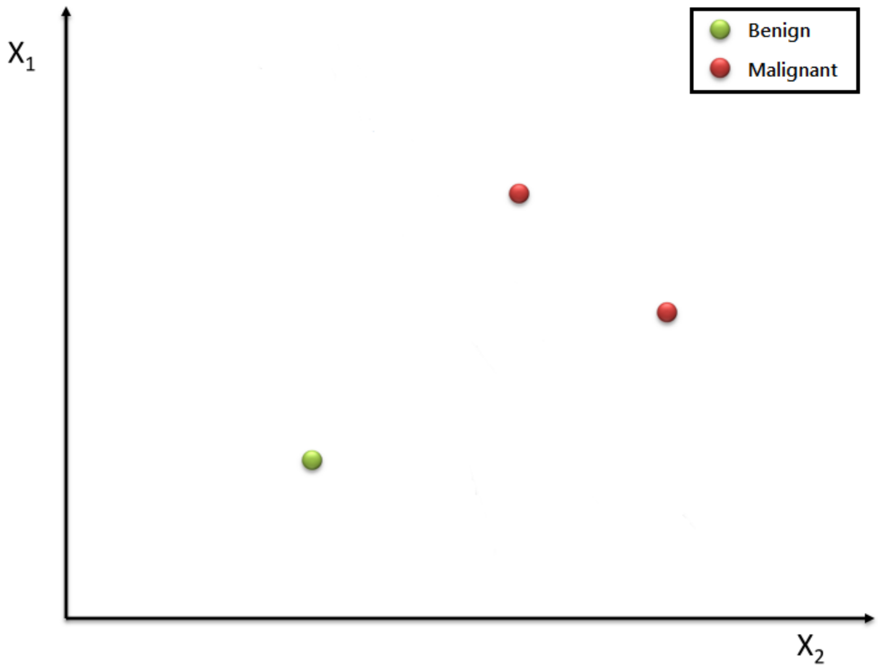


Figure 5. More training images are red by SVM in training phase

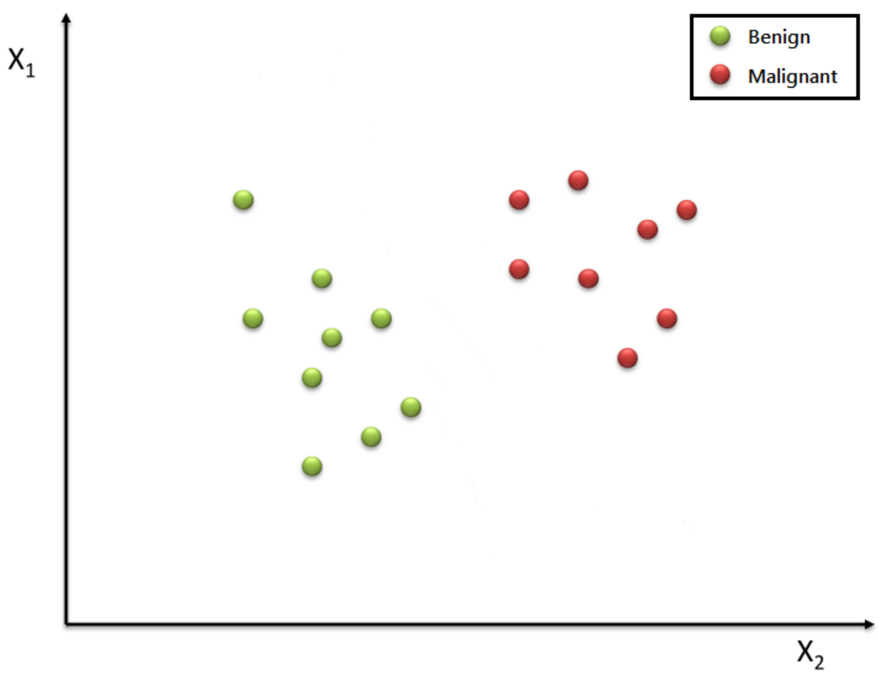


Figure 6. All the input images are red b SVM in the training phase

After SVM red all the input training images, the closest item of each class to the other class is selected, figure 7.

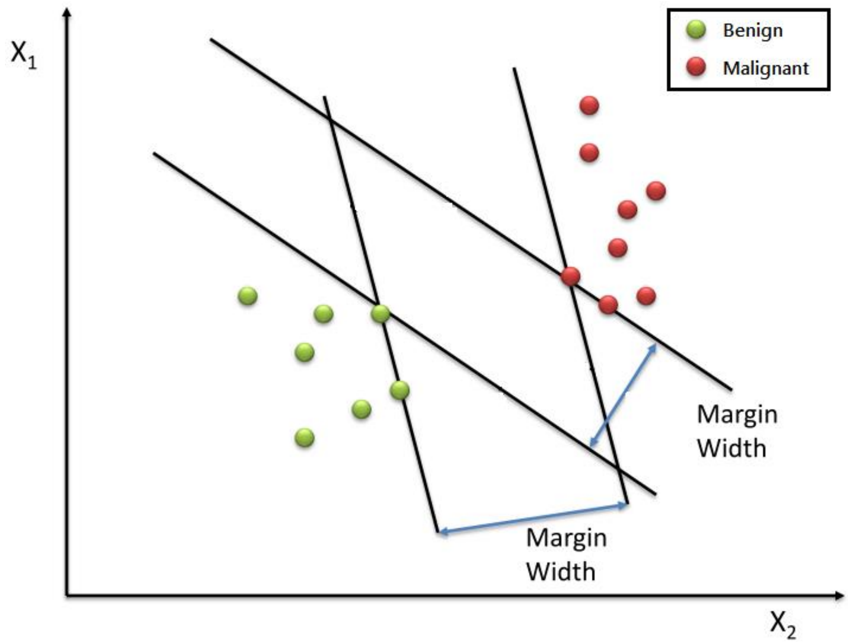


Figure 7. Drawing lines on the closest instances of each class to the other class

Based on the found closest items lines are drawn (black solid lines) crossing the selected items, but as it can be seen there might be more than one way to draw the lines on the instances of each class in which are the closest instances to the other class. The goal is to choose the lines which has the max width, figure 8.

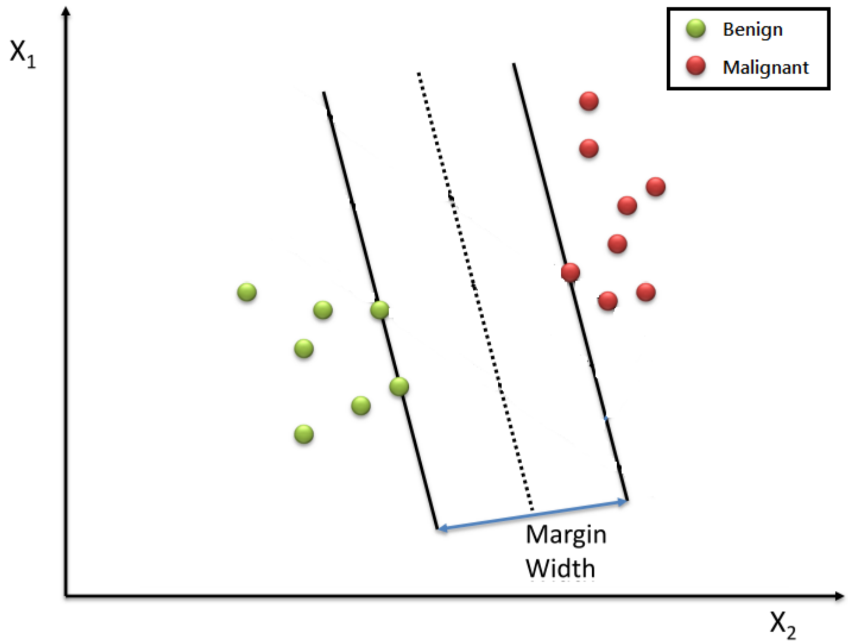


Figure 8. Margin with maximum width

When the lines with maximum margin width are selected, a new line (dashed line) is drawn exactly in the middle. This hyperplane is the measure of how we later classify our unlabeled test data into the predefined classes, the final calculated hyperplane with no testing or training data can be seen in figure 9.

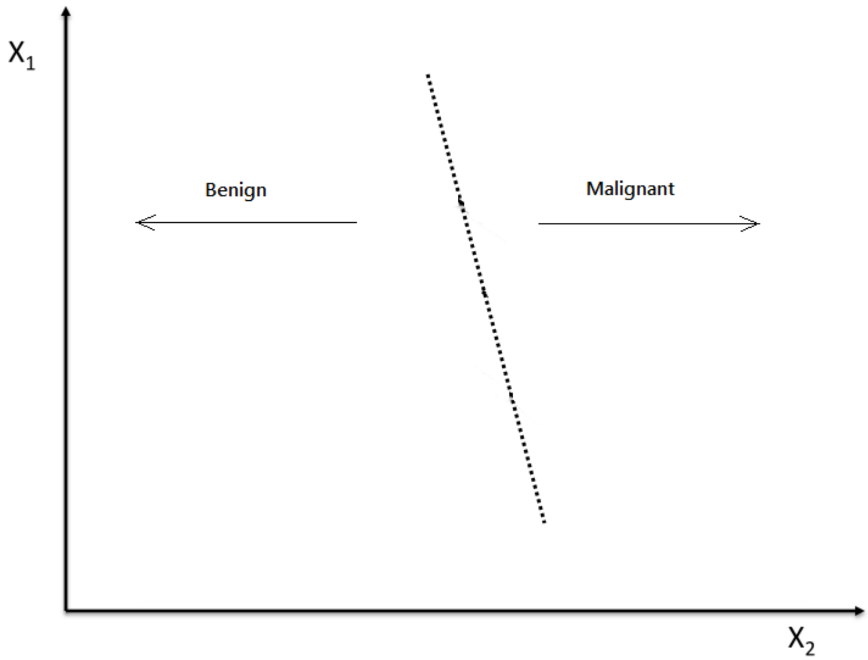


Figure 9. SVM hyperplane and defined classes

After finding the hyperplane, the training phase of the algorithm is done, now we can use this trained model to test our test data set. But in this phase the test data is not labeled anymore as it is the responsibility of the model to identify and classify the data. An example of testing phase with the unlabeled input data is shown in figure 10.

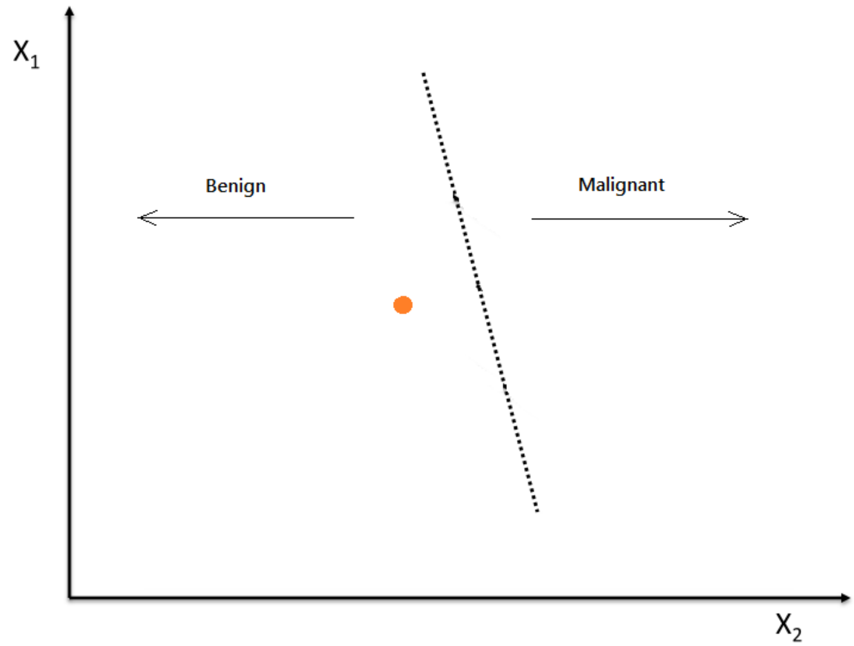


Figure 10. An example of reading test data and classification by SVM

It can be seen the test data has no label. As the item is in the left side of the hyperplane it would be a benign case.

In this study, as there three features used thus, there will be a three-dimensional feature space in which each axis represents one on the features. The feature space can be seen in figure 11. In can be also seen that the line which separates two classes are not linear, which means that the kernel used in this study is a non-leaner kernel.

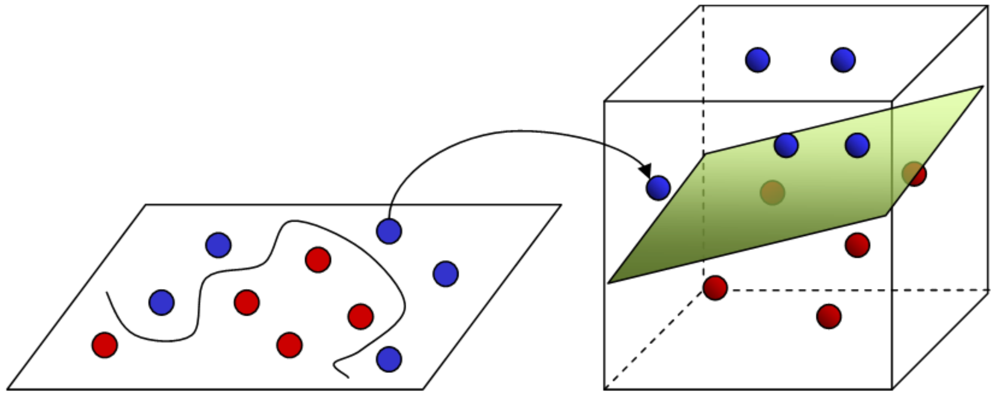


Figure 11. Converting two-dimensional feature space to Three-dimensional

4. PROPOSED METHOD

This study is based on combination of SVM and HCD to classify the benign/malignant breast mammogram images [13] with using more test cases, and automatic thresholding which increased the accuracy rate. The process is shown in figure 12.

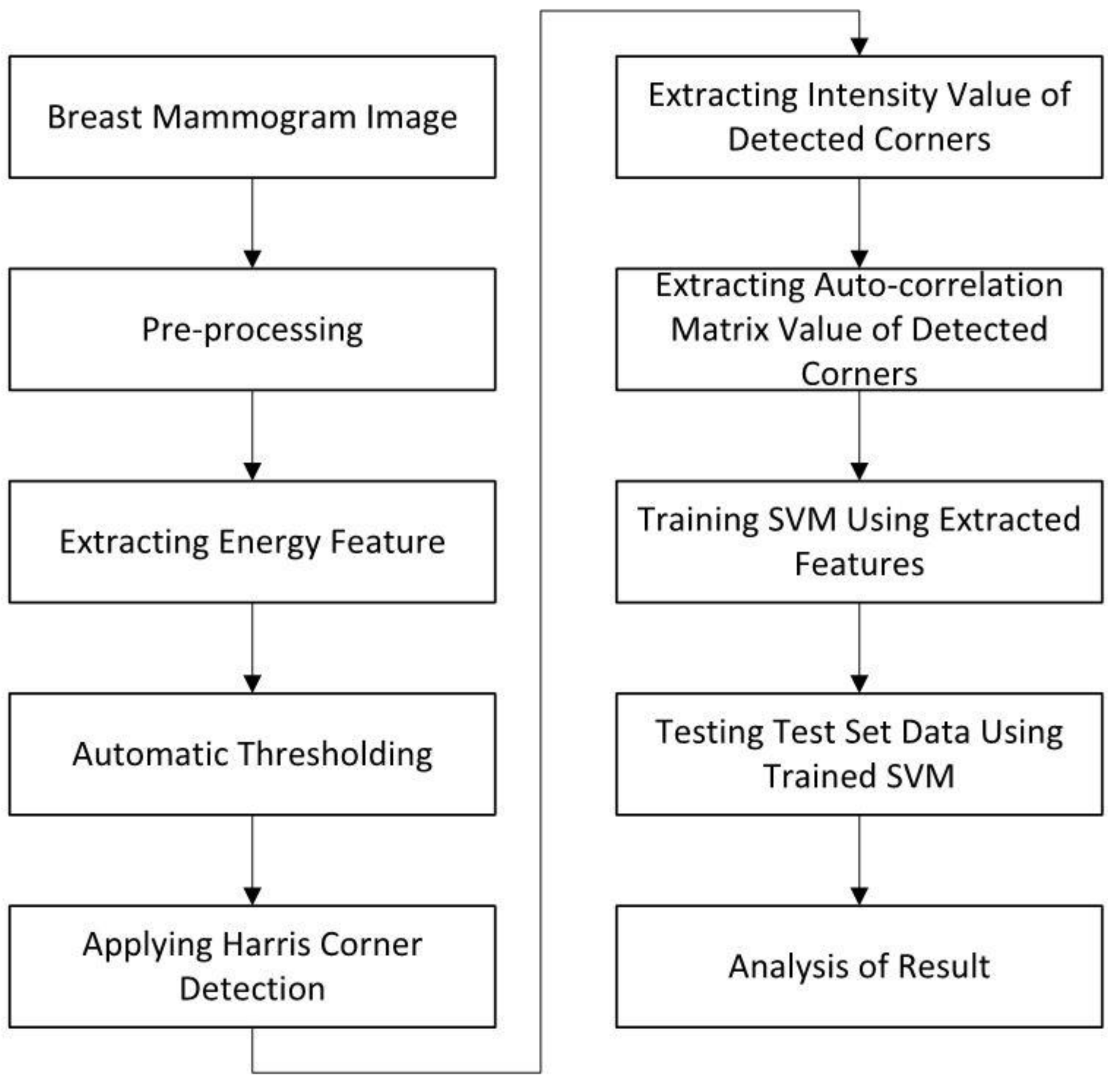
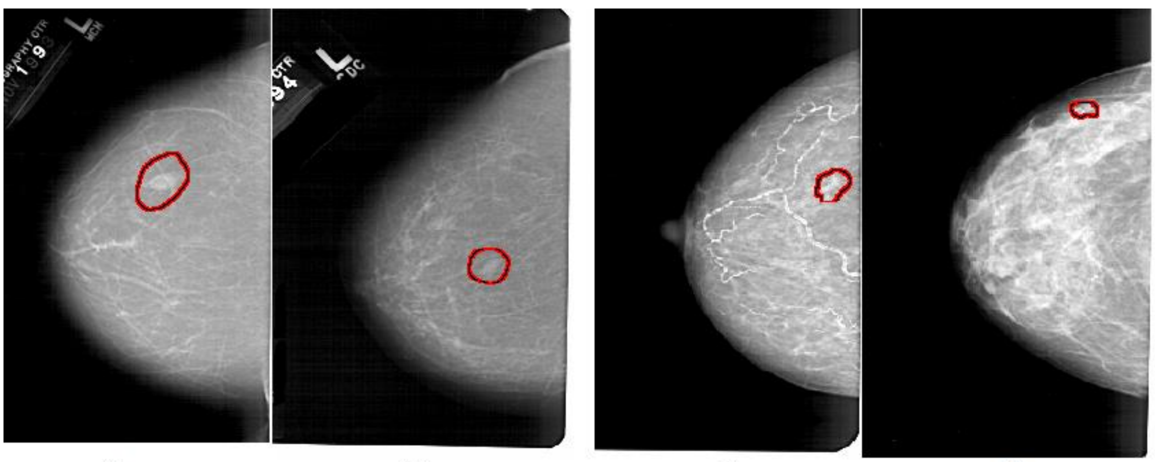


Figure 12. Flowchart of the Proposed Method

4.1. Input Images

The input images were used in this study are gray-scale images, thus, the pixel value is in range (0-255). Four sample input images are shown in figure 13. In which images a) and b) are benign and c) and d) are malignant, and the tumor area is shown inside the breast tissue. As it can be seen patient information and noise are also present in some of the images which were removed later using pre-processing step to increase the processing time and improving the accuracy of the algorithm.



a) b) c) d)

Figure 13. Sample images for both benign and malignant. a) and b) are benign, c) and d) are malignant

4.2. Pre-Processing

This is the initial step is to be done before the main process is being started. For the algorithm to be efficient it should deal with different images with different structures, sizes, brightness, and resolution. Three pre-processing steps were applied to all of the input images both for testing and training purposes.

4.3. Noise Removal

The first step is to remove the noise from the images, for this purpose, there are many filters to choose from, and here the Adaptive Median Filter (AMF) is used to remove the noise of type salt-and-pepper [26].

Noises are removed from the mammogram images using AMF. As a nonlinear filter, AMF with high denoising ability and efficient computational time can remove impulse noises. In this filter, for detecting noisy pixel, the value of an output pixel will be calculated based on the median value in a 3-by-3 neighborhood of the same pixel in the input image [6] [27].

4.4. Removing Unwanted Objects

The second is to remove unwanted objects outside of the breast tissue in the background. As two of the features were extracted using Harris Corner Detection (HCD) algorithm, it is necessary to remove unnecessary extra objects to improve the performance. In addition, if unwanted objects remain in the background, the execution time will be increased. Execution time for removing those objects in the pre-processing step is significantly less in comparison with the expected time of the main process, thus the total execution time will be reduced. An example is shown in the figure 14.

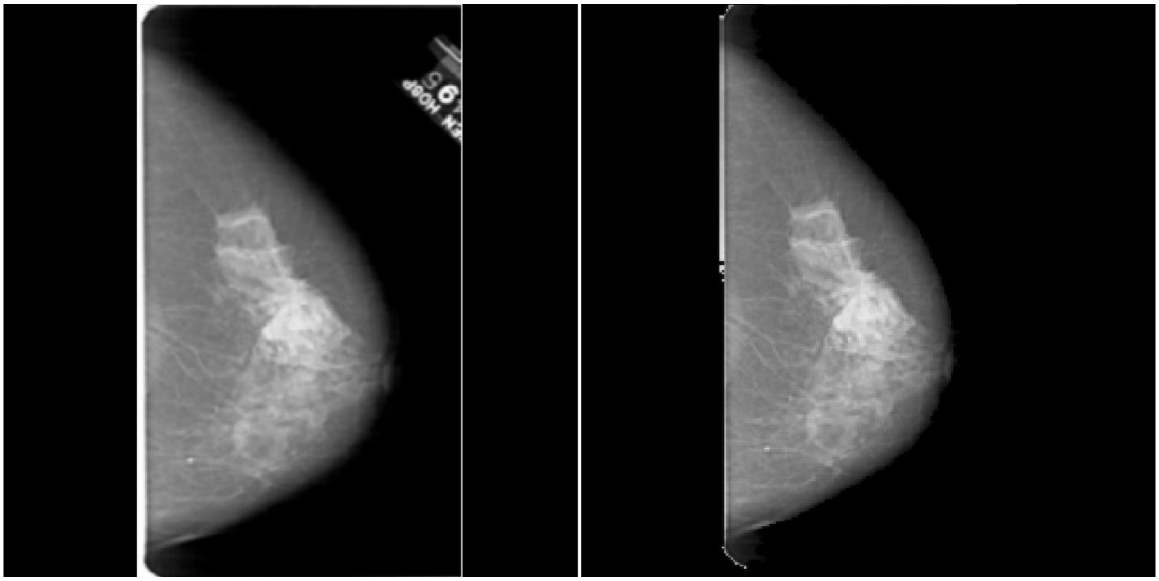


Figure 14. Images, Left: gray form of original image, right: gray form of pre-processed image

4.5. Improving Image Quality

The third is to improve the quality of the mammogram image, which makes applying the main process easier. There exist many algorithms can be used in order to enhance the contrast of an image. Using these algorithms, more details can be extracted and intensity contrast will be maximized [28]. For this purpose, after first two steps the histogram of modified image is extracted and equalized [29].

4.6. Image Acquisition

600 breast mammogram images containing 300 malignant images and 300 benign images were used. 200 out of 600 images were used for training the SVM model and the remaining 400 images were used to testing the SVM. In some studies, such as [13] coordinates of input images were ignored and images were used with the original coordinate sizes because the image’s coordinates were not the same. Using low-

resolution images can improve the efficiency for pattern recognition [30][31], thus in this study for consistency and efficiency all input images are converted to 256 by 256 pixels.

First, the images are imported to the program. These images are then sent through pre-proceeding for noise removal and size-conversion. After pre-processing step is done, the images were used for training the SVM, corners extracted using HCD and automatic thresholding. Intensity value of the detected corners which has a value in range of 0 to 255 is used as one of the input training data. Values of auto-correlation matrix and energy are other input training features.

4.7. Energy Feature

Energy of each image calculated with the equation (3) [15]:

$$Energy = \frac{1}{n} \Sigma_{i=1}^{n} I(x,y)^2 \qquad (3)$$

Where *I* is the pre-processed images, x and y are coordinates of a pixel in the pre-processed images, and n is total number of pixel in the pre-processed image, as it was mentioned earlier the size of the image will be converted to 256 by 256, thus n would be 65536.

4.8. Harris Corner Detection

A pixel is a corner region if its response is the local maximum value among all 8 surrounding neighbors [32]. So there is a significant difference between corner regions and surrounding pixels [33].

Using HCD, some pixels in the input image were detected as corners in the mammogram images based on values in the auto-correlation matrix. The elements of matrix are calculated based on equation (4).

$$M = \begin{bmatrix} A^2 & AB \\ AB & B^2 \end{bmatrix} \qquad (4)$$

Where A and B are directional derivatives, defined as (5).

$$A = \begin{bmatrix} -1 & -1 & -1 \\ 0 & 0 & 0 \\ 1 & 1 & 1 \end{bmatrix} \qquad and \qquad B = \begin{bmatrix} -1 & 0 & 1 \\ -1 & 0 & 1 \\ -1 & 0 & 1 \end{bmatrix} \qquad (5)$$

Derivate masks A and B will be applied to each input image, as it can be seen in figure 15 along with it corresponding pre-processed image.

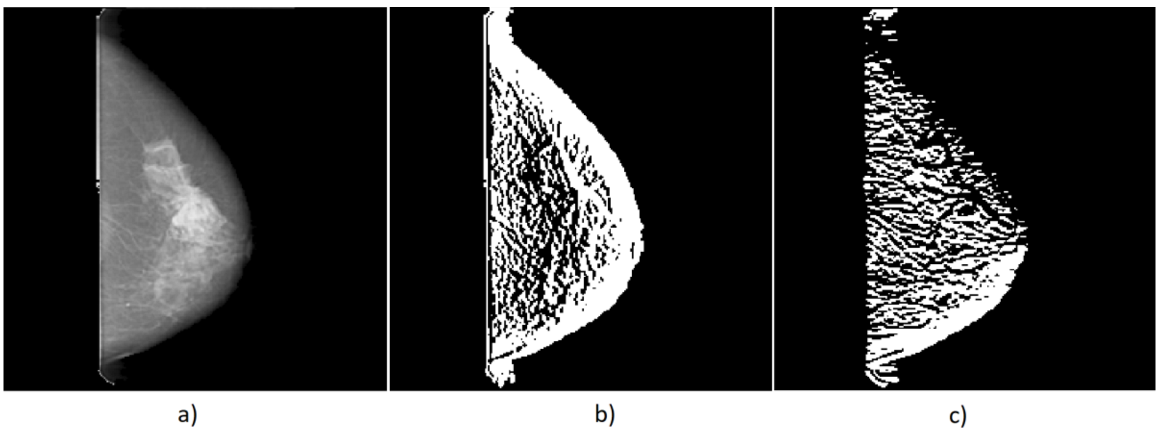


Figure 15. Result of applying two derivatives masks on the input image. a) pre-processed input image, b) result of applying derivative mask B, c) result of applying derivative mask A

As it can be seen some pixels inside of the breast tissue are shown as black which means that those pixels have the value of zero. This is due to the fact that after applying the derivative masks A and B, the result for some pixels were negative. Thus, as we know that out input image are gray-scale image and the pixel range for this type of image as mentioned before is in range [0-255] thus values less than zero will be mapped to zero.

Then Gaussian filter is applied to the matrix M, to generate the smoothed squared image derivatives. Next is to calculate corner response with the equation (6).

$$R = Determinant(M) - (0.04 * Trace^2(M)) \quad (6)$$

An example of generated result of corner response R can be seen in figure 16, this image is a gray-scale image, but for better visualization is converted to a black and white image.

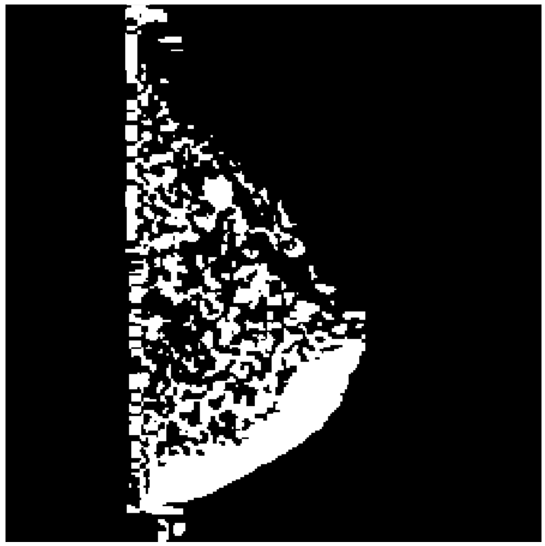
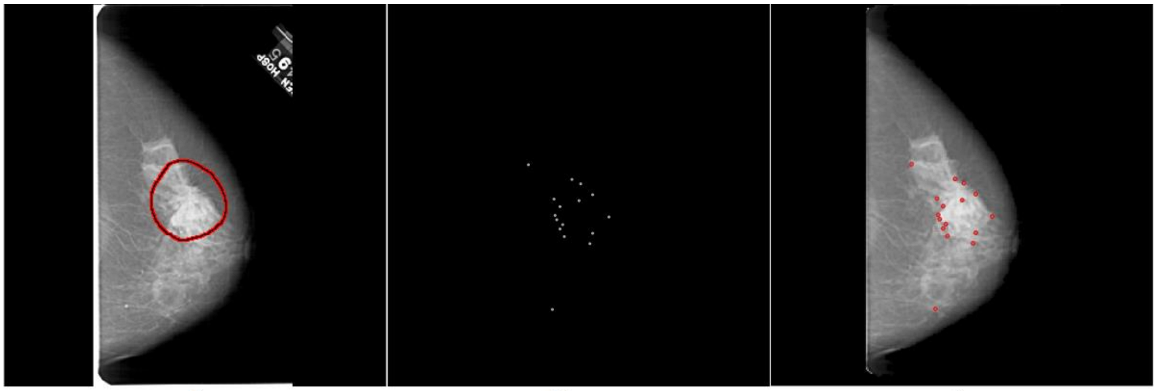


Figure 16.Ggenerated result of corner response R

A pixel will be detected as corner if the value of its response is greater than a specific threshold. This threshold can be set either manually or automatically [32]. In [13] manual thresholding was used to find the optimum threshold. In this study, automatic thresholding was used. The result can be seen in figure 17, a) is the original image with the tumor area shown, b) the detected corners, and c) detected corners on the pre-processed image.



a) b) c)

Figure 17. Result of corner response R after applying the automated thresholding

These detected corner pixels can be used as training feature of SVM along with other features for the purpose of classification [13]. Based on the investigating of the sample test cases, malignant cases have more detected corners than benign cases.

4.9. Support Vector Machine

SVM is a supervised learning model for classification of data implemented based on a separating hyperplane. There are two major steps: training and testing. First the algorithm is trained using labeled data for different classes. To classify data, the algorithm generates a hyperplane which separates different classes and assign every input of test set data to one of the defined classes [9][12].

4.10. Automatic Thresholding

Thresholding can be selected using both manual thresholding and automatic thresholding. If the threshold is selected manually, it might be optimum for a specific image or set of images, but not for different type of images. Using automatic thresholding, it is possible to make the process independent from type of input images. In this study, automatic thresholding was used and based on the result it can be said that the method is more accurate compared to methods using manual thresholding.

There are different automatic thresholding algorithms, and the one used for this study was for computing an optimal threshold for separating the data into two classes, and can be summarized as follows. First the histogram of the input mammogram image is computed, and a random threshold value is set. Using the starting randomly selected threshold the histogram is divided into two parts. Thus, data can be classified into two distinct classes, now the mean of each class is calculated, and a new threshold was calculated as the average of two classes' means. This process will be continued until there is no new value for threshold [34] [35].

4.11. Classification

To train the SVM algorithm two classes were defined as malignant and benign, where each class has a unique label; +1 for malignant and -1 for benign images, along with extracted features. Using the trained SVM classifier, for each input image, the output is an array of labels, called as prediction array. After the SVM is trained using those three features, it was tested using 400 mammogram images, 200 malignant and 200 benign. The result is shown in result and discussion section.

5. EXPERIMENTAL RESULTS AND ANALYSIS

To have a better evaluation of the proposed method in addition to previous steps discussed earlier, the number of test cases was also increased to test the proposed method under more complicated cases. Thus, in this paper the number of test cases was increased up to 400 (200 benign and 200 malignant), compared to existing method 1 [13] and method 2 [14] respectively 200, and 100. In this study, totally 600 mammogram images were used, the images were used is the subset of the same database used in [13] . Based on the method discussed in section 3.1 an image was classified as benign if the total number of plus ones are greater than total number minus ones and vice versa, this method is called ResultByCount [13]. Table 1 and 2 show correctly classified and misclassified images, the only difference between table 1 and 2 is that the numbers in table 2 are percent, and meaning of the labels in table 1 and table 2 are described in table 3.

To have a better evaluation of the results, the experimental result is also compared with proposed result in existing method 1 in [13] and existing method 2 in [14], in table 1, table 2, table 4 and figure 18 and figure 19.

Table 1. Comparison of the proposed method and two existing methods

	Existing Method 1 (out of 100)	Existing Method 2 (out of 50)	Proposed Method (out of 200)
TP	91	48	185
FN	9	2	15
TN	92	45	194
FP	8	5	6

Table 2. Comparison of the proposed method and two existing methods (%)

	Existing Method 1	Existing Method 2	Proposed Method
TP (%)	91	96	92.5
FN (%)	9	4	7.5
TN (%)	92	90	97
FP (%)	8	10	3

Table 3. Meaning of TP, FN, TN, and FP

Labels	Meaning
True Positive (TP)	malignant detected as malignant
False Negative (FN)	malignant detected as benign
True Negative (TN)	benign detected as benign
False Positive (FP)	benign detected as malignant

Precision and sensitivity (recall rate) can also be calculated in order to measure the accuracy of the proposed classification algorithm with the equations (7) and (8).

$$Precision = \frac{TP}{TP+FP} * 100 \qquad (7)$$

$$Sensitivity = \frac{TP}{TP+FN} * 100 \qquad (8)$$

Table 4. Comparison of Precision and Recall Rate of Two Existing Methods and Proposed Method.

	Existing Method 1	Existing Method 2	Proposed Method
Precision (%)	92	90.6	96.8
Sensitivity (%)	91	96	92.5

Precision can be referred as Positive Predicted Value (PPV), and recall rate as positive rate or sensitivity [36]. Figure 18 and figure 19 show the comparison between the proposed method in this study and existing method 1 used in [13] and existing method 2 used in [14] which the authors used Fuzzy Multiple-parameter SVM.

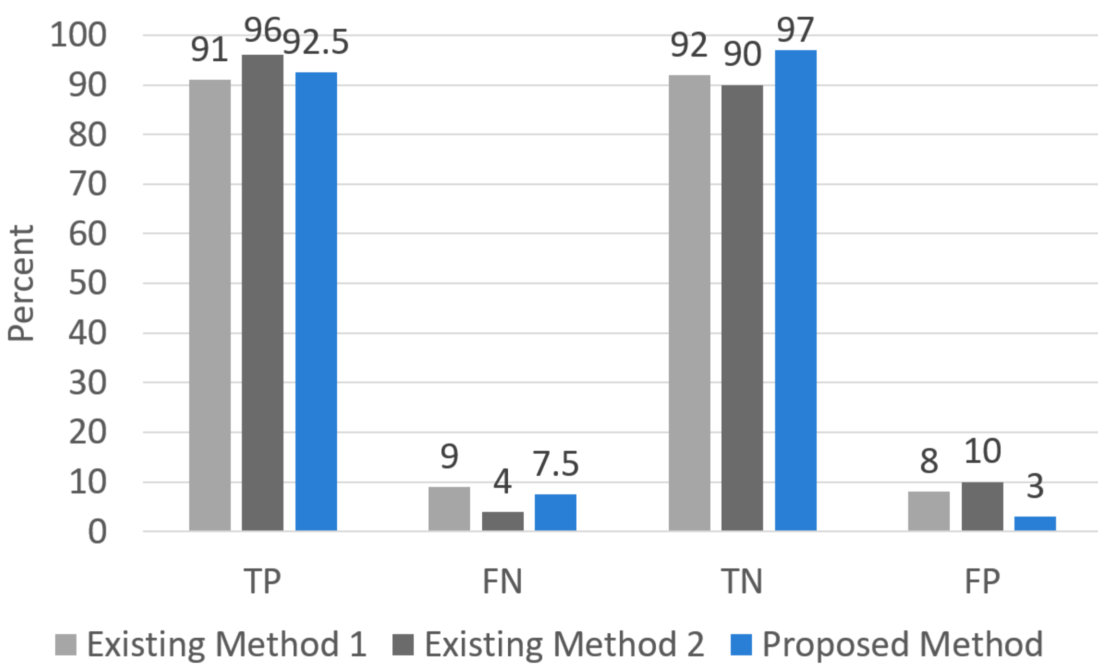


Figure 18. Comparison of the proposed method in this study and two existing methods (TP, FN, TN, FP).

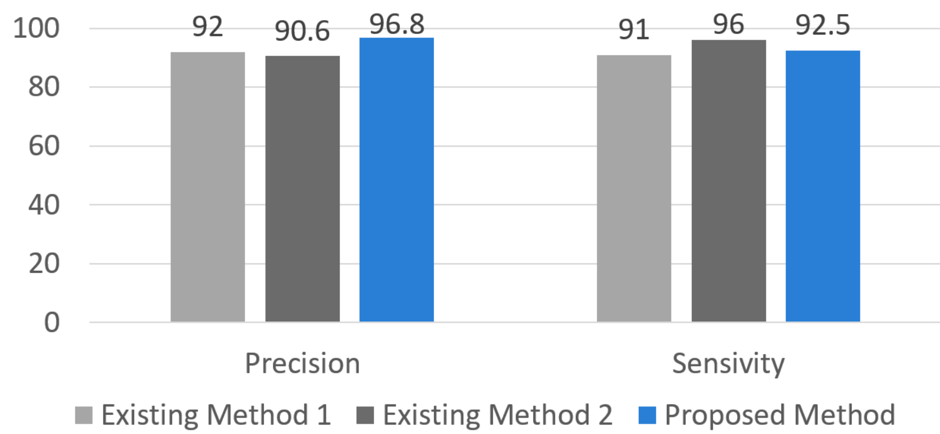


Figure 19. Comparison of the proposed method in this study and two existing methods (Precision and Sensitivity).

According to the figure 18, and figure 19, the proposed method in this paper showed better performance than both existing method 1 and 2, and better performance than existing method 1 in term of sensitivity. Existing method 2 showed better performance in term of classification of true positive and sensitivity, but as it was mentioned in result and discussion they used only 100 test cases to evaluate their method which seems insufficient.

6. CONCLUSIONS

SVM is a popular classification method and has been used in different areas, such as medical image classification. Thus, it can be used for better early detection of abnormalities in a breast tissue. Using suitable and the right number of training features, along with right number of training inputs, we can improve the accuracy, and efficiency of the SVM model for classification, and reduce the execution time. In addition, better results are generated as an effect of using pre-processing, and automatic thresholding, pre-processing step was used for both training and testing the algorithm. This study classified benign/malignant mammogram images using combination of SVM and automatic thresholding based-Harris Corner Detection. The results show that the proposed method has a better accuracy in classification of benign/malignant mammogram images when compared to previous research studies. The experimental result implies that using proposed method, more reliable result can be generated for early and further abnormalities diagnoses.

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