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Multi-classifier method based on voting technique for mammogram image classification

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ABSTRACT

Breast cancer is the disease most common malignancy affects female population and the number of affected people is the second most common leading cause of cancer deaths among all cancer types in the developing countries. Nowadays, there is no sure way to prevent breast cancer, because its cause is not yet fully known. But there are some ways that might lower risk such as early detection of breast cancer can play an important role in reducing the associated morbidity and mortality rates. The basic idea of this paper is to a propose classification method based on multi-classifier voting method that can aid the physician in a mammogram image classification. The study emphasis of five phases starting in collect images, pre-processing (image cropping of ROI), features extracting, classification and end with testing and evaluating. The experimental results show that the voting achieves accuracy of87.50 % which is a good classification result compared to individual ones.

Keywords: mammograms; breast cancer; multi classifier voting; early detection; image classification;

1. INTRODUCTION

Breast cancer affects women of all ages/ethnic groups. In spite of decades old breast cancer research regarding diagnosis and treatment, prevention continues to be the sole way to lower this disease's human toll which currently affects 1 in 8 women in their lifetime [1]. In the United States in 2012, an estimated 227,000 women and 2,200 men are expected to be diagnosed with this cancer, and around 40,000 women are expected to succumb to it [2]. The term "breast cancer" includes more than one disease being an umbrella term for various cancer subtypes of the human breast. Breast cancer subtypes differ in clinical presentations, and show clear cut gene expression patterns in addition to having different genetic/molecular characteristics [3, 4]. Breast cancer subtypes have some shared and unique causes, and contributing factors influencing prevention approaches. Mammography cannot stop or decrease breast cancer but are supportive only in detecting the breast cancer at early stages to increase the survival rate [5]. Regular screening can be a successful strategy to identify the early symptoms of breast cancer in mammographic images [6].

Medical images classification is a form of data analysis that extracts models describing important data classes. Numerous methods have been created to classify masses into benign and malignant categories by using the multi-classifier method [7]. In [8], the researcher proposed a computer aided diagnosis to detect cancer automatically in mammograms without any help of radiologist or medical specialist. After that, enhancement has been performed so that cancer can be clearly visible and identifiable. Results show that proposed method has achieved 96.74% accuracy as well as 98.34% sensitivity.

In [9], researchers compared the performance of an Artificial Neural Network, a Bayesian Network and a Hybrid Network used to predict breast cancer prognosis. The Hybrid Network combined both ANN and Bayesian Network. The Nine variables of SEER data which were clinically accepted were used as inputs for the networks. They achieved accuracy of (88.8%) using ANN and (87.2%) using Hybrid Network, both of the results outperformed the Bayesian Network result.

Classification methods are becoming vast and constantly increasing [10]. The aim of this study is to evaluate the classification methods of medical images and the development of multiple mammography based on the method of voting (fusion). Voting is an assembly method used to combine decisions of multiple works.

In [11], researchers used a voting technique to choose which of the answers based on their functionality equivalent versions produce. More recent research presented in [12], concerned the identification of breast cancer patients for whom chemotherapy could prolong survival time and is treated here as a data mining problem.

In this paper, we use techniques of voting, Voting is an aggregation technique used to combine decisions of multiple classifiers, normal and abnormal (either benign or malignant) mammograms. In its simplest form that based on plurality or majority voting, each individual classifier contributes a single vote. The aggregation prediction is decided by the majority of the votes, i.e. the class with the most votes is finally classified.

The remainder of this paper is organized as follows: Section 2 introduces the materials and methods, voting algorithm and technique. The experiment is given in Section 3. Results and discussions are provided in Section 4. Finally, Section 5 concludes the study.

2. MATERIALS AND METHODS

This study emphasizes on five phases starting with images collection, pre-processing, features extracting, individual classification and end with testing and evaluation followed by detail about each phase Figure 1 shows the five steps research method.

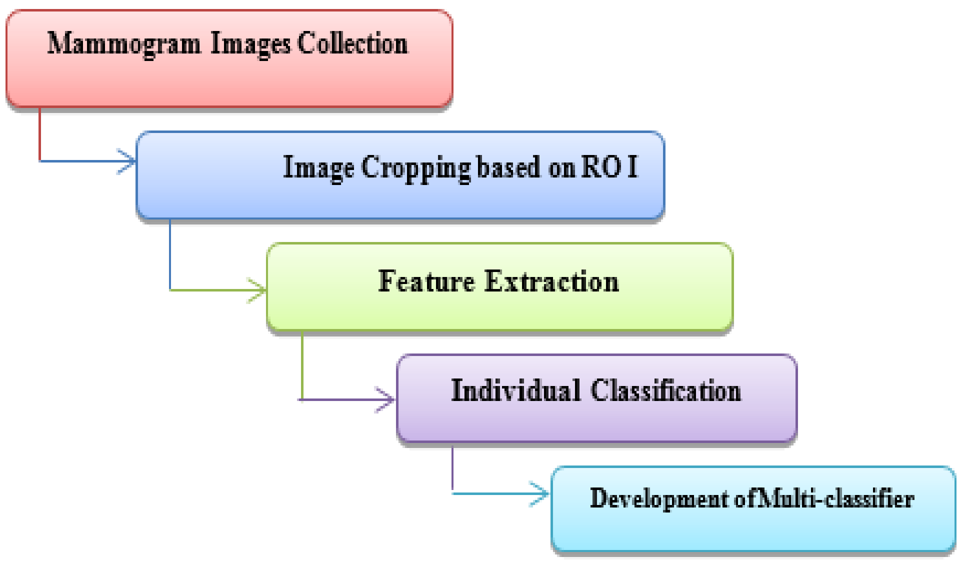

Figure. 1 Research phases

2.1 Mammogram images collection

Dataset used in this study is downloaded from the MIAS (Mammographic Image Analysis) database website [13]. This dataset was recently used by many researchers. MIA's dataset is used for experimentation purpose in this study which is a standard and publicly available dataset. The size of each mammogram is 1024 × 1024 pixels and 200 micron resolution. MIAS contains a total of 322 mammograms of both breasts (left and right) of 161 patients.

2.1.1 Image cropping based on ROI

Next step is to extract Regions of Interest (ROI). ROI's are defined as regions containing user defined objects of interest. Here we applied crop technique to the images; a cropping operation was employed in order to cut the interest parts of the image. Cropping removed the unwanted parts of the image usually peripheral to the regions of interest as shown in Figure 2.

Figure. 2 Full Mammogram with detected region of interest

2.1.2 Feature extraction

The accurate classification and diagnostic rate mainly depends upon robust features, particularly while dealing with mammograms, after cropping the Region of Interest (ROI) from [x] position to [y] position and [radius] depend on the MIAS dataset. This stage applies the six functions (Mean, Standard Deviation, Skewness, Kurtosis, Contrast, Smoothness) to extract the feature values from each mammogram image. The following paragraphs give more details about the six functions used to extract features values.

2.1.3 Individual Classification

The result of the previous three phases converts the data to numeric values. In this stage we apply five individual classifiers, namely SVM, Bayes Naïve and K-nearest Neighbours, Decision Tree and Artificial Neural Network. The process of classifying features into their respective classes, such as normal and abnormal or benign and malignant, is known as classification. In this paper we used the voting method on five classifiers (Decision Tree, NNA, BNC, KNN, SVM) to apply on medical image that is extracted from MIAS data set. In the next paragraphs, we review and present a brief overview of the five classifiers that are used in the classification stage of the mammogram images.

a) Decision tree

Decision tree induction is the learning of decision trees from class-labeled training tuples. A decision tree is a flowchart-like tree structure, where each internal node (non-leaf node) denotes a test on an attribute, each branch represents an outcome of the test, and each leaf node (or terminal node) holds a class label. The topmost node in a tree is the root node [14].

b) Support vector machine classifier

Support vector machine (SVM) is a statistical learning theory to analyse data and to recognize patterns. It is a supervised learning method. SVM has some benefits like it can handle continuous and binary attributes, speed of classification and accuracy is good. But there are few drawbacks such as SVM take longer time for training dataset and do not handle discrete attributes [15].

c) K-nearest neighbours classifier

Pattern classification the k-Nearest Neighbour (K-NN) is a non-parametric algorithm. The k-nearest-neighbour method was first described in the early 1950s. The method is labour intensive when given large training sets, and did not gain popularity until the 1960s when increased computing power became available. It has since been widely used in the area of pattern recognition, Nearest-neighbour classifiers are based on learning by analogy, that is, by comparing a given test tuple with training tuples that are similar to it [16].

d) Artificial neural network classification

Artificial Neural Network (ANN) has emerged as an important tool for classification. Neural networks were introduced by McCollum and Pitts in 1943. The artificial neuron is a computer simulated model stimulated from the natural neurons. The neuron is starting to work and send a signal through the axon once the signal extent to a certain threshold. This signal then transfers through to other neurons and may get to the control unit (the brain) for a proper action [17].

e) Bayes Naïve classifier

Bayesian classifiers are statistical classifiers. They can predict class membership probabilities such as the probability that a given tuple belongs to a particular class. Bayesian classifiers have also exhibited high accuracy and speed when applied to large databases. Naive Bayesian classifiers assume that the effect of an attribute value on a given class is independent of the values of the other attributes [18].

f) Development of multi-classifier based on voting method

In this phase, we proposed a multi-classifier based on the individual results obtained by each single classifier discussed above. The concept of our proposed approach depends on the voting method. Majority of the voting techniques are used to perform the final output of the given data. The voting technique presented by selecting the majority output from the experimental results of the five algorithms. The included Mammogram Image and transport data classification have five classes of output. The voting technique becomes difficult when the results of the five algorithms output equally during majority vote. Figure 3 describes the voting algorithm.

```
Begin
        Read class labels predict by ANNs classifier
        Read class labels predict by BNC classifier
        Read class labels predict by DT   classifier
        Read class labels predict by KNN classifier
        Read class labels predict by SVM classifier

            s = size of test instances
            For counter=1 to s1
        Sum=summation of five predicted instances
                If sum >=5Then
                        Set voting_output =1
                Else
                        Set voting_output =0
                End if
        End for
End
```

Figure. 3 Voting algorithm

3. EXPERIMENT

The study contains two main processes the first one is built for each classifier using the 60,70,85 percentage (119 mammogram 72 images , 84 images , 95 images) to training dataset from the data set and after building the classifier, the 40,30,15 percentage (47 images , 35% images , 24 images) of data is used in test stage. The results are presented in the upcoming section. To test the performance of the proposed method, different quantitative measures have been used. Accuracy has been used. These can be calculated by using mathematical equation 1:

$$\frac{(TP+TPN)}{(TP+TN+FP+FN)} \tag{1}$$

Where TP is True positive, FP is false positive FN is false negative and TN is true negative.

4. RESULTS AND DISCUSSION

In this study, MIAS data set was used for five individual classifiers and applied multi classifier voting based on continues data set. The highest precision was given with a good accuracy for 85% of data splitting, which was 87.50 %, while in 70% the accuracy was 84.28 % and in 60 % the accuracy was 76.59 %. Generally, the accuracy was increased after applying voting in the five precisions as shown in Table 1.

Table. 1 Results of the five classifiers

Data set	Tree	BNC	ANN	KNN	SVM	Voting
60 – 40	72.34 %	57.50 %	57.44 %	68.75 %	51.06 %	**76.59 %**
70 – 30	80.00 %	57.11 %	62.44 %	73.33 %	42.86 %	**84.28 %**
85 – 15	75.00 %	58.33 %	66.67 %	70.00 %	50.00 %	**87.50 %**

After applying three different sizes of training and testing we calculated the overall accuracy, the final results are shown in Table 1 and Figure 4. As a result, our method, namely multi- classifier, outperformed single classifiers. Even the voting produced higher accuracy than these methods. This result shows the accuracy of our method consisting of some classifiers.

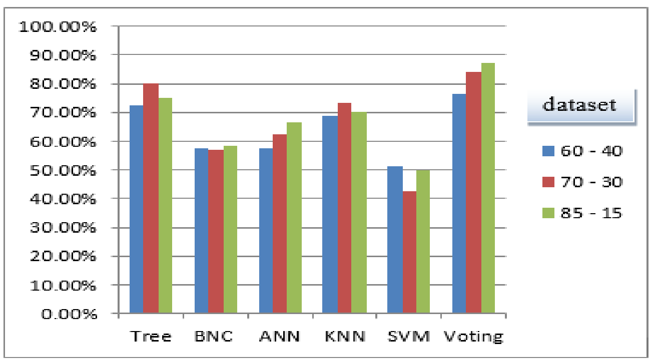

Figure. 4 Result of classification and voting accuracy

We compared five classifiers methods in this experiment: multi- classifiers (Decision Tree, NNA, BNC, KNN, and SVM) and the proposed method based on voting. Figure 5 shows the experimental results of the multi-classifier and voting method.

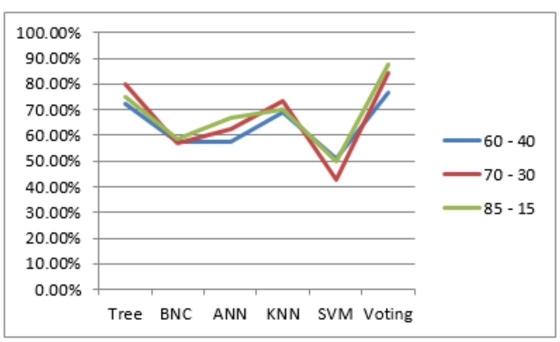

Figure. 5 The compared results multi-classifier and voting method

The main measurement of comparison is accuracy. In a previous study [19] researchers proposed a method to classify movie document into positive or negative opinions, consisted of three classifiers based on Decision Tree, ME and Score calculation. Using two voting method (Naïve and weighted and integration with SVMs, Classification accuracy is achieved by Naïve voting is 85.8%, Weighted voting is 86.4%, SVM is 87.1%. The output results are comparable to the work in the literature which achieves 87.50% accuracy. Future work can explore optimizing the classifiers for improving the accuracy.

5. CONCLUSION

This study aimed to build and implement the voting method on five classifiers (Decision Tree, NNA, BNC, KNN, SVM). The classifiers are applied on medical image that is extracted from MIAS data set. The study contains two main processes the first one is built for each classifier using the 60,70,85 percentage to training set from the data set and after building the classifier, the 40,30,15 percentage of data is used in test stage. The accuracy of the voting is 87.50 %.

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