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A Modular Framework for Multi category feature selection in Digital mammography

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Abstract. Many existing researches utilized many different approaches for recognition in digital mammography using various ANN classifier-modeling techniques. Different types of feature extraction techniques are also used. It has been observed that, beyond a certain point, the inclusion of additional features leads to a worse rather than better performance. Moreover, the choice of features to represent the patterns affects several aspects of pattern recognition problem such as accuracy, required learning time and necessary number of samples. A common problem with the multi category feature classification is the conflict between the categories. None of the feasible solutions allow simultaneous optimal solution for all categories. In order to find an optimal solutions the searching space can be divided based on individual category in each sub region and finally merging them through decision spport system. In this paper we propose a canonical GA based modular feature selection approach combined with standard MLP.

1. Introduction

Breast cancer is a primary cause of death in women. Early detection and diagnosis of breast cancer gives good chance of survival. While late detection and diagnosis often leads patient to unrecoverable stage of cancer ending in casualty. X-ray mammography is currently the most popular, cost-effective, low radiation dose and relatively accurate method of early detection of the disease [1]. The radiographs are searched for signs of abnormality by expert radiologists but mammograms are complex in appearance and signs of early disease are often small or subtle. That’s the main reason of many missed diagnoses that can be mainly attributed to human factors [2,3]. Since the consequences of errors are costly, there has been a considerable interest in developing methods for automatically classifying mammography abnormalities, as a means of aiding radiologists by improving the efficacy of screening programs and avoiding unnecessary biopsies. Neural network computer-aided diagnosis for detecting cases in mammograms, such as microcalcifications, has already been used [4-7].
In general, feature selection algorithms have two components: an evaluation function that scores candidate feature sets, and a search engine for finding those sets. Given a

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set of features the selection algorithm will examine a series of sets of features, and choose the one that maximizes the evaluation function. Recent comparative studies of feature selection algorithms can be found in [8].

In practical pattern recognition problems, a classification function learns through an inductive learning algorithm that maps a given input pattern to one of the existing classes of the systems. However the classifier can work well when a meaningful set of input feature is provided to it. Only a particular type of feature such as statistical or structural alone may not be the best possible choice. Hence a combination of different categories of features from the raw data set might provide very useful information for the classifier. This type of combination however leads to the formulation of multi category features as input set. In an addition the length of the feature vector thus increases to many extent. It has been observed that, beyond a certain point, the inclusion of additional features leads to a worse rather than better performance. Moreover, the choice of features to represent the patterns affects several aspects of pattern recognition problem such as accuracy, required learning time and necessary number of samples. Therefore the main goal of feature subset selection is to reduce the number of features used in the classification while maintaining acceptable classification accuracy.

A common problem with the multi category feature classification is the conflict between the categories. None of the feasible solutions allow simultaneous optimal solution for all categories. Whether an optimal solution for all categories leads to an optimal solution for one combined set of mixed multicategory feature can be another research question.

In this paper we propose a canonical GA based modular feature selection approach combined with standard MLP, which is capable of handling multi category features for the classifier. In order to find an optimal solutions, the search space is divided based on individual category in each sub region and finally merging them through decision spport system. We argue that the modular seletion works much better than general seletion in several aspects as follows:

Independency: The selection modules works independently. Hence each category of featue can be trained and tested independently and parallely,

Recombination: Crossover combines two parent chromosomes to produce a new offspring. The idea behind crossover is that the new chromosome may be better than both of the parents if it takes the best characteristics from each of the parents. In general seletion, each category of features will be terated uniformly. For single characteristics or category it wont cause any problem. But for multiple characteristics of feature, different characteristics will be combined together to produce the offspring. There could be a chance to carry out with mix offspring in next generation that can mislead the results.

Time Complexity: As we are dividing the serach space into different sub regions hence the time for modular selection to reach optimal solution will be much faster than general slelection. A good parallel implementation of the algorithm can have a much better time complexity than the general selection method.

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2. Methodology

The research methodology can broadly be classified into four modules, such as Preprocessing, Feature extraction, Feature subset selection, and Neural network based classifier.

2.1 Preprocessing

We are using the Digital Database for Screening Mammography (DDSM) dataset from university of South Florida. Each volume is a collection of cases of the corresponding type. Each case contains four mammograms from a screening exam. Once digital mammogram decompressed, suspicious area extracted from the mammogram. Suspicious area is marked in all digital mammograms of DDSM by three expert radiologists.

2.2 Feature Extraction

All together 40 features have been extracted that is based on the texture. These features can be sub divided into three categories such as statistical, structural and grey level dependency. Statistical descriptor includes mean, standard deviation, skewness etc. It describes the incentives of the gray level on that area. Structural descriptor contains energy, entropy, histogram, contrasts etc. These give indication of how the grey levels are distributed. Grey level dependency is related to the spatial grey level dependence matrix [1]. The matrix is constructed by counting the number of occurrences of pixel pairs at a given displacement.

2.3 Feature Subset Selection

The gereral framework is described in Figure 1. Each of the modules works independently on its own domain. They are built and trained for its specific task. Each of them is responsible to find out best combination of features from each category. The final decision is made on the results of the individual networks, often called decision system. The decision system is a Nural Network that is responsible to classify the input according .

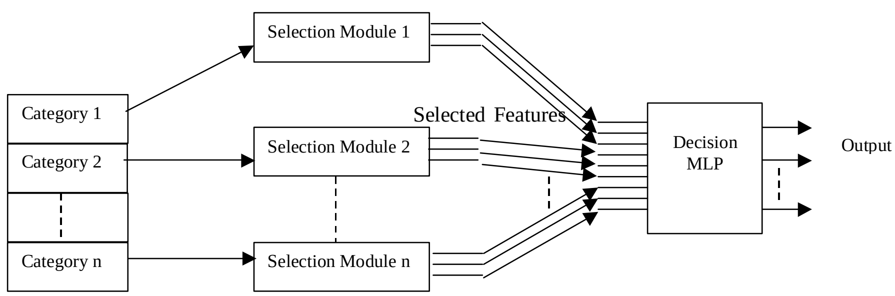

Figure 1 Architecture Framework

Selection Module

As described earlier, each selection module is responsible to select the best combination from a given set of feature as input. Feature selection algorithms have two components: an evaluation function that scores candidate feature sets, and a search engine for finding those sets. The training phase and the evaluation phase work together (Figure 2). In the evaluation phase the population is initialized randomly. For each member in the population, if the bit position holds a zero value the feature is assigned to zero and a new data set is created. With that dataset the neural network is trained. So for individual member in the population, there are individual neural network that has to be trained with the separate dataset. We are using traditional EBP algorithm to train the neural network. Then that trained neural network is used to calculate the fitness. To calculate the fitness of individual population, the feature vector is multiplied by the individual population.

If a particular feature is not selected, that place holds zero value. So the feature is multiplied by zero and neutralizing its effect on fitness. The stopping condition for training the neural network is to be equal for all the members in the population and it is taken as the classification error. The stopping criterion of the genetic algorithm is the number of generation.

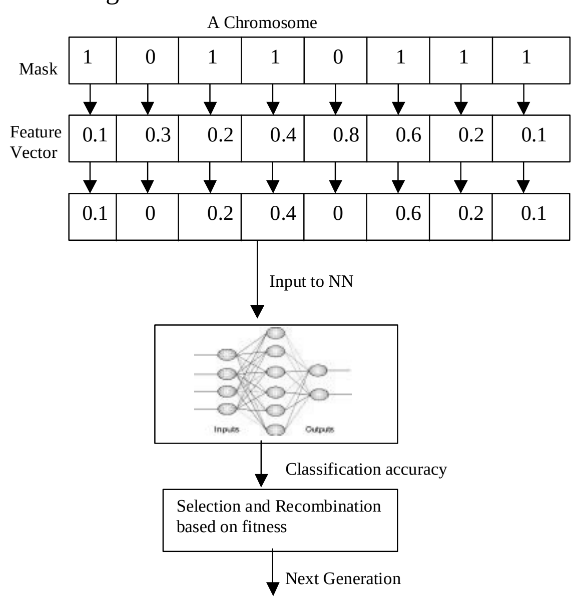

Figure 2 Selection Modules

Decision Module

Decision module is responsible to classify the results on the basis of output of each selection module. We are using a Neural Network as a decision system. Output form each selection module is fed to the decision NN. Depending on the feature selected from the different selection module, the decision neural network classifies the input pattern in three classes (Malignant, Benign, Normal).

3. Experimental Results

The proposed approach has been implemented in C++ and UNIX. We have used 100 cases of each Malignant, Benign and Normal for training. Hence the length of the training dataset was 300. Also we have used 20 cases of each Malignant, Benign and Normal for testing. Hence the length of the testing dataset was 60. The RMS error goal and the number of generation were fixed for all chromosomes to train the network.
The experimental results are shown in Table 1. The percentage classification accuracy given in table 1 is a 10-point cross validation results.

Table1 Experimental Results

Model	Malignant	Benign	Normal	Type I Error	Type II Error	Total	Training Time (m)[1]
Modular	90	85	85	3.33	10	86.66	92
General	80	70	70	6.66	20	73.33	140

4. Analysis and Discussion

Figure 3 shows the improvement of classification accuracy of the Modular neural network over the general model. Figure 4 shows the comparison of Type I and Type II error in both the cases. It is clear from the figure (Figure 3, 4) that the modular model works much better than the general selection model.

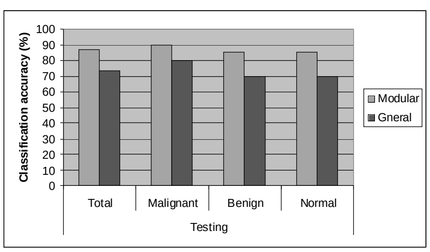

Figure 3 Classification Accuracy (%)

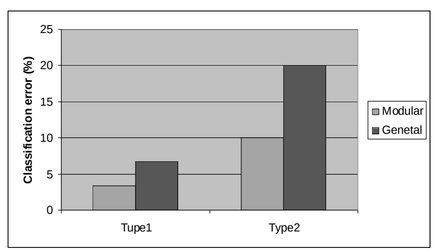

Figure 4 Classification error (%)

Figure 5 shows the improvement of time complexity in Modular neural network selection over the general selection model for 10-point cross validation. The modular neural network works almost 1.5 faster than general model. Figure 6 shows the comparison of number of feature selected in each category by the two models. Total number of feature selected by Modular selection model is less than total number of feature selected by the general selection model.

[1] The time is the total time for training the 10-point cross validation training set.

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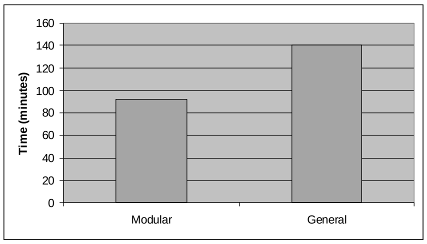

Figure 5 Time Complexity

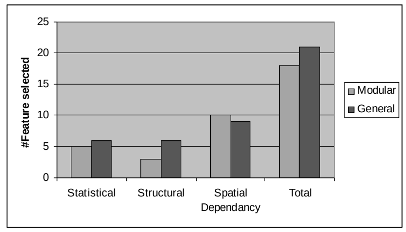

Figure 6 Number of feature selected

5. Conclusion

In this paper a novel modular framework was proposed that is suitable for multi category feature selection. The selection module uses combination of GA and neural network classifier. We have tested with Digital Mammogram dataset. We have used three category of statistical, structural and dependency features. We got 86.66% test classification accuracy. The modular selection model works faster than the general selection.

References

1. I. Christoyianni, E. Dermatas, and G. Kokkinakis: Neural Classification of Abnormal Tissue in Digital Mammography using Statistical Features of the Texture. IEEE, ICECS'99, Pafos, Cyprus, 1, 117-120(1999).
2. J. Martin, M. Moskowitz, and J. Milbrath: Breast cancer missed by mammography. AJR, 132, 737(1979).
3. L. Kalisher: Factors influencing false negative rates in Xerox-mammography. Radiology, 133, 297 (1979).
4. Z. Huo, M. Giger, C. Vyborny, D. Wolverton, R. Schmidt, and K. .Doi: Computer-Aided Diagnosis: Automated Classification of Mammographic Mass Lesions. Proceedings of the 3rd Int. Workshop on Digital Mammograph, Chicago, IL, 207-211(1996).
5. H. Chan, D. Wei, M. Helvie, B. Sahiner, D. Adler, M. Goodsitt, and N. Petrick: Computer-Aided Classification of Mammographic Masses and Normal Tissue: Linear Discriminant analysis in Texture Feature Space. Phys. Med. Biol.,40, 857-876(1995).
6. D. Meersman, P. Scheunders, and D. Van Dyck: Detection of Microcalcifications using Neural Networks. Proceedings of the 3rd Int. Workshop on Digital Mammograph, Chicago, IL, 97-103(1996).
7. A. P. Dhawan, Y. Chite, C. Bonasso, and K. Wheeler: Radial-Basis-Function Based Classification of Mammographic Microcalcifications Using Texture Features. IEEE Engineering in Medicine and Biology & CMBEC, 535-536(1995).
8. A. K. Jain, and D. Zongker: Feature selection: evaluation, application and small sample performance. IEEE Transaction on Pattern Analysis and Machine Intelligence, 19, 2, 153 - 158 (1997).