Evolutionary Modular Neural Network Approach for Breast Cancer Diagnosis

Bipul Pandey[1], Tarun Jain[2], Vishal Kothari[3] and Tarush Grover[4]

[1] Tata Consultancy Services Limited
New Delhi, Delhi, India

[2] Tata Consultancy Services Limited
New Delhi, Delhi, India

[3] Tata Consultancy Services Limited
New Delhi, Delhi, India

[4] Tata Consultancy Services Limited
New Delhi, Delhi, India

Abstract

Knowledge Discovery paradigms especially Soft Computing techniques like Artificial Neural Networks have been at the fore front of research aimed at solving the problem areas involved in many diverse fields of application. Automated diagnosis of deadly diseases is one of such fields that have seen much effort from researchers in the last few years. One area where this effort has been most felt is the diagnosis of breast cancer in women. However, development of a computationally efficient, detection-wise effective and robust framework for the diagnosis of breast cancer has still not materialized. The major problem here is the presence of a number of decision variables involved that makes this problem of diagnosis much more complex and intricate. This makes it difficult to be tackled by traditional computing paradigms efficiently. In this paper, we explain how the paradigms of modularity and optimization using evolutionary technique could be used to solve the aforesaid problem with significant success. Here, to take benefit of modularity, we make of use modular neural network instead of the traditional monolithic neural network for the recognition of input vectors implying breast cancer. Also, to make the architecture more optimal, we make use of genetic algorithms to achieve optimal connections (weights) among the neurons in each of the individual experts of the modular neural network. Experimental results show that the proposed approach has been significantly successful in dealing with aforesaid problem of breast cancer diagnosis with a training accuracy of 95.97% and testing accuracy of 96.5%. That is well above what shown by traditional approaches as described later on.

Keywords: *Breast Cancer Diagnosis, Genetic Algorithm, Modularity, Artificial Neural Network, Hybrid Computing.*

1. Introduction

Need for automated diagnosis of diseases has been closely felt in the last few decades. This need has been most acute in case of deadly diseases like cancer where early detection leads to much higher chances of successful treatment and recovery of the patient with considerable savings of financial resources. An example is the case of Breast Cancer in women. Breast is an extremely dangerous disease for the womenfolk. It has proved to be one of the biggest causes of mortality among women in the last many years. In USA, it is considered to be second leading cause of mortality among women and the most common cause of mortality in the age group 40 to 55 years among women [1]. In fact, in every thirteen minutes four American women develop this disease and one woman suffers death due to this disease [2]. Early detection is considered the best key to save the patient from the mortality due to this disease [3]. Because of such a scenario, researchers have focused their efforts for creating a diagnostic system for breast cancer.

Traditionally, diagnosis of diseases is done based on a number of tests done on the patient. The results of these tests are used by the medical practitioner to predict the presence/absence of a disease. However in case of many dangerous diseases, this task becomes rather myriad because the plethora of these tests not only confuses the medical practitioner, but also gives conflicting and non-conclusive results many a times. Hence, comes the need for an intelligent, automated diagnostic system for diseases. As this problem can be computationally modeled as a problem of retrieving relevant information from a plethora of reports or tests, the development of a computationally efficient and detection-wise effective system for disease diagnosis can be seen be an issue from the field of Knowledge Discovery from Data (or KDD). KDD is the nontrivial process of identifying valid, novel, potentially useful, and ultimately understandable patterns in data [4]. Being cross-dimensional, Knowledge Discovery from data uses algorithms and techniques from a vast array fields like Soft Computing, Pattern Recognition, Machine Learning statistics, AI, Natural Language Processing etc. [5]. This field of Knowledge Discovery from data sources has seen a massive upsurge of interest from researchers for last few years. This is due to an increasing usage of information retrieved from data sources towards the development and functioning of intelligent systems in diverse applications along with an increasing capacity to capture and store very large amount of data. Also, with ever increasing demand for valuable information from seemingly mundane sources, researchers are concentrating on the task of developing novel methods and applications for the efficient discovery and retrieval of such information. However, the complex nature of the data and massive amount of inputs makes designing such methods an extremely difficult task [6].

As explained earlier, disease diagnostic via computational methods can be considered to be an application area of Knowledge Discovery from Data. However in addition to deal with the usual complexity of such tasks, here an added problem is the presence of a very large number of decision dimensions that used to classify the input vectors properly. In this paper, we have tried to deal with this task by proposing a hybrid framework. This framework combines the twin paradigms of modularity and genetic algorithm to lead a more optimal solution to the problem at hand. In place of a traditional monolithic neural classifier, we use a modular neural network that combines a number of individual experts to act independently upon the input to give individual outputs which are then combined by an integrator. In order to have an optimal architecture for each of the individual experts, we make use of genetic algorithm to give an optimal set of connections among the neurons of each of the individual experts involved. The breast cancer diagnosis system so developed consists of a Modular Neural Network for classifying the input data vectors as cancerous or non-cancerous. This classifier consists of six individual neural network experts. These individual experts are Feed-forward neural networks with single hidden layers. The integrator used to combine their outputs is the fuzzy C-means Integrator. Each of the individual experts is trained by using genetic algorithm with the training data set. After training, the system so obtained is tested on the testing data set to classify and diagnose the input data vectors as either belonging to a patient with breast cancer or a non-cancerous patient.

2.The State of Art

Today, there are a number of screening techniques being used for the detection of breast cancer. A few are: positron emission tomography (PET), magnetic resonance imaging (MRI), CT Scan, X-ray, ultra sound, photo-acoustic imaging, tomography, diffuse optical tomography, elastography, electrical impedance tomography, opto-acoustic imaging, ophthalmology, mammogram etc. Though, all of these have their own advantage mammogram is the most popularly used technique and is considered the most reliable [7]. But, even this technique suffers from some serious limitations. Up to 30% of the breast grazes couldn't be spotted in mammogram during screening. Also, images on mammogram could lead to not required biopsies [8].This absence of any fully effective, efficient method of breast cancer diagnosis has led to a spurt of efforts by researchers in the field of KDD towards developing an automated computational system for breast cancer diagnosis.

Soft Computing paradigms have been a valuable source of methods and techniques to be used for the task of discovering, capturing and retrieving knowledge and relevant information from data sources [9]. Several major soft computing paradigms including artificial neural network, fuzzy logic, evolutionary algorithms have found themselves being applied to the problem of KDD in general [1]. These paradigms have also found increasing usage for disease diagnostics especially breast cancer diagnosis. Early works focused on using simple feed-forward neural networks trained with back propagation algorithm for breast cancer diagnosis with screening techniques like mammography [10, 11]. Even with these primary investigations, the accuracy rate achieved was very significant as compared to other non-computational, human-intensive diagnostics. Such early successes prompted further investigation into the problem using other neural classifiers and techniques. In [12], Support Vector Machine (SVM) is successfully employed as a Classifier for diagnosing breast cancer. Principal Component Analysis (PCA) is used to extract relevant knowledge in the form of features from ultrasound images of the patients. These relevant, independent features so obtained are then used as input to the SVM classifier to label each input as either cancerous or non-cancerous. Further research has focused on employing SVM based classifier along with feature selection technique for more accurate classification. Feature selection has been employed in order to reduce the number of inputs in order to decrease the complexity involved and increase computational efficiency [13]. Clustering has also been attempted on the problem. In [14], Self Organizing Map (SOM) technique has been used. Here, the analog video signal in sonography is used to obtain a digitized sonographic image. On this image, the SOM model is applied which uses 24 autocorrelation texture features for the classification task. Probabilistic Neural Network and General Regression Neural Network have also been applied on the said task [15]. The results so obtained show that General Regression Neural Network have been the most success in accurately identifying the nature of the input (cancerous or non-cancerous) as compared to other traditional neural classifiers used like Radial Basis Network (RBN) and Multi-Layer Perceptron (MLP). Some other researchers have used traditional data mining techniques like association rules along with artificial neural network to deal with the problem [16].

Though the use of these traditional monolithic neural models have been significantly successful for dealing with diagnostic task at hand, but further development of computationally more efficient and more accurate systems using neural network classifiers has suffered because of two major issues. The first is the problem of dimensionality. The problem of breast cancer diagnosis involves a large number of dimensions or attributes on which the classification is done and class labels decided. To deal with a large number of dimensions, Neural Network classifiers have to have a large number of neurons leading to a much more complex network. But such complex networks have lower performance [17]. Also, training becomes cumbersome and couldn't be done properly. The solution to this concern is the introduction of modularity. This is done by modular neural network which has a number of experts (neural networks) in contrast of the traditional monolithic neural network. This approach has been tested on the problem of breast cancer diagnosis. In [18], features selected from stepwise LDA have been classified by a modular neural network for the task of diagnosis. In several other efforts also, modularity approach has been found to be successful in providing a more efficient way for diagnosis of breast cancer [19, 20]. This paradigm of modular neural network has also been tested on similar problem of large decision dimensions like Biometrics, Financial Prediction [21, 22, 23, 24] and has been found to be much better as compared to other approaches involving traditional monolithic neural models.

The second concern is regarding the architecture of the neural network classifier used. The task of determining the architecture is human-intensive, hence prone to be sub-optimal. Researchers have tried to rectify this trouble by using evolutionary algorithms like genetic algorithm, particle swarm optimization etc. for getting an optimal topology (number of neurons, layers etc.) and optimal connections among neurons (i.e. evolutionary training). In [25], the problem of multi-modal biometrics is to be solved. Here, genetic algorithm has been used to optimize the modular neural network being used for the recognition task at hand. In [26], an evolutionary programming algorithm has been used to optimize both the connections and topology of the feed-forward neural network classifier being used. The optimized classifier thus used is then applied to the task of breast cancer giving fairly good results.

3.Methodology

In this paper, we have used the paradigms of modular neural network and genetic algorithm to deal with the twin concerns of dimensionality and sub-optimality of architecture. For the task of classifying the input data vectors, we have used a modular neural network (MNN) instead of a monolithic neural classifier. The MNN used comprises of six individual experts which independently work on the input vectors to produce their own output. These outputs are combined by an integrator (here, a fuzzy C-means integrator). In addition to it, genetic algorithm is used to obtain an optimal set of connections among the neurons in each of the individual experts involved by training each of the experts of the MNN.

3.1 Modular Neural Network

A Computational system that has two or more sub-systems that can work upon same or different inputs independently is said to show modularity. As such modular neural network are said to be those that comprise of two or more individual neural modules that can independently act on the inputs to produce output. This "Divide and Conquer" approach imbibes a number of advantages to such a neural network. These include complexity reduction in model, scalability, flexibility in design and implementation, robustness, and computational efficiency [6]. These properties make modeling of problems with a large number of dimensions very efficient and easy while using modularity.

The framework of the proposed approach is as shown in figure 1.

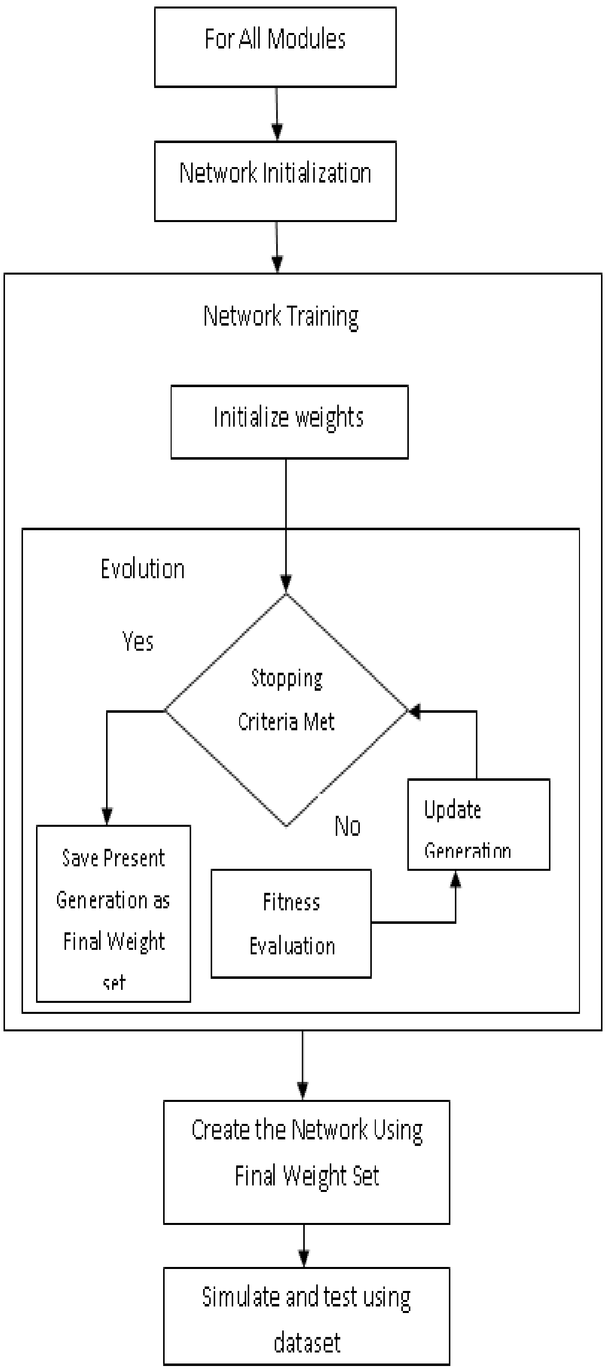

Fig 1. The Framework of the Proposed Approach

3.2 Genetic Algorithm

Genetic Algorithms are the most widely used among the evolutionary techniques for the task of optimization. They have been successfully used to give optimal architecture for the experts of a modular neural network. Therefore using the twin paradigms of modularity and genetic algorithms are considered to lead to far more efficient and successful solutions as compared to traditional monolithic modular neural networks [25, 26, 27]. Being an evolutionary technique, a Genetic Algorithm can be defined as a search and optimization heuristics that follows the natural process of evolution. The defining features that separate a GA from other evolutionary techniques are: Population of Chromosomes, selection according to fitness, crossover to produce new offspring and random mutation of new offspring [28]. Chromosomes are strings that encode prospective solutions for the problem being tackled. A population of these chromosomes is used for evolution. This evolution occurs over a number of generations. After each generation, the suitability (fitness) of each solution for the problem is checked using an objective function called fitness function according to which selection of solution set is done. These selected candidate solutions are then acted upon by genetic operators to produce the population set for the next generation. A few of these operators are: crossover, mutation, elite, add attribute, delete attribute, mutate number of neurons, and repair. Crossover uses two candidate solutions from the solution set and exchanges their data over a single or several crossover points to produce two candidate solutions. Mutation uses single candidate solutions from the solution set and changes a single data in the chromosome to give a new prospective solution. Mutation is used to give diversity to the solution. Elite takes a few of the fittest candidate solutions from the solution set and transfer them to the population of the next generation. It is used to preserve some local minima points in case one of them may be the global minima and hence, the most optimal solution to the problem. This process takes place until either the fitness threshold is achieved or number of generations is exhausted.

The first step here is to collect the relevant data for breast cancer from patients or subjects. The framework is to be used to classify and recognize which data set is cancerous or non-cancerous based on cell descriptions gathered by FNA image test. The data set used here is the breast cancer data from the UCI Machine Learning Repository for this purpose

(Wolberg, Mangasarian and Aha, 1992) [29]. The data set is then used to obtain training set and testing set. 70% of the entire data set goes into the training set while 30% goes into the testing set. Each data set comprises of data vectors with 30 decision variables and a class variable. The training data set is to be used for the supervised learning of each individual expert of the modular neural network. Now, the modular neural network is initialized. The modular neural network comprises of six individual neural modules. Each of these is a Feed-forward Neural Network. Each of the experts has one input layer with 30 neurons and one hidden layer with 30 neurons. The output layer has two nodes. Now, each of the experts is trained. Here, we have relied on Genetic Algorithm for achieving optimized connections among the neurons. This is done by using GA for training each of the experts. The genetic operators to be used in the approach are: Crossover (70%), Mutation (20%) and Elite (10%). For each expert, the weights are randomly initialized in the set [1,-1] equal to the number of the connections among the neurons of the expert. 30 such sets are taken as the initial population for the GA. The maximum number of generations is taken as 100. The maximum number of generations is also the stopping criteria for the Genetic Algorithm. After the first generation, the fitness of each of its member is evaluated.

The fitness function used here is the Root Mean Square Error (RMSE):

$$RMSE = (\sum(f(x_i) - y_i)^2 / 2)^{1/2} \quad (1)$$

Where $f(x_i)$ is the target and 'y_i' is the actual value and 'n' is the number of patterns used for training.

After this, the population is acted upon by crossover, mutation and elite to produce the population for the next generation. This process is carried on till the maximum number of generation is exhausted. After this, the set with the least RMSE is taken as the set of weights for the individual experts of the modular neural network. After using GA to train each of the experts in the way described above, the testing data set is used to test the approach.

4. Experimental Results

The objective is to apply and check the performance of the proposed approach (using training and testing accuracy) over the breast cancer diagnosis problem. The proposed approach is used to classify the given data vectors of the subjects as either cancerous or non-cancerous. The dataset used is the breast cancer data from the UCI Machine Learning Repository for this purpose (Wolberg, Mangasarian and Aha, 1992) [29]. The data set comprises of data vectors from 569 patients out of which 212 patients have breast cancer. Each data vector of the data set comprises of 30 decision attributes and a single class attributes. Attributes in the data set include radius mean of distances from center to points on the perimeter, texture means standard deviation of gray-scale values, smoothness means local variation in radius lengths, perimeter, area, smoothness (local variation in radius lengths) , compactness (perimeter2 / area - 1.0), concavity (severity of concave portions of the contour), concave points (number of concave portions of the contour), symmetry and fractal dimension (coastline approximation - 1).These are measured for a total of 3 cells. The data set has been initially divided into a training set and a testing set. The training set comprises of 398 vectors i.e. about 70% of the data set. The testing data set comprises of the rest 30% of the data set.

Matlab is used as the implementation platform. The Modular Neural Network has been coded on the Matlab while Genetic Algorithm of the GA toolbox is used in the implementation.

Initially, each of the individual neural modules of the MNN is initialized and trained with Genetic Algorithm using the training set. After this, the approach is tested using the testing data set. This process is repeated fifteen times. Then the mean training accuracy and the mean testing accuracy is calculated by calculating the average number of correctly identified and incorrectly identified data vectors. The results obtained are as listed in Table 1.

Table 1. Experimental Results Obtained from the Proposed Approach

S. No.	Property	Value
1.	Mean Training Accuracy	95.97%
2.	Mean Testing Accuracy	96.5 %
4.	Mean Correctly Identified Instances (Training)	382
5.	Mean Incorrectly Identified Instances (Training)	16
6.	Mean Correctly Identified Instances (Testing)	165
7.	Mean Incorrectly Identified Instances (Testing)	6

For comparison, we have also implemented and used four other widely used approaches for the same task in Matlab. These were: Multi-Layer Perceptron

(MLP) with BPA training, Fixed Architecture Evolutionary ANN, Variable Architecture Evolutionary ANN, and Modular Neural Network. The comparative results of these approaches along with that of the proposed approach could be seen in Table 2.

Table 2. Comparison of Experimental Results Obtained from Various Approaches

S. No.	Algorithm	Training Accuracy	Testing Accuracy
1.	Proposed Approach	95.97 %	96.5 %
2.	MLP with BPA	97.10%	94.52%
3.	Fixed Architecture Evolutionary ANN	94.00%	95.27%
4.	Variable Architecture Evolutionary ANN	97.16%	95.00%
5.	Modular Neural Network	97.54%	95.60%

5. Conclusion

The experimental results show that the proposed approach shows a very high training and testing accuracy for breast cancer diagnosis. The accuracy achieved for both training and testing is much better than that of the four other popular approaches used here. This shows that the proposed approach could be used to give better solutions to complex problems where we have deal with the problem of dimensionality.

Hence, the proposed approach could be used for other such complex problems like Biometrics, Robot Coordination etc. Also, other optimization techniques could be used in place of Genetic Algorithm like Particle Swarm Optimization, Ant Colony Optimization etc. All this is planned to be done in future.

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Bipul Pandey received his Bachelor (B.Tech) and Master degree (M.Tech) from Indian Institute of Information Technology and Management, Gwalior, India. He is currently employed as Assistant Systems Engineer at Tata Consultancy Limited, India. He has authored six research papers published in reputed international journals and conferences. His areas of research are soft computing, hybrid system design, Bioinformatics, Biomedicals and Biometrics. He focuses his research initiatives for presenting innovative technological solutions involving soft computing for connecting common problems to their more intelligent solutions.

Tarun Jain received his Bachelor Degree in Biotechnology from Thapar University, Patiala, India. He is currently Assistant Systems Engineer at Tata Consultancy Services, India.He is author of various International Journals in field of Biopharmaceuticals and Nanobiotechnology. Also, his research has been presented in various National and International Conferences. He focuses his interdisciplinary research on the field of Life science and Healthcare related issues.

Vishal Kothari received his Bachelors Degree From MIT, Ujjain, India. He received his Masters Degree from Indian Institute of Information Technology and Management, Gwalior, India. He is currently employed as Assistant Systems Engineer at Tata Consultancy Limited, India. He focuses his research initiative in the field of Bioinformatics and Soft Computing.

Tarush Grover received his Bachelor Degree from Thapar University, Patiala, India. He is currently Assistant Systems Engineer at Tata Consultancy Services, India. His areas of interest include Soft Computing and Biometrics.