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A Novel approach in Classification by Evolutionary Neural Networks

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Abstract

Artificial neural network is an interconnected group of natural or artificial neurons that uses a mathematical or computational model for information processing based on a connectionist approach to computation. Neural network optimization based on three basic parameters topology, weights and the learning rate. The over fitting is a problem in NN and it produced when discordant input data with before data. We introduce optimal method for solving this problem. In this paper genetic algorithm with mutation and crossover operators by two approaches on coding solutions by optimizing the weights and network structure is encoded. Also used the simulated annealing by this idea that coordination between mutation rate in GA and Temperature in SA is suitable for grid of local optimum, Plateau and fast learning.

Keywords: Classification, Artificial Neural Networks, Genetic algorithm, simulated annealing.

1. Introduction

A neural network (NN), in the case of artificial neurons called artificial neural network (ANN) or simulated neural network (SNN), is an interconnected group of natural or artificial neurons that uses a mathematical or computational model for information processing based on a connectionist approach to computation. In most cases an ANN is an adaptive system that changes its structure based on external or internal information that flows through the network. In more practical terms neural networks are nonlinear statistical data modelling or decision making tools. They can be used to

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model complex relationships between inputs and outputs or to find patterns in data. Genetic algorithm is a generalized search and optimization technique. It works with populations or chromosomes of "individuals", each representing a possible solution to a given problem. Each individual is evaluated to give some measure of its fitness to the problem from the objective functions. Three basic operations namely: reproduction, crossover, and mutation are adopted in the evolution to generate new offspring. The idea of combining GA and NN was introduced in 1980s. The idea is based on neural network by a genetic algorithm parameters are adjusted. The mutation and crossover operators can use the network to model artificial structures close to natural.

In one of the papers, idea is to combine the three hidden layers with 5, 10, and 20 neuron network structure is built and optimized by genetic algorithm hidden layer with 10 neurons and 50 iterations to converge the network has high accuracy and low overfitting. The accuracy even with repeated 5 and 20 neurons in the 100 and 1000 is not convergent and efficiency as much as 90% can be achieved [1]. The use of back propagation and cross validation in neural network with optimization by genetic algorithm. The results show that this method is better that random topology [2].

One serious problem in neural networks to avoid over fitting is a generalization of the network inputs is high. The solution to this problem is to avoid non-useful data on the network is using best practices. In fact, the use of a validation set can detect any irregularities in the data and prevents the optimal weights for the network[3]. The algorithm uses three fuzzy neural networks and genetic algorithm is the subject of another article. Firstly a fuzzy system, and network structure by training data to estimate the KNN method is optimized by genetic algorithm and the second stage is to remove excess neurons. Results due to the constant variance of fuzzy set parameters and accelerated learning algorithm will be reduced [4]. Balance between genetic programming and neural networks, the network topology are an interesting topic. In advance of his generation program using appropriate structure for the network gets updated. Performance results on some math functions show that the algorithm has several training and testing compared to

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the mean value of 90.32% is reached[5]. Combinations of genetic algorithms and neural networks in another two problems in NN that are permutation and convergence are discussed. This method tested on Cloud Classification. By weights of neural network by Genetic Algorithm optimization amounts to about 3% error is reached[6]. The face classification of game dices is other paper that used of back propagation in NN and delta coding in GA. Those results showed this method is effective for image and signal processing problems[7]. The Combination methods of genetic algorithm and simulated annealing are based on this idea that diversity rate and convergence to goal in genetic algorithm caused to general optimization.

Simulated annealing have a key parameter called temperature that if it is low then algorithm would be close to goal. Heuristic function for the combination this two algorithms is use of coordination in decreasing of temperature and mutation rate while reach to optimal goal. Another method for combination this two algorithms is using of suitable scheduling for temperature annealing for the people generation in the new generation also using of another idea whereas temperature calculation function in simulated annealing algorithm and fitness in the genetic algorithm [8]. We introduce a new approach on the combination of neural network and genetic algorithms. Our method is based on optimization weights on NN and change on structure of NN by GA. Indian Pima dataset used for method test. In following, we will describe how it worked. We obtain salient result of this work than other methods.

2. Combining GA and NN

The NN inputs to the forward and backward errors in the learning network and the number of turns. You can use the genetic operators and the output of the network structure was improved over generations. Also, a genetic algorithm, neural networks, thereby getting rid of the problem of local optimum and the plateau is gradient descend[9][10]. The combination ideas from nature, as human beings, their achievements and their understanding of the knowledge and experience acquired.

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In this work we tried to introduce a new approach for the combination of NN and GA with solving of overfitting problem. In our work, GA is a learning algorithm for NN, the structure of goal function is not important for us because that is hidden in neural network. Our solution is based on two model of genetic operator. We change mutation and crossover operators by the changes in NN weights and structure. Of course changes in structure of Neural Network have to be meaningful. We show two methods with different Challenges and results.

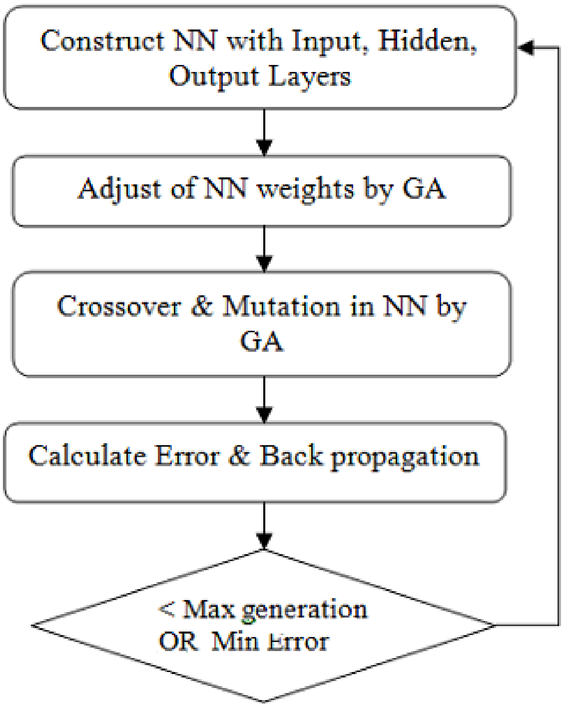

Figure 1: Flowchart of GA and NN

In Figure.1 the genetic algorithm used for optimization of neural network. The ring of algorithm finishes until reach to maximum generation number and or reach to minimum error.

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3. Neural Networks

A neural network (NN), in the case of artificial neurons called artificial neural network (ANN) or simulated neural network (SNN), is an interconnected group of natural or artificial neurons that uses a mathematical or computational model for information processing based on a connectionist approach to computation. In most cases an ANN is an adaptive system that changes its structure based on external or internal information that flows through the network. In more practical terms neural networks are nonlinear statistical data modelling or decision making tools. They can be used to model complex relationships between inputs and outputs or to find patterns in data. Two neurons neural network active in memory (ON or 1) or disable (Off or 0), and each edge (synapses or connections between nodes) is a weight. Edges with positive weight, stimulate or activate next active node, and edges with negative weight, disable or inhibit the next connected node (if it is active) ones.

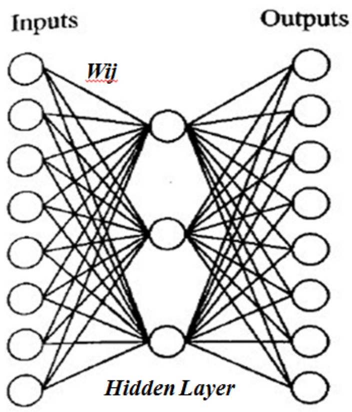

Figure 2. The Structure of Neural Network

The error in each output unit:

$$\delta_k = o_k\,(1\text{-}ok)(t_k - o_k) \tag{1}$$

The error in each hidden unit:

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$$\delta_h = oh\ (1\text{-}o_h)\ \Sigma_k\ w_{kh}\ \delta_k \tag{2}$$

Update weights:

$$\Delta w_{ji}\ (n) = \eta\ \delta_j\ x_{ji} + \alpha\Delta w_{ji}\ (n\text{-}1) \tag{3}$$

$\alpha\Delta wji$ (n-1), with $0 <= \alpha <= 1$: In order to avoid oscillations for rapid learning and the acceleration of the learning speed, a modified version of the back propagation learning algorithm may be derived using the concept of momentum term[11][12]. The effect of the momentum term for the narrow steep regions of the weight learning space is to focus the movement in a downhill direction by averaging out the components of the gradient which alternate in sign.

The value of weights:

$$w_{ji} = w_{ji} + \Delta w_{ji} \tag{4}$$

4. Overfitting Problem

One classical problem of neural networks is called overfitting, which occurs especially with noisy data. Is has been observed that excessive training results in decreased generalization. Instead of finding general properties of the different input patterns that match to a certain output, the training brings the network closer to each of the given input patterns. This results in less tolerance in dealing with new patterns. One Solution is using of evaluation of the network performance a different set of patterns than for the training. Hence, only networks that generate the ability to generalize are evaluated high[13]. To avoid overfitting problem, we have used a different method. When training a neural network with training data Overfitting Whenever we train stop and give the error propagates backward, and the training continues. Mean Square Error is very suitable method for this problem[14][15].

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In order to apply neural networks to data that is not yet the network architecture is very powerful. During the investigation we found that the results of large structures in many cases were successful and error trials are few. Genetic algorithm to obtain the optimal weights is very useful and convenient.

5. Weight Optimization

GA algorithm to adjust the weights of a back propagation neural network has a better performance than random search. Using crossover operator and without the mutation operator, better results can be achieved. Given that it is difficult to extract the function of neural network weights and may not be accurate mathematical model of it, but investigations show that such networks is a sine function. However, the GA can easily optimize this function[16][17]. Genetic algorithm combined with neural networks to solve problems with large number of features can be very effective. GA finds the optimal solution than local optimum solutions.

6. Genetic Algorithm

Genetic algorithm is a generalized search and optimization technique. It works with populations or chromosomes of "individuals", each representing a possible solution to a given problem. Each individual is evaluated to give some measure of its fitness to the problem from the objective functions. Three basic operations namely: reproduction, crossover, and mutation are adopted in the evolution to generate new offspring. To optimization of multi paths to destinations will construct one routing table that shows all finding paths in network. In this problem, each path assumed as a chromosome that first gene is source node and last gene is destination node and each row of table show multi path to destinations.

3.1 Chromosome structure

We have to encode and decode phenotype patterns versus genotype; this work is need to genetic operators. The chromosome is encoded in the weights in each layer are coded

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with values of zero and one. In the first step of the algorithm, the values are randomly selected and completed to the best of their coming generations. We have two encoding. Model1: Index Bit and Weight Encoding Bits:

1 01000001 1 10001111 1 11100110 1 10000001 0 10110110 1 00101000.

The distinct 1 is for each Layer and distinct 0 is other layer.

Model 2: The certain numbers of NN structures the same of above with this difference that each value of genome is the number of nodes in layer.

1 00001010 1 00000011 1 0000110 1 00000001 .

For example in above chromosome there are three layers in sequence ten inputs, two and six hidden layer and one output layer.

3.2 Population

In initialization steps the population size (PS) of chromosomes assigned by 100. The repeated chromosomes are removed in the initialization phase (all chromosomes are different from each other). This work decrease search space at different places (randomly) which increases the convergence rate.

3.3 Fitness function

The Back-propagation training cycles and its maximum value are suitable for fitness function. The Evaluating function for an individual is:

$$\text{Fitness} = \text{BP Number} / \text{Max (BP Number)} * \text{Network Error}$$

To obtain the maximum number of back propagation by field surveys should be obtained from networks of different sizes.

3.4 Crossover

We introduce two methods for crossover operator:

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A. Weighted Crossover

Crossover is used to cross breed the individuals, Using crossover operator, information between two chromosomes are exchanged which mimic the mating process. This operator exchanges half of two parent chromosomes and generates two Childs with by condition that paths to destination not miss. For the exchange each of genes checked before and after genes in parent chromosome that not cause missing of paths. Figure 5 show the crossover operator on two parents.

Before Crossing

Father 011110010011 001011011000

Mother 010100111110 010101111101

After Crossing

Child1 011110010011 010101111101

Child2 010100111110 001011011000

Figure 3: Crossover operator

We would like maintenance population diversity in preliminary generations and increase the convergence in end generations, at result assume crossover rate in first half generations equal 5.0% and in the second half generations equal 44.0%.

B. Structural Crossover

Guided crossover operator is based on the two point separation from parents are selected Left and right parts of them are related to each other by the condition to be meaningful With this new child of his parents is at[18][19]. But a new generation of the random choice to have reached this stage.

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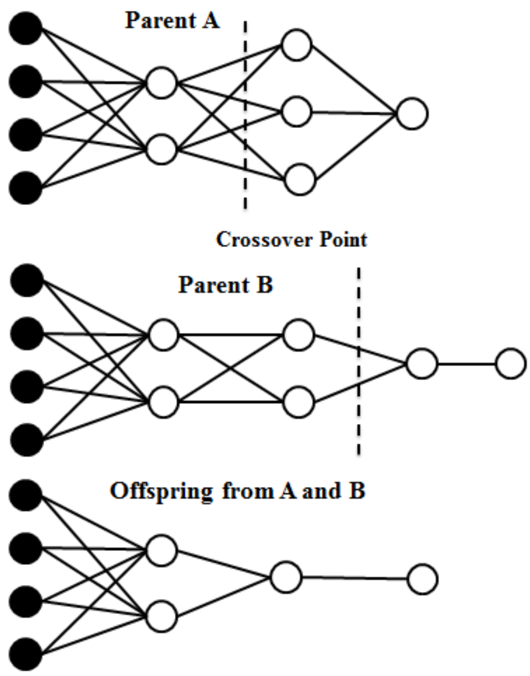

Figure 4: Structural Crossover

3.5Mutation

We introduce two methods for mutation operator:

A. Weighted Mutation

Mutation operator changes 1 to 0 and vice versa with small probability Pm. The mutation operator introduces new genetic structures in the population by randomly modifying some of the genes, helping the search algorithm to escape from local loop[20][21]. The values of gene is digit between one to eight and mutate gene had been different with pervious gene also had select that not miss path to destination.

Before	011110010011 001011011000
Mask	000101001001 100001001011
After	011011011010 101001110011

Figure 5: Mutation Operator

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Mutation operator maintenance the diversity in population so in the start of generations maintenance high diversity and in the end generations decrease this rate, at result this rate on the first half generation is equal 54% and on the second half is equal 15%.

B. Structural Mutation

Change in NN structure is other method that we used to optimization of solution. Insertion a hidden layer caused to mutation operator is much natural. As connection with father and mother nodes is easily. Weights of node and errors automatically calculated.

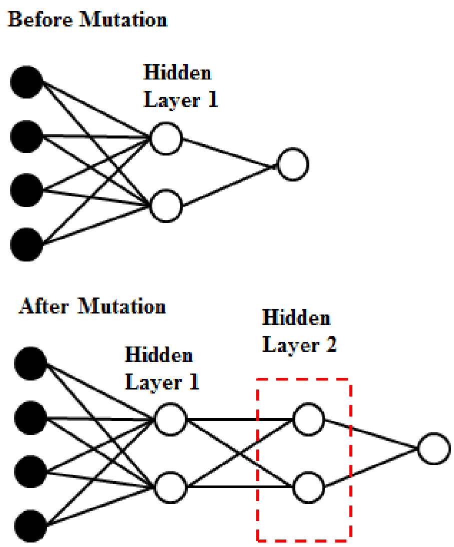

Figure 6: Insertion and Deletion Hidden Layer in NN

As an added layer can adjust the weights and the connection to the parent node of a network layer to be removed.

7. Simulated annealing algorithm in combination with GA

Simulated annealing algorithm (SA) is a general-purpose optimization technique and has been applied to many combinatorial optimization problems. The main idea behind SA

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is an analogy with the way in which liquids freeze and crystallize. When liquids are at a high temperature their molecules can move freely in relation to each other. As the liquid's temperature is lowered, this freedom of movement is lost and the liquid begins to solidify. If the liquid is cooled slowly enough, the molecules may become arranged in a crystallize structure. The molecules making up the crystallize structure will be in a minimum energy state. If the liquid is cooled very rapidly it does not form such a crystallize structure, but instead forms a solid whose molecules will not be in a minimum energy state. The fundamental idea of SA is therefore that the moves made by an iterative improvement algorithm are like the re-arrangement of the molecules in a liquid that occur as it is cooled and that the energy of those molecules corresponds to the cost function which is being optimized by the iterative improvement algorithm. Thus, the SA aims to achieve a global optimum by slowly convergence to a final solution, making downwards moves with occasional upwards moves and thus hopefully ending up in a global optimum [3].

SA algorithm is the following steps:

1. Create the decrease list of temperature with value in range [0,1]. (Annealing Cooling schedule)

2. Initializing population called by Path0 and assignment maximum value to path0. (Objective function)

3. Change in the population and create Path.

4. If fitness of path is great than maximum fitness then goes to 5 else go to 6.

5. New Path equal Path0 and maximum fitness is for Path.

6. If T[i] > Random (0,1) then (Acceptance function)

Path0 = Path.

7. If end of generation go to 3 else go to 8.

8. End

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Simulated annealing algorithm is useful method than genetic algorithm because of cause scape of local optimum goal. Also runtime of this algorithm is very lower of genetic algorithm. The Combination methods of genetic algorithm and simulated annealing are based on this idea that diversity rate and convergence to goal in genetic algorithm caused to general optimization. Simulated annealing have a key parameter called temperature that if it is low then algorithm would be close to goal. Heuristic function for the combination this two algorithms is use of coordination in decreasing of temperature and mutation rate while reach to optimal goal. Another method for combination this two algorithms is using of suitable scheduling for temperature annealing for the people generation in the new generation also using of another idea whereas temperature calculation function in simulated annealing algorithm and fitness in the genetic algorithm. The algorithm is combined to form two parent crossover and mutation operators selected to run after the worst fitness value of each of the four members of the child with fitness less than charges. The amount obtained by multiplying the inverse temperature,

$$\text{Exp}\ ((\text{Fitness } i\ - \text{Worst Fitness})/\ \text{Temperature}) \tag{4}$$

And if that digit number is 1 less than the value children place one parent put it. In the algorithm, the only work remaining, multiplied by the current value of a random value between 0 and 1 is the temperature and the amount obtained by multiplying the rate of mutation operator charges.

$$\text{Mutation Rate} = \text{Mutation Rate} * \text{Temperature}*\text{value}\ [0,1] \tag{5}$$

The new mutation rate is much better than common ide of change rating and is very effective for diversity in population. The Combination of GSA and Evolutionary Game Theory is based on optimization of EGT parameters by GSA. In fact each of the players wants to reach best fitness value. GSA algorithm is suitable solution for scape of local optimum obtain best fitness value that in result. We call combination of two algorithms by GSA-EGT and compare results to gather.

8. Simulation and Results

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For the test of algorithm performance designed a simulator by matlab software Simulink. First we designed all of the approach that describe on above and then implemented by algorithms in the software. The Pima Indians Diabetes database data refers to a medical problem, in which the diagnosis is carried out on several patients, in order to investigate whether a patient shows signs of diabetes according to World Health Organization criteria (i.e., if the 2 hour post-load plasma glucose is at least 200 mg/dl at any survey examination or if it has been found during routine medical care) [22]. The dataset available for this problem has been uploaded into the UCI repository in 1990, and includes 768 instances, composed of 8 attributes plus a binary class value, which corresponds to the target classification value. A value equal to 1 for this attribute means that the patient tested positive for diabetes, while a 0 value means that the test was negative for that disease. All input and output features are summarized in Table1.

Table 1: Dataset of Pima

Number	Attribute
1	Number of times pregnant
2	Plasma glucose concentration a 2 hours in an oral glucose tolerance test
3	Diastolic blood pressure (mm Hg)
4	Triceps skin fold thickness (mm)
5	2-Hour serum insulin (mu U/ml)
6	Body mass index, with weight expressed in kg and height expressed in m (kg/m2)
7	Diabetes pedigree function
8	8 Age (years)
9	Class variable (0 or 1)

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We distinct dataset to two set for training and testing of neural network. Training set have 30% and Testing set have 70% of total data. In the structural model of GANN, we had to increment number of generations for more learning by GA. Feature selection and classification is an important part of learning problems. There are many features will reduce the efficiency of the algorithm and its complexity. Among the methods for selecting the appropriate features, the algorithm is a decision tree. Learning algorithm of decision tree is ID3. The two features are closely correlated and the data used to select the appropriate features.One of the important parameters for testing methods is error rate on progress generation. As reader can compare the results of our paper with another works.

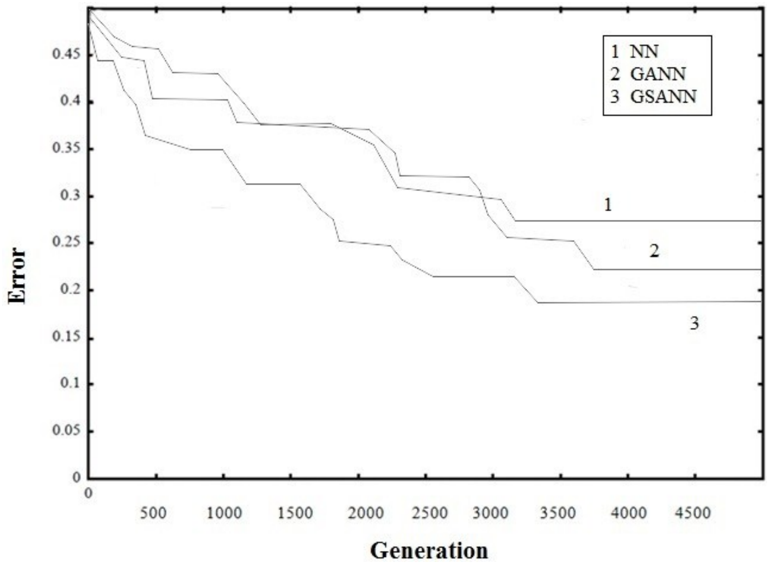

Figure 7: Error reduction with prograess generation

This Figure.7 shows that combination of three methods NN, GA and SA is the best result. We conclude that adjusting the NN parameters by GA is a good method and it can be better when combination with simulated annealing.

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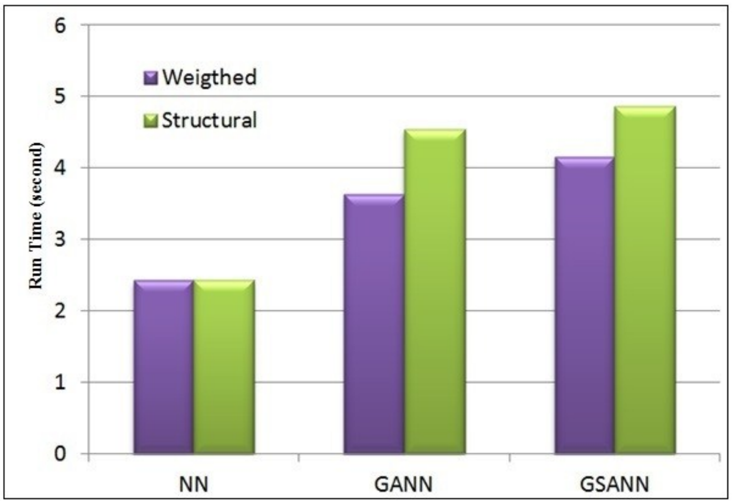

Figure 8: The Comparison of Run Time for different methods

This Figure.8 shows The Comparison of Run Time for different methods. The weighted model for GA same genetic programming need to more time for execution. In fact change and update neurons and layers in neural network are the complicated work. Table 2 show ten best results for Pima dataset by different methods.

Table 2: Results obtained with Pima Dataset

Method	Accuracy%	Reference
Logdisc	77.7	Statlog
IncNet	77.6	Norbert Jankowski
DIPOL92	77.6	Statlog
Linear Discr. Anal.	77.5-77.2	Statlog; Ster & Dobnikar
SVM, linear, C=0.01	77.5±4.2	WD-GM, 10XCV averaged 10x
SVM, Gauss, C, sigma opt	77.4±4.3	WD-GM, 10XCV averaged 10x
SMART	76.8	Statlog
GTO DT (5xCV)	76.8	Bennet and Blue
kNN, k=23, Manh, raw, W	76.7±4.0	WD-GM, feature weighting 3CV
kNN, k=1:25, Manh, raw	76.6±3.4	WD-GM, most cases k=23

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The results of simulation show that our approaches are very effective in solving classification problem. The use of common Pima dataset is a power benchmark for our works in compare with other methods. The weighted model reach good result but structured model reaches an excellent result. We obtain this result that structured model similar to Genetic Programming caused to the algorithm converge to optimal answer with more speed.

Table 3: Compare of Results

Accuracy%	**NN**	**GANN**	**GSANN**
Weighted	75%	78%	80%
Structural	75%	79%	84%

The number of hidden layer neurone is important problem for NN. The natural selection by GA help finding the number of hidden layer neurone and it progress on duration generations. The structured model of GANN finds better answer than NN but with much run time in simulation. The learning of GA is much better than NN with back propagation because BP is a method based on gradient descend and local optimum is a serious risk for that.Also the simulated annealing with GA is an effective solution for increase performance of total algorithm.

Conclusion and discussion

In this paper genetic algorithm with mutation and crossover operators by two approaches on coding solutions by optimizing the weights and network structure is encoded. This two model are very important in reach best result. The grid of local optimum, plateau and also create a natural selection for problem are power point of our method. We solve overfitting problem in NN with combination of evolutionary algorithms. Adjusting algorithm parameters are very vital. The obtain network is very

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robust versus noisy input data. To reach high accuracy, we spend more run time than other algorithms. Of course our method is optimal by simulated annealing and that is one of the reasons for increment of run time and another reason is change and update of neural network structure. The GSANN method with 84% accuracy is more better that other introduced methods in this paper. We suggest the machine learning methods for future work. Also other soft computing methods are suitable for classification problems.

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