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Successful evaluation of early term birth using hybrid ant colony: Genetic optimization algorithm

M. Varusai Mohamed
Assistant Professor, Department of Computer Science, Einstein College of Arts and Science, Seethaparpanallur

Dr. Mayilvahanan
Professor, School of Computing, VISTAS, Vels University, Chennai

***Abstract*---**Machine learning (ML) involves data mining, which is part of the science of data solving more problems. Machine learning application predicts the results depending on available data set. There are many predictive strategies available. The important method is dividing the most powerful predictions. Some of them predict results satisfactorily and some are accurately predicted. This research has carried out a process called as bagging based hybrid ensemble process that collects the accuracy of weak algorithms by combining many class dividers for improvement. This evaluation helps us to see the integration process that improves the accuracy in the result of preterm birth. This is not only the evaluation of weak separation algorithms, but also the use of algorithms using medical data, which predicts prematurely. This evaluation proves to be an effective method of classification by combining to improve the prediction accuracy of 96.2%.

***Keywords*---**category classification, data mining, machine learning, preterm birth, ant colony, genetic optimization.

Introduction

The complete gestation period is considered at 40 weeks of gestation. At 20 to 37 weeks of gestation, the onset of menopause should be delayed due to uterine contractions that result in the opening and closing of the cervix [1]. Identifying women who is pregnant at high risk of premature birth requires high accuracy to determine who will benefit from certain clinical interventions. Further improvement in outcomes to extend the gestation period from 28 to 36 weeks determines survival and reduces the cost of intensive care for newborns. 70% of premature births are more likely to die than premature babies [2]. Most

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premature babies are at risk for life-threatening complications such as infections, and behavioural problems [3].

Multiple analyzes have identified various independent risk factors alone through consistent analysis of their association with preterm birth. All of these studies have identified the problem of PTB but are unable to predict adequately. The results of this database using the multivariate logistic regression model show 24% and 18.2% sensitivity, as well as 28.6% and 33.3% specificity [4]. Early prognosis and diagnosis are important for health and economic well-being. Increased focus has been on reducing the effects of premature birth. This method is very expensive and also recommended to produce good outcomes [6]. Another talented approach which is to use Electrohysterography (EHG). It interacts with electrical activity in the uterus which is a form of electromyography (EMG). Lot of numerous studies have revealed that the record may vary for women., depending on the actual cut or false cut. EHG is a solid basis for predicting and diagnosing premature birth. Many studies have used EHG to predict or detect actual activity. Many machine learning variants, that are tested which obtains high accuracy using the new optimization algorithm [7]. In terms of results, these show that the selected class dividers perform much better than a particular method of doing things.

Literature survey

Tuyen Tran et.al explored the various predictive methods of predictability that are available to detect risk factors, to find interpretive predictive rules and the use of steady regression of educational and quantitative measurement programs, in order to get linear prediction models[8]. Batoul et.al used an artificial neural network (ANN) model for predicting early term birth in the PPPESO database based on physician insertion, eight birth variables namely Equality, Child Gender, Breastfeeding Purpose, Smoking, Pre-term and Premature Children. He has proven by using ANN broadcast transmission is the effect of change on the pre - distribtion of the data is operational and has acknowledged the effective performance of the function in improving accuracy [9].

M-M. M. Van Dyne et.al has used Learning from Examples using Incorrect Sets (LERS) where rules are applied to preterm birth data directly. The LERS model provided accurate results that predicted full-time cases of 78% and 90% of pre-trial cases and these were conducted separately and with 73% accuracy in them [10]. Nynke R. van den Broek et al. Studied regression associated with various factors obtained to find related factors independently of premature birth, premature and premature birth. Identify potential risk factors such as Women's pregnancy history, low birth weight, anemia and malaria during premature birth [11]. Masaki Ogawa et al. statistical analysis was used to identify the correlation between causative determinant and obstertric regression as well as unconditional regression used in multivariate analysis [12]. Colin Joseph Brown., (2017) noted that millions of babies are born prematurely (before 32 weeks of postmestral age) each year.

Infants are most affected by premature birth a very premature births with a high risk of delayed or modified neurodevelopment and premature birth [13]. S. Karger

AG., Analyzed in his research that fetal related respiratory disease is more common and more severe. It has found a clinical effect on bilirubin respiratory disease that combines both the potent neurotoxin and the antioxidant [14]. Ryan W Loftin, who proposed in his study that electromyography (EMG) uterine monitoring transmission (EUMTS), a real time non-lost transmission which solves such problems by using the unmistakable concentration of effective EMG data [15].

Proposed methodology

Classification in data mining is one of the most important functions. Separation algorithms also play an important part in predicting clinical data. The proposed system uses flexible separation methods to predict heart disease more accurately and effectively. Data mining uses patterns to identify relationships that can generate information so that decisions can be made effectively. The proposed method uses conventional mining class dividers that update the automatic integration model to represent the most recent concepts in data distribution. The concept used after the discovery of a novel class is that data points for one class should be closer and farther away from the data of other categories.

Measurement of Attributes

There is a data set with the N label on the set {x p: i = 1 to N} and p, k class labels. Every xr vector is with n parts. And every component is associated with the attribute value. Each Cp class has np data. The intraclass distance is calculated average and shows the density of data within the classroom. Therefore the average distance between the data is calculated as well as the average distance of the corresponding classes:

$$\mathrm{D}\ (1) = 1/\mathrm{N}\ \sum_{r=0}^{n} d(x(i), m(p)) \qquad (1)$$

Where m(p) = ($\sum_{i=0}^{n}$y(i)/np denotes the midpoint of class Cp and d represents the Euclidean distance.

Class-to-class distinctions are calculated by splitting into different categories defined as intermediate distances between the centers of all classes and the central area of all data sets.

$$\mathrm{D}\ (2) = 1/\mathrm{N}\ \sum_{r=0}^{n} d(y(i), n(r)) \qquad (2)$$

Qualifications weights are included in those classes as the Euclidean range involved in (1) and (2) should be replaced with

$$D\ (x,y) = \sqrt{\sum_{i=1}^{n} w\char`^2(x(i) - y(i)\char`^2} \qquad (3)$$

Database attributes with risk factors

Glucose Level : 3.9 ± 1.4, 4.8 ± 2.1
Maternal age: > = 40,31-39,21-30,15-20
Smoking : no / yes
Hemoglobin level : 10, over 10
Pregnancy number : 1, 2, 3, over 3
The number of low / high red cells is normal, abnormal
Funtus uterus-length : low / high
Types of birth: C-Section / vagin
Gender of the child: female / male
Perimeter of the baby's head : a very common abnormality
Weight gain during pregnancy : more / less

Hybrid optimization algorithm

GA is adopted for available solutions, and it updates the initial pheromone values. ACO searches as far as possible. In order to achieve a consolidation time that is approximately ta, they have developed a flexible integration strategy that sets the minimum Gemin (tb minute) multiplication, maximum xmax (tc minute) multiplication, and their fixed Gc fa of death. If the evolutionary loop returns a subtitle effect to Gedie generation, then the hybrid algorithm will end the loop of GA and initiate search of ACO.

$$\text{F-score (x)}= \frac{\sum_{i=1}^{n}(x-x(c))\char`^2}{\frac{1}{n}\sum_{j=1}^{n} x(j)-x(c)} \qquad (1)$$

Pseudo code:
Input: ACO data set input: ants number and ACO parameters (a, b, c and d)
GA input: chromosome number, total replication, cross-country and conversion rate
Output: selected features of the subset
Set the same amount of pheromones and heuristic information (Eq. 1)
% Chromosome production
Random Chromosome value activation
Do (for each repetition)
Measure demographic suitability (accuracy of segmentation based on organization policy)
Parental choice with roulette wheel policy
Crossover and Mutation (if their conditions apply)
Remove additional Chromosomes (by default)
% Ants production
Feature assign each ant individually and test it
Do (for each ant)
Read State Rule

Select the following feature.
Measure Ant (accuracy classification based on organization policy)
If three consecutive steps do not improve accuracy
Continue;
AcoGa ← Combine chromosomes with ants
Sort AcoGa according to category accuracy
Check termination condition (multiplication or accuracy number)
Return the best set below
Best_AcoGa ← Choose the best of AcoGa
Use Best_AcoGa in the next GA community without the number of random people
Review the pheromones of all ants
Finish

The complex time of the proposed algorithm is O (Imn), in which I am the multiplication number, m the number of ants, and the number of physical elements. In extreme cases, each ant picks up every aspect. As the heuristic test is performed after each element has been added to the sub-candidate set, this will result in testing for each ant. After the first repetition in this algorithm, the mn test will be performed. After repetition, the heuristic will be examined at Imn times.

Performance analysis

Mathematical measures that can be considered for sensitivity, clarity, and accuracy
Sensitivity = True Positive / (True Positive + False Negative) * 100
Specification = True Negative / (True Negative + False Positive) * 100
Positive prediction value (PPV) = True Positive / (True Positive + False Positive) * 100
Negative prediction value (NPV) = True Negative / (True Positive + False Negative) * 100
Accuracy = TP + TN/(TP + FP + FN + TN)

Given the two classes, we can say about the good records compared to the bad records. True credits refer to favourable records that are properly labelled by the divider, whereas true negative notes are negative records appropriately labelled by the divider. False positive negative records labelled incorrectly.

Table 2
Comparison of cost functions with multiple iterations

No. of iterations	AntColony+Genetic Algorithm	COA	GA
n = 50	0.011	0.120	0.005
n = 100	0.014	0.052	0.148
n = 150	0.025	0.001	0.030
n = 200	0.020	0.123	0.217
n = 250	0.015	0.011	0.001

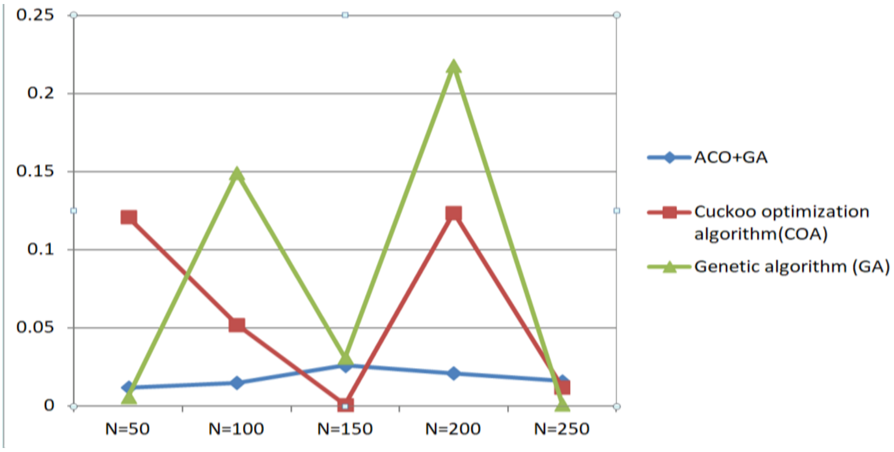

Figure 1. Cost function analysis

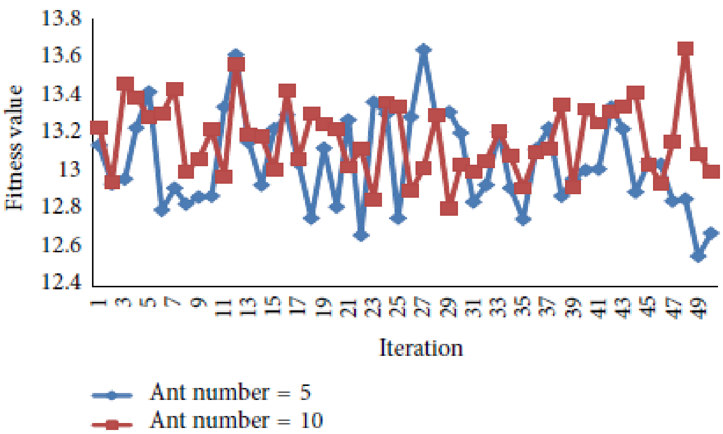

Figure 2. Calculating fitness function

The correct values of coefficient *a*, coefficient *b*, and volatilization coefficient *r* were 0.4, 8, and 0.3, respectively; these outcomes were similar to those of the normal method, but were achieved after 60 repetitions.

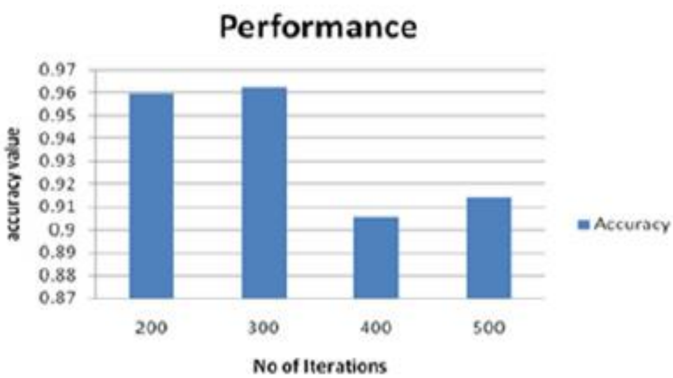

Figure 3. measurement of accuracy

A high accuracy of 0.9629 is obtained from the proposed algorithm which is very efficient according to the categories of premature birth data sets.

Conclusion

This finding concluded that this algorithm improved the accuracy of 0.9629 [96%] in duplicate=200 which provides the best performance of this effective algorithm and reduces the rules related to number of predictions needed to separate training and database analysis. The premature birth phase can be successfully implemented using the division of attributes into two groups as opponents and the number of attributes can be changed competitively between generations using a hybrid algorithm.

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