Birth Asphyxia Classification Using AdaBoost Ensemble Method

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***Abstract*—Birth asphyxia is a major public health problem in the maternal and child health. It is the cause of illness, death or disability of a newborn baby. If doctors and staff have awareness to prevent and provide the proper treatments in timely manner, it will affect the quality of life of children in long-term. The purpose of this research is to predict birth asphyxia occurring using three base classifiers; Backpropagation Neural Network (BPNN), Support Vector Machines (SVMs), and Decision Tree (DT). Moreover, the popular ensemble learning, AdaBoost, also applied with the three base classifiers to improve their performances. The data used in this research were birth asphyxia data collected from Chaoprayayomraj Hospital, Thailand during 2006 – 2011. The results showed that DT model gives the best performance in all evaluation measures. However, AdaBoostBPNN model, instead, gives the best improvement with the accuracy of 87.80%. This model can be used to guide doctors and staff for preparing intensive care in special cases to prevent birth asphyxia occurring and reduce the rate of death and disability of the newborn.**

***Index Terms*—birth asphyxia, classification, ensemble classifier, AdaBoost method**

I. Introduction

Birth asphyxia is characterized by hypoxemia (decreased PaCO2), hypercarbia (increased PaCO2), and acidosis (lowered pH) [1] and [2]. It is a major public health problem in the maternal and child health. Birth asphyxia is the cause of illness, death or disability of a newborn baby. If doctors and staff having awareness and trying to prevent or provide the proper treatment in time, it will affect the quality of life of children in long-term. The birth asphyxia [1] can occur during pregnancy, childbirth and postpartum period. The risk factors can be grouped into three areas: delivery factors, maternal factors and infant factors. The World Health Organization [3] was classified the birth asphyxia into two levels: severe birth asphyxia level that is level with the APGAR score at 1 minute was 0-3, and mild or moderate birth asphyxia level that the APGAR score at 1 minute was 4-7. The APGAR score [4] is an assessment of the newborn which considering: observing the color, pulse or heart rate, reaction in response to stimuli, movement or tightening of the muscles and baby's breath. The measuring points are in the first minute of birth and repeat in 5 minutes after birth. In Thailand, determining criteria of birth asphyxia is the APGAR score at the first minute is less than or equal to 7 [3], [5]. In addition, the extension of the Maternal and Child Health Department of Health has set a goal in rate of occurrence of birth asphyxia not more than 30 per 1,000 live births and in 11th National Health Development Plan (A.D. 2012-2016) required the warning system that can be dealt Health threat with effectively.

There are number of researchers studied important factors that cause birth asphyxia, such as: Montri Puripunyavanich [6] studied risk factors related to birth asphyxia of newborns at Sena Hospital. The data was analyzed in terms of frequency, percentage, mean, chi-square and multiple regressions. The significant risk factors related to a newborn Apgar score at the first minute were gestational age, hypertensive disorders in pregnancy, delivery method, premature rupture of the membranes, prolonged 2nd stage of labor, narcotic drug used (Pethidine) in the 1st stage of labor, birth weight, meconium stained amniotic fluid, fetal presentation and fetal distress. N. Fatemeh et al. [7] studied risk factors for newborn babies due to lack of oxygen in a Tehran Hospital, Iran. It is found that the factors are premature, baby weight, the use of the respirator, the placenta in the womb, APGAR score, and maternal infertility.

Computer technology is widely used for collecting data for searching causes and trends, analyzing and making decision for management plan. Predicting the occurrence of birth asphyxia, will be beneficial to all mothers and child. The research process will start to explore potential factors then bring the data mining techniques to analyze the data in order to get the knowledge that benefit can be applied to help in decision strategic. It is popular to apply for forecast or predict the occurrence of various diseases in the field of public health. Therefore, in this research has adopted the concept of data mining techniques to predict birth asphyxia by using the ensemble learning, AdaBoost with three base classifiers. The remainder of this paper is organized as follows. Overviews of related theories are briefly described. After that, evaluation metrics are defined. Then, the experimental studies are presented. Finally, conclusions and discussions are drawn.

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II. Related Theories

A. Classification

Classification or Prediction is a task in data mining that involves decision or forecast in an unknown or a feature situation. It is the process of constructing a model that descripts and distinguishes different data classes or estimating target values, for the purpose of being able to use the model to predict the class of objects or the expected value of unknown attribute [8]-[10]. The classification techniques are available in a variety of techniques.

B. Backpropagation Neural Network

The backpropagation neural network (BPNN) [10] is approach of multilayer perceptron that learns by adjusting the weights in the connections between the appropriate nodes. The adjustment is based on the difference of the calculated output with the actual training data. It has learning basics of imported, and will affect the spread of the system into the network layer-by-layer with a through the weights until the output of the network. In turn, the process of backpropagation that is the weights of the network will be modified depending on the error of the calculated result of network [10] and [11]. The BPNN architecture consists of three layers that are (1) Input layer represents the input variables, which use the linear transformation function, (2) Hidden layer represents the interaction among the input nodes, which use a nonlinear transformation that is a sigmoid function, and (3) Output layer represents the output variables. The number of the output nodes is determined by the problem [12].

C. Support Vector Machines

Support Vector Machines (SVMs) are supervised learning machines that can be used for pattern recognition and regression. The model is a representation of the examples as points in space, mapped so that the examples of the separate categories are divided by a clear gap that is as wide as possible. It has strategy to find the best hyperplane on input space called the structural minimization principle based on statistical learning theory [13]. All possible hyperplanes that separate the training examples, the one is chosen which maximizes the margin, the sum of the distances between the hyperplane and the nearest positive and negative example. SVMs can also efficiently perform non-linear classification using a nonlinear kernel function, implicitly mapping their inputs into high-dimensional feature spaces [8], [10] and [12].

D. Decision Tree

Among several classification algorithms, decision tree learning (DT) is one of the most popular methods. Decision tree structures are constructed in top-down recursive divide-and-conquer strategy manner. Its structure includes nodes and branches modeling from the training data. The algorithm will find the most powerful feature that will be used to separate training data into two or more subsets based on the values of that feature. The first node is called root node. Each data subset then continued separated until a termination criterion is satisfied. Decision Tree is supervised learning by using the data which the answers have already known and used for building the tree [8], [10] and [12].

E. AdaBoost Ensemble Method

Ensemble classifier is a method that relies on more than one classifier which each classifier has its own process and execute with the same data. The result for classification of each classifier which these result is taken through to vote for the best results of a single classification [14]. The most popular ensemble learning methods are bagging and boosting method [15] and [16]. AdaBoost is an algorithm for constructing a strong classifier as linear combination of simple (weak) classifiers [16] and [17]. The goal of this algorithm is to find a final model with low error relative to a given distribution over the training examples. The method tries to adaptively adjust the errors of the weak classifiers. AdaBoost can improve the performance of a base classifier by giving a more refined analysis to reduce error in the previous weak classifier. Fortunately, AdaBoost tends not to over-fit even after hundreds of rounds of boosting. Several successful experiments have been conducted using AdaBoost [16]-[19].

III. Evaluation Metrics

To evaluate the effectiveness of the analysis models, three evaluation metrics used in this work are accuracy, precision and recall. These metrics computed from number of elements in confusion matrix which are commonly evaluated [20]. The confusion matrix, in case of two classes prediction contains true positive (TP), true negative (TN), false positive (FP), and false negative (FN). Accuracy, precision and recall are defined by the following formula:

$$Accurancy = \frac{TP+TN}{TP+TN+FP+FN} \tag{1}$$

$$\Pr ecision = \frac{TP}{TP+FP} \tag{2}$$

$$\mathrm{Re}\,call = \frac{TP}{TP+FN} \tag{3}$$

IV. Experiments

This research was carried out by the standard process, which used in the solutions business called CRIPS-DM [9]. Our study framework is shown in Fig. 1.

The details of each step are as follows.

A. Business Understanding

First, we studied the problems and factors affecting birth asphyxia to get the major factors in predicting birth asphyxia and to inquiries data from Chaoprayayomraj Hospital, Suphanburi, Thailand.

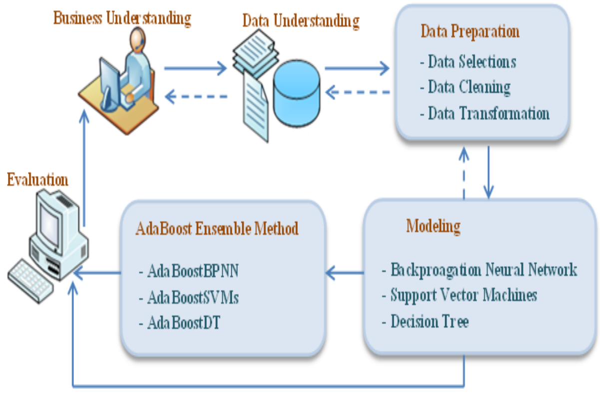

Figure 1. Experimental Workflow

B. Data Understanding

The training data set of 16,327 records obtained from the hospital was recorded during the year 2006 -2011. Only involved factors were extracted from all other data of the original data.

C. Data Preparation

All of the data 16,327 records found those occurrences of birth asphyxia only 571 records which are much less than the birth normal. Therefore, birth normal data were randomized in order to obtain a balance data set of birth normal cases 571 records and birth asphyxia cases 571 records resulting all 1,142 records to be used in this research. There are eight input variables which are maternal age, gestational age, antenatal care, amniotic fluid, hematocrit of delivery, mode of delivery, infants' weight, and complications from pregnancy.

D. Modeling

Three classification models using BPNN, SVMs and DT techniques were fitted using 10-fold cross validation to avoid over-fitting of each prediction method. Then, AdaBoost ensemble method using base classifiers of the three models also applied. The performances of three base classifier models and AdaBoost with base classifier models are presented in Table 1 and Table 2, respectively.

TABLE I. THREE BASE CLASSIFIER MODELS

Models	Precision (%)	Recall (%)	Accuracy (%)
BPNN	83.50	83.40	83.41
SVMs	82.80	82.00	81.97
DT	84.60	84.50	**84.48**

TABLE II. ADABOOST WITH BASE CLASSIFIER MODELS

Models	Precision (%)	Recall (%)	Accuracy (%)
AdaBoostBPNN	88.00	87.80	**87.80**
AdaBoostSVMs	84.00	83.90	83.86
AdaBoostDT	87.00	86.90	86.91

D. Evaluations

Fig. 2 and Fig. 3 present the comparison of prediction performances of all base classifier model alone and performances of AdaBoost with base classifier models, respectively. The results show that among three techniques, DT model gives the best performance at 84.48% accuracy but after applied AdaBoost ensemble method AdaBoostBPNN model gives the best performance at 87.80% accuracy.

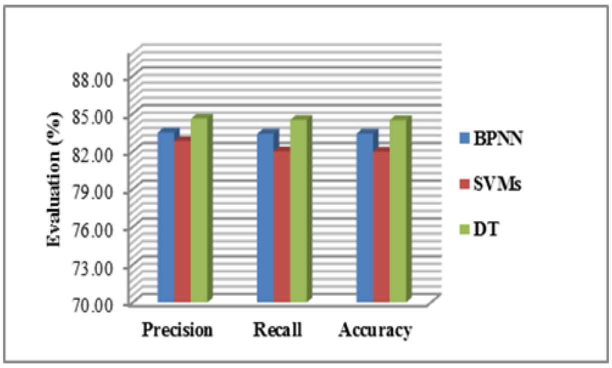

Figure 2. Comparisons of before ensemble performance

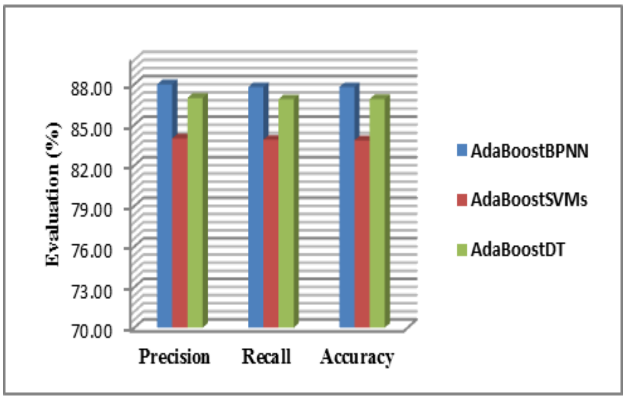

Figure 3. Comparisons of after ensemble performance

V. CONCLUSIONS AND DISCUSSIONS

This research selected eight variables that affect the birth which are correspond to the variables of the research works in [3], [6] and [7]. The data used in the experiment that was derived from original data at Chaoprayayomraj Hospital. AdaBoost ensemble method can substantial improve all three base classification models. The final classifier's accuracy is 87.80% obtained from the AdaBoostBPNN model. This model can be used as a practical aid to help predict birth asphyxia occurring. Doctors and staff can prepare intensive care to reduce the rate of death and disability of the newborn.

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