Suggesting Mode of Delivery by Using Iterative Dichotomiser 3 (ID3) Algorithm

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Abstract

Data mining is a process that has a variety of data analysis tools to discover patterns and relationships in data that may be used to make valid predictions. Classification is the process of finding a set of models that describe and distinguish data classes or concepts , for the purpose of being able to use the model to predict the class of objects whose class label is unknown. Classification of complex measurements is used in many application domain. This system intended to implement a suggesting system for OG (Obetetrics Gyanaecology) knowledge in predicting mode of delivery (method of labour process) by using ID3 classification method. Patient's 4 CTG outline information , patient's age , patient's gestation week , condition of AF (Amniotic Fluid) guess , condition of fetal distress guess are used for predicting mode of delivery. Depending on these 8 attributes values , the system can generate two categories of mode of delivery (namely :Normal Vaginal Delivery [NVD] and Lower Segment Caesarean Section [LSCS]) for new born baby. This system use hold-out accuracy method to approve the system accuracy.

Keywords: data mining, classification, decision tree, ID3 algorithm, mode of delivery, CTG, hold-out accuracy method.

1. Introduction

Data mining refers to extracting or mining knowledge from large amount of data where the data can be stored in databases, data warehouses or other information repositories. It is young interdisciplinary field drawing from areas such as database systems, data warehousing, statistics, machine learning , data visualization, information retrieval and high-performance computing. Classification approach is the process of extracting rules and patterns from huge data sets for given training points to be able to make predictions on new data samples. Classification can be used for predicting the class label of data objects. There are many kinds of data classification techniques such as Bayesian classification, Bayesian belief networks, Decision tree induction, Association based classification (indegration of data warehouse technology with classification), K-nearest neighbour classifier, Case-based reasoning, Generic algorithms, Rough sets and Fuzzy logic techniques[8]. The basis algorithms for decision tree induction is a greedy algorithm that constructs decision trees in top-down recursive divide and conquer manner. The ID3 algorithm is well known decision tree induction algorithm. ID3 is a typical decision tree algorithm. It introduces information entropy as the splitting attribute's choosing measure[2]. This system use ID3 algorithm in medical field. There are 8 attributes[Patient's 4 CTG outline information , patient's age , patient's gestation week , condition of AF (Amniotic Fluid) guess , condition of fetal distress guess] are used in this system and Iterative Dichotomiser 3 [ID3] is commonly used to have gaining information for the purpose of decision making to give what kind of mode of delivery is best suitable and save for pregnant woman. The input to a classifier (ID3) is training dataset, each of which is a tuple of 8 attributes' values aged with a class label (NVD,LSCS). The main point of this system is to guess the mode of delivery and is presented by matching the user's inputs with the rules gained by ID3 algorithm.

2. Related Work

D.V.Chandra Shekar and V.Sesha presented "An Approach for Identification of Refractive Errors" In this paper,the main abjective of the study was to classify the sample data according to age, gender and type of refractive error (myopia , hyperopia) using data mining techniques decision tree that was constructed using ID3 algorithm. The study on refractive errors in schools going children identifies the need of mining the clinical data. The huge data was analyzed by decision tree algorithm and finally we found that myopia was most common refractive error for both male and female students[5].

Mirijana Pecjic Bach and Dijiama Cosis presented "Data Mining Usage in heatlh care management. literature survey and decision tree application": In this paper, show a way to raise awareness of woman in terms of contraceptive methods they use or do not use. Goals of the data mining analysis was to determined if they are common charactertistic of the woman according to their choice of contraception. Therefore , use decision tree algorithm. The samples contain married women who were either not pregnant or did not know if they were pregnant at the time of interview. The database consists of 1473 cases[14].

Qasem A. AI-Radaideh, Emad M. AI-Shawakfa, and Mustafa I.AI-Najjar presented "Mining Student Data Using Decision Trees". In this paper, student performance in university courses is of great concern to the higher education managements where several factors may affect the performance. This paper is an attempt to use the data mining processes, particularly classification, to help in enhancing the quality of the higher educational system by evaluating student data to study the main attributes that may affect the student performance in courses. The classification rule generation process is based on the decision tree as a classification method where the generated rules are studied and evaluated. A system that facilitates the use of the generated rules is build which allows students to predict the final grade in a course under study[15].

3. Theory Background

3.1. Data Preprocessing

Data preprocessing techniques can improve the quality of data, thereby helping to improve the accuracy and efficiency of subsequent mining process. Data preprocessing is an important step in knowledge discovery process. Databases are highly susceptible to noisy, missing and inconsistent data due to their typically huge size. Attributes of interest may not always be available. Therefore , preprocessing is always a necessity whenever the data to be mined is noisy or incomplete and this process significantly improves the effectiveness of the data classification. Data preprocessing techniques are data cleaning, data integration, data transformation data reduction.

Data cleaning : routines work to clean the data by filling in missing values, smoothing noisy data, identifying or removing outliers and resolving inconsistencies. Dirty data can cause confusion for mining procedure, resulting in unreliable output.

Data integration : data analysis task will involve data integration, which combines data from multiple sources into a conherent data store, as in data warehousing. These sources may include multiple databases, data cubes, flat files.

Data transformation : data transformation such as normalization, may improve the accuracy and efficiency of the mining algorithms involving distance measurements.

Data reduction : can reduce the data size by aggregating, eliminating redundant features,or clustering, for instance. These data preprocessing techniques, when applied prior to mining, can substantially improve the overall quality of the patterns mined and/or the time required for the actual mining[10].

3.2. Decision Tree

Decision tree is a method of approximating discrete valued target functions. The learned function is represented by a tree structure. It is a search of a completely, expressive hypothesis space. Instance exploited in decision tree algorithm have attribute-value pairs ie: set of attributes and their values. Decision tree methods can also be easily extended to learning functions with more than possible output values. Decision tree learning methods are robust to errors.

Decision tree method can be used even when some training examples have unknown values. Learned tree represented as a set of IF……THEN rules to improve human readability. A decision tree is a flow-chat like tree structure, where each internal nodes (non-leaf nodes) denote a test on an attributes, each branch represents an outcome of test and leaf nodes (terminal nodes) represent class label. Decision tree can be easily converted to classification rules[2].

3.3. Types of Decision Tree Algorithm

There are many techniques for classification. They are:

- Iterative Dichotomiser [ID3]
- Extended version of ID3 [C4.5]
- C5.0
- Classification And Regression Tree [CART]
- Chi-square Automatic Interaction Detector [CHAID]
- CN2
- Support Vector machine [SVM].

This system will implement the classification of mode of delivery by using ID3 algorithm of decision tree induction.

3.4. Iterative Dichotomiser 3 (ID 3)

ID3 is a greedy algorithm for decision tree construction developed by J.ROSS QUIALAN CIRCA 1987. A mathematical algorithm for building the decision tree. Builds the tree from top-down, with no backtracking. Information Gain used to select the most useful attribute for classification.

Informal formulation of ID3:

- Determine the attribute that the highest information gain on training set.
- Use the attribute as the root of the tree; create a branch for each of the values that the attribute can take.
- For each of the branches, repeat this process with the subset of the training set that is classified by this branch[13].

3.4.1. ID3 Algorithm

- Input: The training samples, represented by discrete-valued attributes, set of candidate attributes, attribute-list.
- Output: A decision tree.
- Steps of the method:
  1) Create a node N;
  2) If samples are all of the sample class, C then
  3) Return N as a leaf node labeled with the class C;
  4) If attribute-list is empty then
  5) Return N as a leaf node labeled with the most common class in samples; //majority voting
  6) Select test attribute, the attribute among attribute-list with the highest information gain;
  7) Label node N with test attribute;
  8) for each known value a_i of test attribute //partition the samples
  9) grow a branch from node N for the condition test-attribute= a_i
  10) let s_i be the set of sample in samples for which test-attribute=a_i; //a partition
  11) if s_i is empty then
  12) attach a leaf labeled with the most common class in samples;
  13) else attach the node returned by generate-decision tree (s_i , attribute-list,test attribute);

3.4.2. Attribute Selection Measure

The information gain measure is used to select the test attribute at each node in the tree. Such in measure is referred to as an attribute selection measure or a measure of the goodness of split. The attribute with the highest information gain or greatest entropy reduction is chosen as the test attribute for the current node. Let S be a set of consisting of s data samples. Suppose the class level attribute has m distinct values defining m distinct classes, C_i (for i=1,…,m). Let s_i be the number of samples of S in class C_i. The expected information needed to classify a given sample is given by

$$I(s_1,s_2,\ldots,s_m)=-\Sigma^{m}_{i=1}\, p_i \log_2(p_i) \qquad \text{Eq(1)}$$

Where p_i is the probability that an arbitrary sample belongs to class C_i and is estimated by s_i/s.

Let attribute A have v distinct values ,$\{a_1,a_2,\ldots,a_v\}$. Attribute A can be used to partition S into v subsets, $\{S_1,S_2,\ldots,S_v\}$, where S_j contains those samples in S that have values a_j of A. If A were selected as the test attribute (i.e., the best attribute for splitting), then these subsets would correspond to the branches grown from the node containing the set S. Let S_{ij} be the number of samples of class C_i in a subset S_j. The entropy of expected information based on the partitioning into subsets by A is given by

$$E(A)= - \Sigma^{v}_{j=1}(sij+\ldots..+smj)/ s * (Sij,..,Smjj) \quad Eq(2)$$

The term (sij+…..+smj)/ s acts as the weight of the jth subset and is the number of samples in the subset (i.e, having value a_j of A) divided by the total number of samples in S. The smaller the entropy value, the greater the purity of the subset partitions. Note that for a given subset S_j,

$$I(s_{1j},s_{2j},\ldots,s_{mj})=-\Sigma^{m}_{i=1} p_{ij} \log_2(p_{ij}) \quad Eq(3)$$

Where $p_{ij}=s_{ij}/|S_j|$ and is the probability that a sample in S_j belongs to C_i.

The encoding information that would be gained by branching on A is

$$Gain(A) = I(s_1,s_2,\ldots,s_m)-E(A) \quad Eq(4)$$

Gain (A) is the expected reduction in entropy caused by knowing the value of attribute A.

3.4.3. Advantages of Using ID3 Algorithm

Understandable prediction rules are created from the training data. Builds the fastest tree. Only need to test enough attributes until all data is classified. Finding leaf nodes enables test data to be pruned, reducing number of tests. Whole dataset is searched to create tree.

4. Classifier Accuracy

Estimating classifier accuracy is important in that it allows one to evaluate how accurately a given classifier has not been trained. Accuracy is measured using a test set of objects for which the class labels are known. Accuracy is estimated as the number of correct class predictions, divided by the total number of test samples. To classify an object, a path is traced (based on the attribute values of the object) from the root of the tree to a leaf node. The majority class at the node is deemed the class prediction of the given objects. For each test object, the class prediction is compared to known class of object. If the two match, the class prediction is counted as correct. Otherwise, it is counted as incorrect[13].

Classifier accuracy methods are

1) Hold_Out method
2) Random_Sub Sampling method
3) K_fold Cross Validation method
4) Stratified Cross Validation method
5) Bootstrapping method
6) .Leave_One_Out method
7) Bagging(bootstrap aggregation) method
8) Boosting method

4.1. Hold-out Accuracy Method

Accuracy can be used both as a heuristic for guiding the search, as well as a rule quality evaluation heuristic for deciding when to stop the search. For this applications, two other measures are more frequently used than the classification accuracy, sensitivity and specificity. Sensitivity measures the fraction of positive. Specificity measure the fraction of negative cases classified as negative.

Sensitivity =t-pos/$_{pos}$

Specificity =t-neg/$_{neg}$

Accuracy=Sensitivity pos/$_{(pos+neg)}$+Specificity neg/$_{(pos+neg)}$

where , pos =positive case
neg=negative case
t-pos=true positive case
t-neg=true negative case.

Two third of the data are stored in training database and one third of the data are stored in testing database. Estimate accuracy by using data from testing database with the rules provided by the classifier[13].

5. Application Background

CTG means cardiotoocography or electronic fetal monitoring (EFM). The meaning of “cardio” is the heart-rate and “toco” means uterine contraction. By looking this CTG final result, we guess the situation of fetal in mother’s uterine and the situation of maternal uterine. CTG provides electronic FHR (fetal heart rate) monitoring and uterine contraction monitoring [11].

5.1. CTG Outline Features

Interpretation of CTG traces requires a definition of what is normal. CTG has four easily outline features :

1. Baseline fetal heart rate
2. Baseline variability
3. Accelerations
4. Decelerations

5.1.1. Baseline Fetal Heart Rate

The mean level of FHR(fetal heart rate) when this is stable, excluding accelerations and decelerations. It is determined over a time period of 5 or 10 minutes and expressed in beats per minutes(bpm). The values of baseline fetal heart rate are

1. moderate bradycardia
2. moderate tachycardia
3. abnormal bradycardia
4. abnormal tachycardia

5.1.2. Baseline Variability

The minor fluctation in baseline FHR occuring at 3 to 5 cycles per minutes. It is measured by estimating the difference in beats per minutes between the highest peak and lowest through of fluctuation in one_minute segment of the trace. The values of baseline variability are

1. Normal baseline variability
2. Non-reassuring baseline variability
3. Abnormal baseline variability

5.1.3. Acceleration

Transient increases in FHR of 15 bpm or more and lasting 15 seconds or more. The significance of no accelerations on an otherwise normal CTG is unclear. The values of acceleration are

1. Present
2. Absent

5.1.4. Deceleration

Transient episodes of slowing of FHR below the baseline level of more than 15 bpm and lasting 15 seconds or more. The values of deceleration are

1. Early decelerations
2. Late decelerations
3. Variable decelerations
4. A typical variable decelerations
5. Single Prolonged decelerations upto 3
6. Single Prolonged decelerations > 3
7. None decelerations

5.2. Amniotic Fluid (AF)

Amniotic fluid (AF) is one of the important feature of fetal outcome. The values of the amniotic fluid are:

1. Clear Amniotic Fluid (Clear AF): Clear AF is a normal condition for fetus.
2. Meconium Stained Amniotic Fluid (MSAF): Meconium stained AF was considered to be a sign of fetal death or impending death and many studies were designed to address the association between fetal hypoxia and meconium staining of the amniotic fluid.

5.3. Fetal Distress

Fetal distress is related to asphysia. The Task Force of the World Federation of Neurology Group defined asphyxia as condition of impaired gas exchange leading, if it persists ,to progressive hypoxaemia and hypercapnia. The values of fetal distress are

1. Yes
2. No

6. Proposed System

6.1. Overview of the System

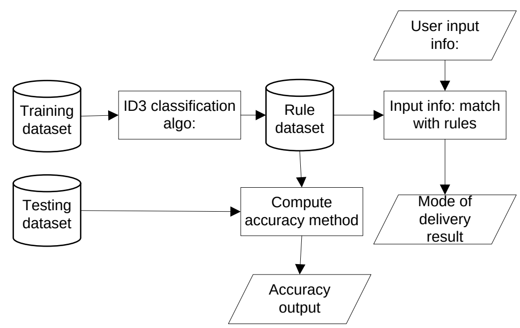


Figure1. System overview architecture

In this system,there are two datasets,training dataset and testing dataset. The training dataset is used for classifying rules by using ID3 algorithm and the classifying rules stored in rule dataset. The testing data is used to calculate the accuracy of the system. The patient’s 4 CTG outline features, age, gestation week, AF guess, fetal distress guess will be input to the system. The incoming input informations match with the rules and generate the mode of delivery result, NVD(normal vaginal delivery) {or} LSCS(lower segment caesarean section).

6.2. Process Flow of the System

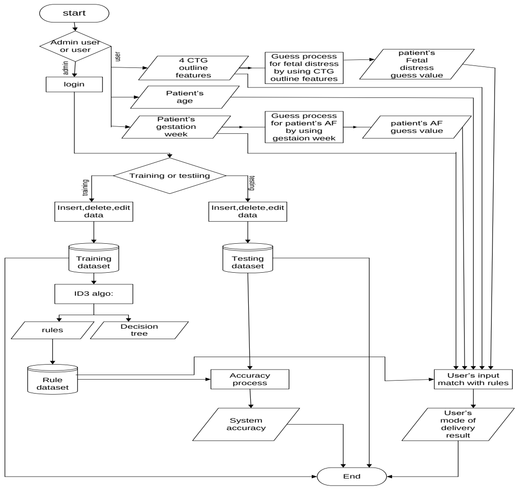
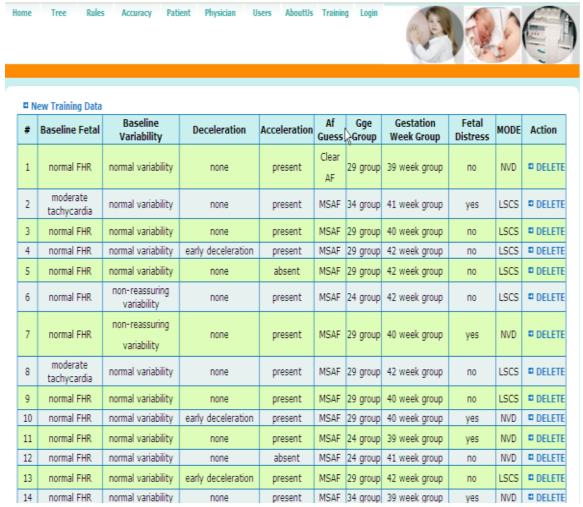


Figure 2. System Flow Diagram

In this system there are two parts, admin user and user. In admin part, the admin user pass the login. After passing the login, can insert, delete and edit the training data in training dataset and testing data in testing dataset. Using training dataset and ID3 classification algorithm , produce the rules and decision tree. The producing rules stored in rule dataset. Using the testing dataset and rule dataset, can calculate the system accuracy by using hold-out method. In the user part, user input the 4 CTG outline features, patient's age and gestation week. Using 4 CTG outline features, compute the CTG final result to guess the fetal distress value. Using patient's gestation week, can guess the patient's amniotic fluid (AF) value. These 8 inputs / attributes (4 CTG outline features, patient age, patient gestation week, AF guess, fetal distress guess) match with the rules in rule dataset. And then, the system produce the final result of mode of delivery (NVD, Normal Vaginal Delivery or LSCS Lower Segment Caesarean Section) . This system use 2000 training data and 700 testing data.

6.3. Sample Data Set



Home Tree Rules Accuracy Patient Physician Users AboutUs Training Login

New Training Data

#	Baseline Fetal	Baseline Variability	Deceleration	Acceleration	Af Guess	Gge Group	Gestation Week Group	Fetal Distress	MODE	Action
1	normal FHR	normal variability	none	present	Clear AF	29 group	39 week group	no	NVD	DELETE
2	moderate tachycardia	normal variability	none	present	MSAF	34 group	41 week group	yes	LSCS	DELETE
3	normal FHR	normal variability	none	present	MSAF	29 group	40 week group	no	LSCS	DELETE
4	normal FHR	normal variability	early deceleration	present	MSAF	29 group	42 week group	no	LSCS	DELETE
5	normal FHR	normal variability	none	absent	MSAF	29 group	42 week group	no	LSCS	DELETE
6	normal FHR	non-reassuring variability	none	present	MSAF	24 group	42 week group	no	LSCS	DELETE
7	normal FHR	non-reassuring variability	none	present	MSAF	29 group	40 week group	yes	NVD	DELETE
8	moderate tachycardia	normal variability	none	present	MSAF	29 group	42 week group	no	LSCS	DELETE
9	normal FHR	normal variability	none	present	MSAF	29 group	40 week group	no	LSCS	DELETE
10	normal FHR	normal variability	early deceleration	present	MSAF	29 group	40 week group	yes	NVD	DELETE
11	normal FHR	normal variability	none	present	MSAF	24 group	39 week group	yes	NVD	DELETE
12	normal FHR	normal variability	none	absent	MSAF	24 group	41 week group	no	NVD	DELETE
13	normal FHR	normal variability	early deceleration	present	MSAF	29 group	42 week group	no	LSCS	DELETE
14	normal FHR	normal variability	none	present	MSAF	34 group	39 week group	yes	NVD	DELETE

Figure 3. Training Data Set of the System

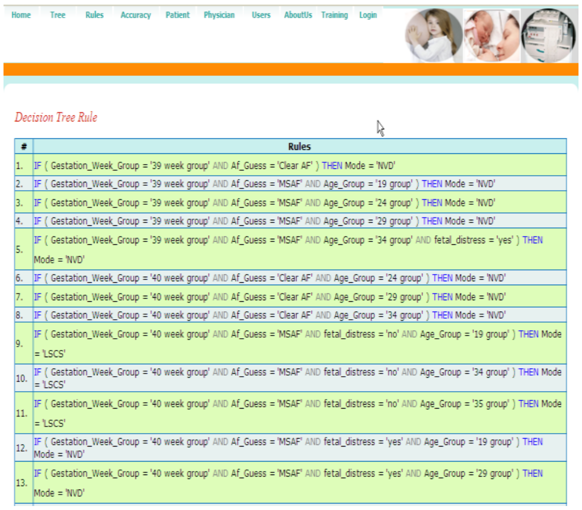
Figure 3 shows the training database of the system. The training database includes the old cases of the dataset that include 8 attributes values and the related mode of delivery result. In this system, the training database consist 2000 cases. In training database, admin can see the existing data records, can insert new data record and can delete existing data record that admin wants to delete.

6.4. Decision Tree

Figure 4. Decision Tree of the System

The decision tree is generated according to the ID3 algorithm and the training dataset as shown in figure 3. These decision tree shown in figure 4. The initial state of a decision tree is the root node that is assigned the examples from the training data.

6.5. Rules Data Set



#	Rules
1.	IF (Gestation_Week_Group = '39 week group' AND Af_Guess = 'Clear AF') THEN Mode = 'NVD'
2.	IF (Gestation_Week_Group = '39 week group' AND Af_Guess = 'MSAF' AND Age_Group = '19 group') THEN Mode = 'NVD'
3.	IF (Gestation_Week_Group = '39 week group' AND Af_Guess = 'MSAF' AND Age_Group = '24 group') THEN Mode = 'NVD'
4.	IF (Gestation_Week_Group = '39 week group' AND Af_Guess = 'MSAF' AND Age_Group = '29 group') THEN Mode = 'NVD'
5.	IF (Gestation_Week_Group = '39 week group' AND Af_Guess = 'MSAF' AND Age_Group = '34 group' AND fetal_distress = 'yes') THEN Mode = 'NVD'
6.	IF (Gestation_Week_Group = '40 week group' AND Af_Guess = 'Clear AF' AND Age_Group = '24 group') THEN Mode = 'NVD'
7.	IF (Gestation_Week_Group = '40 week group' AND Af_Guess = 'Clear AF' AND Age_Group = '29 group') THEN Mode = 'NVD'
8.	IF (Gestation_Week_Group = '40 week group' AND Af_Guess = 'Clear AF' AND Age_Group = '34 group') THEN Mode = 'NVD'
9.	IF (Gestation_Week_Group = '40 week group' AND Af_Guess = 'MSAF' AND fetal_distress = 'no' AND Age_Group = '19 group') THEN Mode = 'LSCS'
10.	IF (Gestation_Week_Group = '40 week group' AND Af_Guess = 'MSAF' AND fetal_distress = 'no' AND Age_Group = '34 group') THEN Mode = 'LSCS'
11.	IF (Gestation_Week_Group = '40 week group' AND Af_Guess = 'MSAF' AND fetal_distress = 'no' AND Age_Group = '35 group') THEN Mode = 'LSCS'
12.	IF (Gestation_Week_Group = '40 week group' AND Af_Guess = 'MSAF' AND fetal_distress = 'yes' AND Age_Group = '19 group') THEN Mode = 'NVD'
13.	IF (Gestation_Week_Group = '40 week group' AND Af_Guess = 'MSAF' AND fetal_distress = 'yes' AND Age_Group = '29 group') THEN Mode = 'NVD'

Figure 5. Decision Rules of the System

Figure 5 shows the decision rules for the system. These rules are extracted from the decision tree as shown in figure 4. It shows each rule with IF…..THEN rule from the root node to target class.

6.6. Suggesting Mode of Delivery

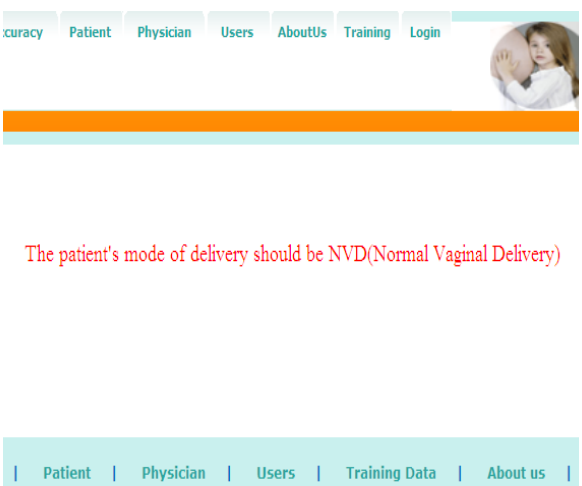
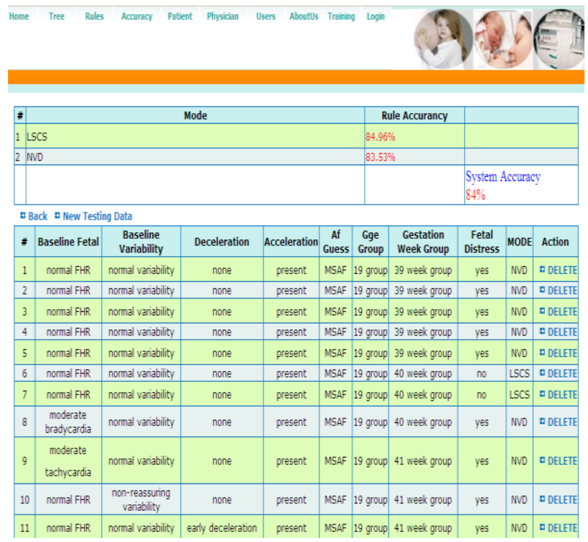


Figure 6. Suggesting mode of delivery

In this system, user insert 4 CTG outline attributes , patient's age, patient's gestation week, patient's AF guess value, fetal distress guess value. These user's inputs match with the rules. And then, the system produce the correct mode of delivery result. Patient's mode of delivery result shown in figure 6.

6.7. System Accuracy



#	Mode	Rule Accurancy	
1	LSCS	84.96%	
2	NVD	83.53%	
			System Accuracy 84%

#	Baseline Fetal	Baseline Variability	Deceleration	Acceleration	Af Guess	Gge Group	Gestation Week Group	Fetal Distress	MODE	Action
1	normal FHR	normal variability	none	present	MSAF	19 group	39 week group	yes	NVD	DELETE
2	normal FHR	normal variability	none	present	MSAF	19 group	39 week group	yes	NVD	DELETE
3	normal FHR	normal variability	none	present	MSAF	19 group	39 week group	yes	NVD	DELETE
4	normal FHR	normal variability	none	present	MSAF	19 group	39 week group	yes	NVD	DELETE
5	normal FHR	normal variability	none	present	MSAF	19 group	39 week group	yes	NVD	DELETE
6	normal FHR	normal variability	none	present	MSAF	19 group	40 week group	no	LSCS	DELETE
7	normal FHR	normal variability	none	present	MSAF	19 group	40 week group	no	LSCS	DELETE
8	moderate bradycardia	normal variability	none	present	MSAF	19 group	40 week group	yes	NVD	DELETE
9	moderate tachycardia	normal variability	none	present	MSAF	19 group	41 week group	yes	NVD	DELETE
10	normal FHR	non-reassuring variability	none	present	MSAF	19 group	41 week group	yes	NVD	DELETE
11	normal FHR	normal variability	early deceleration	present	MSAF	19 group	41 week group	yes	NVD	DELETE

Figure 7. Accuracy of the System

Figure 7 shows the accuracy of the system and the testing dataset. The system accuracy is based on the testing dataset. If the testing dataset change, the accuracy of the system are changed. Now , the system use 700 testing data and system accuracy is 84%.

7. Conclusion

In this system, suggesting mode of delivery are provided by using classification of ID3 algorithm under decision tree method. ID3 algorithm is faster in calculation and more accurate to get true goal. The application domain, mode of delivery result can obtain accurately by using ID3 classifier. In addition, by getting accurate mode of delivery result can save the lifes for both mothers and their fetus from dangerous condition, morbidities and fetal death. Doctors, civil-assistant doctors , house-surgeon and medical students are also used this system easily and effectively.

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