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FETAL STATE ASSESSMENT USING MULTILAYER PERCEPTRON BY FEATURE EXTRACTION APPROACH WITH FIREFLY ALGORITHM

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Abstract— **Cardiotocography is a process of recording the heartbeat of the fetal and the uterine contractions during the last trimester of pregnancy. It helps in reviewing patterns related to the fetal activity and in detecting pathologies. The major challenge faced in medical domain is the extraction of intelligible knowledge from medical diagnosis data such as Cardiotocogram data. On observation of the CTG trace patterns doctors would be able to understand the state of the fetus. Several signal processing as well as computer based programming techniques are available for interpretation of a typical Cardiotocography data. The capacity to predict the condition is inaccurate even after cardiotocograph was found. In this work, cardiotocogram (CTG) data is analyzed using Multi Layer Perceptron (MLP) for predicting fetal risk. Firefly algorithm (FA) is proposed to extract the relevant features that maximize the classification performance of MLP.The obtained results show that Firefly algorithm improves the performance of the classification.**

Keywords—Cardiotocography, Fetal heart rate, Feature Selection, Firefly algorithm, Multilayer Perceptron.

I. INTRODUCTION

Data Mining had provided many new developments, technologies, and methods in the recent decade. Anyhow, the application of data mining in medical field is still in the beginning stage and so the possibilities of the implementation are yet limitless. The improvement in the techniques as well as the application of those techniques had helped in handling of new types of data types and applications. The extraction of knowledge from medical diagnosis data such as CTG data is the most important challenge. The use of various classification methods and recognition systems has improved with effectiveness to help medical experts in diagnosing diseases.

II. PROBLEM DEFINITION

The most common desires of all mothers is experiencing normal stage of pregnancy and delivery and having a healthy baby since it is a lifetime event. Predominating the fetal status, preparing psychologically and physically, obstetricianss would determine the appropriate delivery method if there were any abnormal situation according to the diagnostic result of the examination, then the fetal risk or adverse outcome could be minimized and even eliminated [1]. Therefore, detecting and diagnosing of maternal and fetal condition is greatly critical and necessary for both the mother and baby during pregnancy and labor.

To achieve the above goal, cardiotocography (CTG) is a non-invasive and cost-effective instrument to monitor fetal status and evaluate fetal well-being of prenatal examination during antepartum and intrapartum periods. CTG, also known as electronic fetal monitoring (EFM), consists of simultaneously monitoring fetal heart rate (FHR) signal, through a Doppler ultrasound probe, and uterine contractions (UC), by means of a pressure transducer, both applied externally to the abdomen of the pregnant woman [2]. Figure.1 depicts digitized samples of a typical CTG signal obtained from CTUUHB, an intrapartum cardiotocography open-access database [3].

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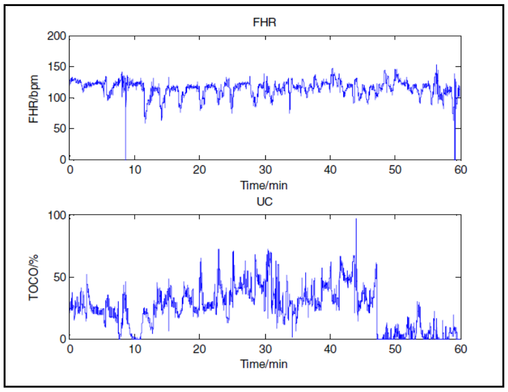

Fig. 1. *typical CTG recording including FHR and UC*

We should make full use of detailed physiological information extracted from CTG signal in order to detect fetal abnormal state and avoid undesirable disease timely, including congenital heart defect and IUGR (Intrauterine Growth Restriction) because of the lacking of oxygen. However, this technique has a drawback on the decrease in spontaneous delivery and the increase in cesarean section. The obstetrician can predominate fetal state at all times and get involved before fetal suffers permanent damage (such as birth asphyxia) according to the analysis result of the trace patterns of CTG. So real-time monitoring and timely intervention are indispensable for reducing fetal morbidity and mortality.

Unfortunately, when the technique of CTG was introduced into the clinical practice, recordings were interpreted by gynecologist and midwife through visual inspection, with the obvious consequence of great inter- and intra-observer variability, leading to unreliable conclusion about fetal morbidity, so designing a computerized system based on powerful artificial intelligence algorithms is quite prospective to analyze the CTG recording to decrease human error rate objectively. With the rapid development of advanced computing technologies in two aspects of software and hardware, the related research community has been able to quantify the cardiotocography and assess the fetal state more accurately [2].

Machine learning (ML) aims at classifying fetal state as pathological or normal through CTG recording using attributes extracted from both the

FHR and UC signals to assist obstetrician to make decisions.

In this paper, Firefly algorithm (OBFA) together with Multi Layer Perceptron (MLP) classifier has been proposed for classification of CTG data. FA has been used to produce optimal and reduced feature set which results in improvement of performance of the MLP classifier. Initially, CTG data are classified using the full feature set. Then, optimal feature set has been produced using FA along with MLP classification. The experimental results reveal that the use of optimal feature set generated with FA improves the accuracy of classification.

III. Related Terms

A. *Cardiotocography*

Cardiotocography is a medical test conducted during pregnancy that records FHR and UC. Tests may be conducted by either internal or external methods. In internal testing, a catheter is placed in the uterus after a specific amount of dilation has taken place. With external tests, a pair of sensory nodes is affixed to the mother's stomach. CTG trace generally shows two lines. The upper line is a record of the fetal heart rate in beats per minute. The lower line is a recording of uterine contractions from the TOCO. Uterine contractions, Four fetal heart rate features-Baseline heart rate, Variability, Accelerations, Decelerations. Uterine contractions are quantified as the number of contractions present in a 10 min period and averaged over 30 min. Normal: ≤ 5 contractions in 10 min and High: ≥ 5 contractions in 10 min represent uterine tachysystole. Baseline heart rate is the average baseline fetal heart rate. Reassuring feature: 110 – 160 beat per minute (bpm), Non-reassuring feature: 100 – 109 bpm OR 161 – 180 bpm and Abnormal feature: < 100 bpm OR > 180 bpm.

Variability is the fluctuations in the fetal heart rate this causes the tracing to appear as a jagged, rather than a smooth, line. Variability is indicative of a mature fetal neurologic system and is seen as a

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measure of fetal reserve. Reassuring feature: ≥ 5 bpm, Non reassuring feature: < 5 bpm for ≥ 40 minutes but < 90 minutes and Abnormal feature: < 5 bpm for > 90 minutes. Decelerations are decreases in fetal heart rate from the baseline by at least 15 beats per minute, lasting for at least 15 seconds. There are three types of decelerations, depending on their relationship with uterine contraction.

Early deceleration begins at the start of uterine contraction and ends with the conclusion of contraction. It is due to increased vagal tone due to fetal head compression. Variable deceleration occurs at any time irrespective of uterine contractions. It is due to the umbilical cord compression. Late deceleration begins at or after the peak of a contraction and ends long after it, hence "late" when compared to early decelerations. Reassuring feature: No deceleration, Non reassuring feature: Early deceleration, variable deceleration or single Prolonged deceleration up to 3 minutes and Abnormal feature: Atypical variable decelerations, late deceleration or single prolonged deceleration greater than 3 minutes. Three categories of CTG traces are as follows: Normal trace: Tracings with all four features: Baseline rate 110-160 bpm, Normal variability, Absence of decelerations, and Accelerations (may or may not be present). Suspicious trace: Tracing with ONE non reassuring feature and the other three are reassuring. Pathological trace: Tracing with TWO or more non reassuring features or ONE or more abnormal feature.

B. *Data Mining*

With the internet age the data and information explosion have resulted in the huge amount of data. Fortunately to gather knowledge from such abundant data, there exist data mining techniques. The data mining is - Extraction of interesting, non-trivial, implicit, previously unknown and potentially useful patterns or knowledge from huge amount of data. Data mining is the process of discovering patterns in large data sets. The overall is to extract information from a data set and transform it into an understandable structure for further use.

Data mining has been used in various areas like Health care, business intelligence, financial trade analysis, network intrusion detection etc. General process of knowledge discovery from data involves data cleaning, data integration, data selection, data mining, pattern evaluation and knowledge presentation. Data cleaning, data integration constitutes data pre-processing. Here data is processed so that it becomes appropriate for the data mining process. Data mining forms the core part of the knowledge discovery process. There exist various data mining techniques viz Classification, Clustering, Association rule mining etc.

C. *Classification*

It is a three class classification problem. The three classes are:

- Normal - A CTG where all four features fall into the reassuring category,
- Suspicious - A CTG whose features fall into one of the non-reassuring categories and the reassuring category and the remainder of features are reassuring and
- Pathological - A CTG whose features fall into two or more of the Non-reassuring the reassuring category or two or more abnormal categories.
- **Methodology**

D. *Process of Knowledge Discovery*

Step involved in the process of knowledge discovery to achieve insight from CTG data is as follows

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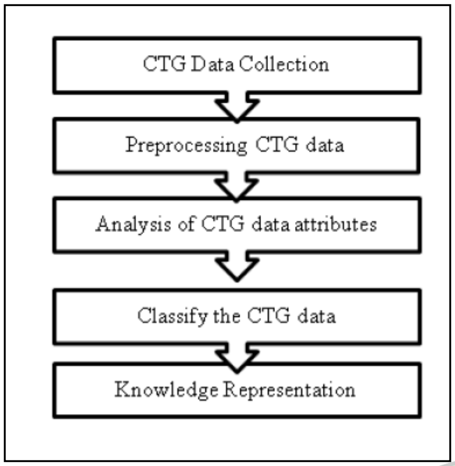

Fig. 2. *Process of Knowledge Discovery from CTG data*

E. Data Description

In this research, we chose the CTG dataset from publicly available UCI Machine Learning Repository [5] .The dataset contains 21 features obtained from CTG (both related with FHR and UC signals) and 2 type of classes classified by three expert obstetricians, including the class pattern (1-10) and fetal state class (N=Normal, S=Suspect, P=Pathologic) chosen to be the target attribute in this study. The above data were gathered from total 2126 instances and three fetal status of normal, suspicious and pathological have 1655, 295, 176 samples, respectively.

Attribute information is given as:

LB—FHR baseline (beats per minute)

AC—# of accelerations per second

FM—# of fetal movements per second

UC—# of uterine contractions per second

DL—# of light decelerations per second

DS—# of severe decelerations per second

DP—# of prolongued decelerations per second

ASTV—percentage of time with abnormal short term variability

MSTV—mean value of short term variability

ALTV—percentage of time with abnormal long term variability

MLTV—mean value of long term variability

Width—width of FHR histogram

Min—minimum of FHR histogram

Max—Maximum of FHR histogram

Nmax—# of histogram peaks

Nzeros—# of histogram zeros

Mode—histogram mode

Mean—histogram mean

Median—histogram median

Variance—histogram variance

Tendency—histogram tendency

CLASS—FHR pattern class code (1 to 10)

NSP—fetal state class code (N = normal; S = suspect;

P = pathologic)

F. Multilayer Perceptron

Multilayer Perceptron classifier is based on back propagation algorithm to classify instances of data the nodes in this neural network are all sigmoid. The back propagation neural network is referred as the network of simple processing elements working together to produce an output. It should be learned by a set of weights for predicting the class label of tuples.

There are three layers in the neural network such as the input layer, one or more hidden layers, and an output layer [20]. Each layer must be made up of units. The input layer of the network refers to the attributes. To make input layer, the inputs are provided simultaneously into the units. These inputs are given through the input layer and are then they are weighted and provided simultaneously to a second layer of neuron like units, which is referred to as a the hidden layer. The outputs of the hidden layer units could be input to another hidden layer, and so on. The number of hidden layers is arbitrary, although in practice, usually only one is used [4]. Back propagation is an efficient method for calculating all the derivatives of a single target

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quantity with respect to a large set of input quantities [20].

G. Firefly Algorithm

Firefly algorithm is one of the efficient optimization algorithms [21]. Fireflies are insects producing a flashing light. Firefly algorithm makes use of three idealised rules. First, all fireflies are considered unisex which means that one firefly will be attracted to other fireflies regardless of their sex. Secondly, the degree of the attractiveness of a firefly is proportion to its light intensity, thus for any two flashing fireflies, the less brighter one will move towards the more brighter one. Finally, the light intensity of a firefly is somehow related with the analytical form of the fitness function. The basic steps of the FA are summarized as the pseudo code shown in figure 3.

```
begin
  Fitness function f(M), M=(m1,...,md)^c
  Generate initial population of fireflies Mi(i=1,...,n)
  Brightness Li at Mi is determined by f(Mi)
  Define light absorption coefficient α
  s=1
  while (s< smax)
  for i=1:n all n fireflies
    for j=1:n all n fireflies
      if (Lj>Li)
          Move firefly i towards j in d-dimension
      end if
      Attractiveness varies with distance via exp[-α p²]
      Evaluate new solutions and update brightness
    end for j
  end for i
 Rank the fireflies and find the current best
 s=s+1
 end while
 Post process results and visualization
end
```

Fig. 3. *Pseudocode of Standard firefly Algorithm.*

The dimension of the function to be optimized is given by d, n is the number of fireflies, smax is the maximum number of generations, a is the light absorption coefficient, Li is the light intensity and the distance p between any two fireflies i and j located at positions Mi and Mj can be evaluated as follows.

$$p_{ij} = Distance\left(\mathrm{M}_i, \mathrm{M}_j\right) = \sqrt{\sum_{k=1}^{d}\left(m_{i,k} - m_{j,k}\right)^2} \quad (1)$$

The light intensity (L) decreases as the square of the distance increases (p2). It can be approximated using the following form.

$$\mathrm{L}\,(\mathrm{p}) = \mathrm{L}_0 \mathrm{e}^{-\alpha p^2} \quad (2)$$

where, L0 is the light intensity at source. As the firefly's attractiveness is proportional to the light intensity, we can define the attractiveness s as follows;

$$\sigma\,(\mathrm{p}) = \sigma_0\, \mathrm{e}^{-\alpha p^2} \quad (3)$$

Here, s0 is the attractiveness at p = 0. Now the movement of a firefly i attracted to another more attractive firefly j is given by,

$$m_{i+1} = m_i + \sigma_0\, e^{-\alpha p_{ij}^2}\left(m_j - m_i\right) + \lambda\left(rand() - 0.5\right) \quad (4)$$

where, is the randomization parameter and rand ( ) is a random number generator.

IV. Experimentation Result

A. Performance Evaluation

Classification results are presented by using precision, recall and F-measure. Precision or positive predictive value (PPV) can be defined as the proportion of instances which belongs to a class (TP: True Positive) out of the total instances including TP and FP (False Positive) classified by the classifier as belong to this particular class

$$Precision = \frac{TP}{TP+FP}$$

Recall or Sensitivity is the proportion of instances classified in one class out of the total instances belonging to that class. Total number of instances of a class includes TP and FN (False Negative)

$$Recall = \frac{TP}{TP+FN}$$

F-measure is the combination of precision and recall and defined as

$$F - measure = \frac{2 \times Precision \times Recall}{Precision + Recall}$$

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TABLE I. PERFORMANCE METRICS OF MLP WITH AND WITHOUT FEATURE SELECTION

Performance Metrics (%)	Without FS	With FS
Precision	81.45	86.13
Recall	91.60	94.54
F-Measure	79.87	85.52

V. CONCLUSION

In this paper, Firefly algorithm is proposed for producing optimal feature set for CTG classification . I have evaluated the performance of Multilayer Perceptron using three different performance measures, namely Precision, Recall and F-measure to identify the pathological and suspicious states of the fetus from the normal state. The performance of Multilayer Perceptron with and without Feature selection is evaluated. We can observe that there is a significant improvement in the performance of the proposed classifier when compared to the classifier with full feature set (without feature selection). This improvement in performance will ensure that the obstetricians can make more accurate decisions from CTG recordings. Even though the standard FA outperforms the evolutionary algorithms like genetic algorithm it faces some difficulties like premature convergence and obtaining better solutions. Future work would be to find out a improved Feature selection model which could overcome these shortcomings.

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