Classification of fetal abnormalities based on CTG signal

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Abstract:

The fetal heart rate (FHR) signal processing based on Artificial Neural Networks (ANN),Fuzzy Logic (FL) and frequency domain Discrete Wavelet Transform(DWT) were analysis in order to perform automatic analysis using personal computers. Cardiotocography (CTG) is a primary biophysical method of fetal monitoring. The assessment of the printed CTG traces was based on the visual analysis of patterns that describing the variability of fetal heart rate signal. Fetal heart rate data of pregnant women with pregnancy between 38 and 40 weeks of gestation were studied. The first stage in the system was to convert the cardiotocograghy (CTG) tracing in to digital series so that the system can be analyzed ,while the second stage ,the FHR time series was transformed using transform domains Discrete Wavelet Transform(DWT) in order to obtain the system features .At the last stage the approximation coefficients result from the Discrete Wavelet Transform were fed to the Artificial Neural Networks and to the Fuzzy Logic, then compared between two results to obtain the best for classifying fetal heart rate.

Key words: fetal heart rate monitoring, heart rate analysis by neural network,fuzzy classification,FHR wavelet transform.

Introduction

Many methods are used in fetal heart rate analysis, time and frequency domain analysis of heart rate variability are the most commonly used noninvasive methods to evaluate autonomic regulation of heart rate in healthy fetus [1].
Cardiotocography (simultaneous recording of fetal heart rate (FHR) and uterine contractions) is one of the most used diagnostic techniques to evaluate fetal well-being and to investigate the functional state of the fetal autonomic nervous system. Great interest has been paid to the variability of the FHR, and its frequency analysis, as a base for a more objective analysis of the cardiotocographic (CTG) tracings [2].

Fetal heart rate monitoring-signal intervals were determined in a high precision autocorrelation method, and a time series of fetal heart rate fluctuation was obtained. The distribution of the amplitude of temporal fluctuation in the low-frequency component of fetal heart rate frequency was studied using a method of time-frequency analysis called wavelet transform[3]. The aims of this research is to present an algorithm that will be suitable for fetal HR wave classification using ANN and FLS. In the present work, a comparison between DWT combined with neural networks and DWT combined with Fuzzy Logic System based on fetal heart rate baseline record in (20min)are done. This will allow adding a new mode for fetal HR device(EFM) as an indicator of fetal state. This will assist the physician in early diagnosis of fetal abnormalities especially in fetal hypoxia.

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Tools used in the research

The ANN and FLS systems used in this research are trained and simulated using the MATLAB software program (V.7.7R2008b). Both programs are trained and tested using a P4 personal computer a 1.8 GHz CPU and 750 MB of RAM with professional Microsoft windows XP (V.2002).

External Monitoring of the Fetal Heart Rate

External monitoring can be done at different times during pregnancy, or during labor.which can be done by listening to fetal heart beat with a special stethoscope, using a microphone device (transducer) placed on the maternal abdomen to obtain a continuous record of the FHR the signal source is the fetus heart sound .

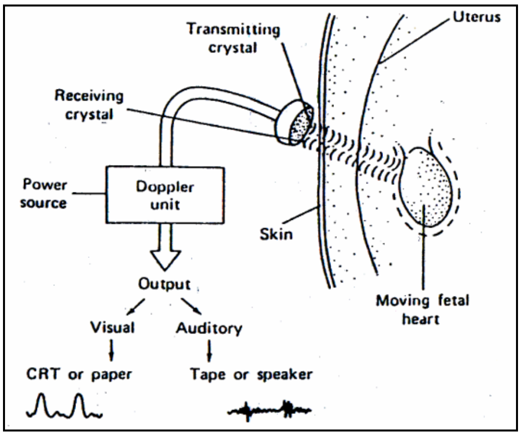


Fig. (1) The transducer arrangement for monitoring the fetal heart [1].

The CTG Paper Display

The distance of the CTG paper is in the centimeters .The chart paper advances in a certain period of time (minutes) which represents horizontal scale. Most fetal monitors have two record speeds available, 1cm and 3cm per minute or 1cm and 2 cm per minute. 3 cm per minute paper speed is recommended for clear evaluation of data obtained as shown in Fig.(2)

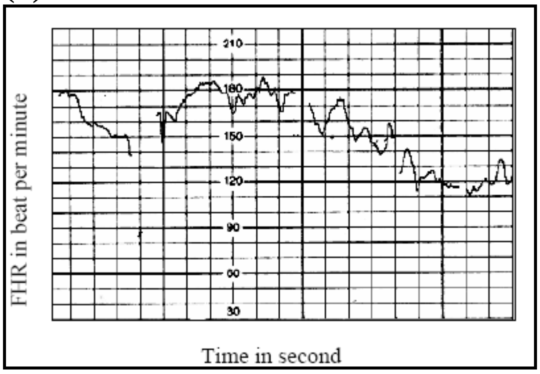
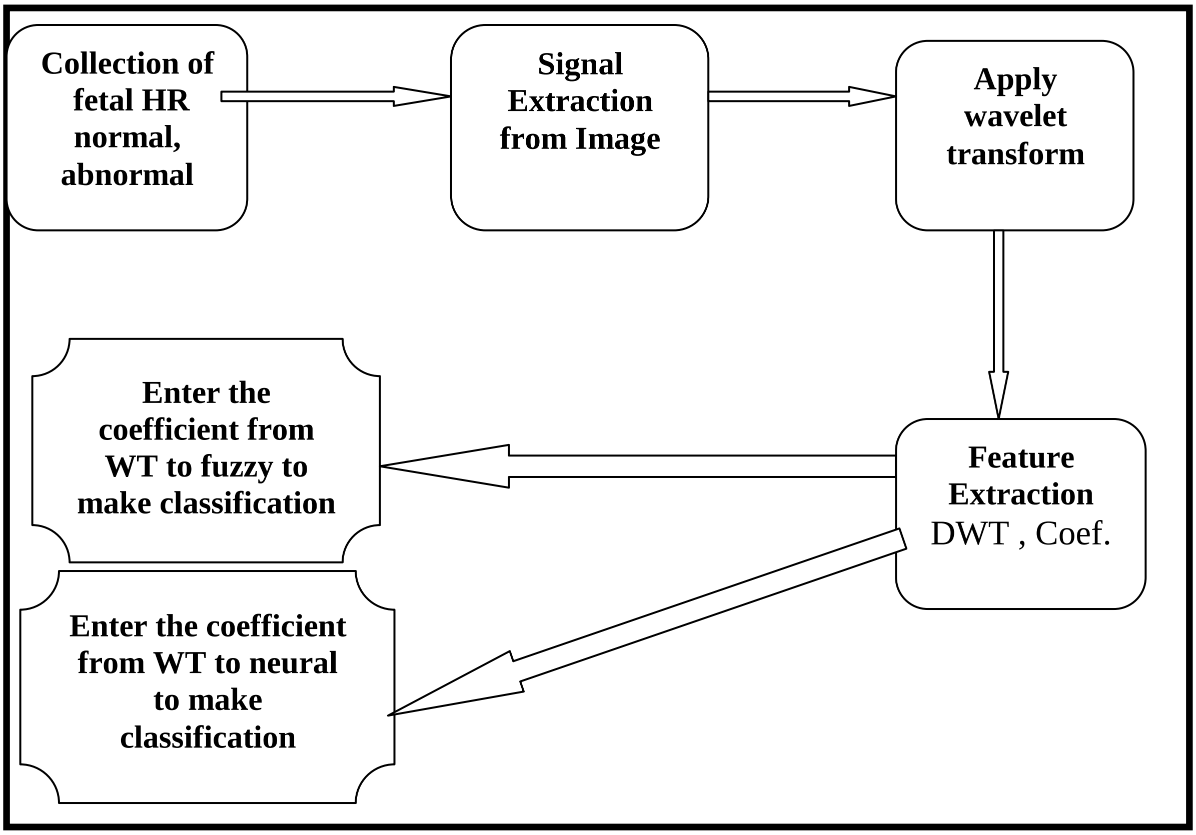


Fig.(2) CTG paper tracing of fetal heart rate [5]

Implementation stages of the work

In the present work, MATLAB software package version 7.7 R2008b is used to implement the software design and algorithms. The general block diagram for the proposed system of the classification is shown below.



Conversion of Fetal HR Paper

The fetal HR papers are converted to image file in the computer by using Smart Scan high-resolution scanner. The resulting image file is saved as a JPEG image[6]. The original images that were taken by scanner were have size range (2220*1700) to (3500*2560) pixels and they were reduced by Photoshop to the range (1000*203) to (1000*230) pixels.

Discrete Wavelet Transform Coefficients Extraction

In the present work Db4 wavelet have been used as the mother wavelets. MATLAB software package version 7.7R2008b is used to extract the DWT coefficients.

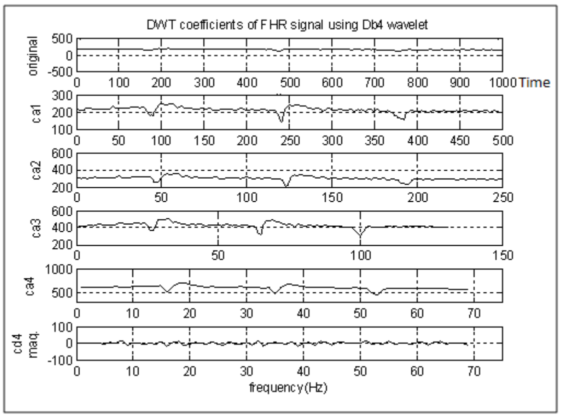


Fig. (3) CWT coefficient of FHR signal using Db4 wavelet.

Neural Network design

In the present work, these steps consist of:

1- Identify the parameters of the network

2- Initialize the weights

3- Input the training pattern &desired matrixes

4- Normalize the input matrix

5- Training the Network with Bp algorithm

6-At the end Denormalize of the output

Fuzzy System design

In the present work, these steps consist of :

1- <u>Input scaling</u>:- The input parameters of the FS are described in table (1). The input of the FLS contain five parameters.

2-<u>Fuzzifiction</u>:- The fuzzfiction for the normalized input vector consists of finding the membership degree of the normalized measurement. It is triangle function in this research.

3-<u>Rule Firing</u>:- For a two input / single output case the rule of the set of (if-then) rules has the form: *if a is* x_1 *and b is* x_m *then output is y* .Table 1. show the rule of this research.

Max / Min	Abnormal (a1)	Average	Normal	Average	Abnormal (a2)
Abnormal(1) (a1)	Large abnormal (La)	Abnormal (a)	Check (CH)	Abnormal (a)	Large abnormal (La)
Average	Abnormal (a)	Check (CH)	Normal (N)	Check(CH)	Abnormal (a)
Normal	Check(CH)	Normal(N)	Large normal(LN)	Normal(N)	Check(CH)
Average	Abnormal (a)	Check (CH)	Normal (N)	Check(CH)	Abnormal (a)
Abnormal(2) (a2)	Large abnormal (La)	Abnormal (a)	Check (CH)	Abnormal (a)	Large abnormal (La)

Where abnormal(1) represent bradycardia cases and abnormal(2) represent tachycardia cases. For example of rules

- If (min is abnormal 1) and (max is abnormal 1) then (output1 is Large abnormal)
- If (min is average) and (max is abnormal1) then (output1 is abnormal)
- If (min is normal) and (max is abnormal 1) then (output1 is check)
- If (min is average) and (max is average) then (output1 is check)
- If (min is abnormal 1) and (max is average) then (output1 is abnormal)

4- <u>Defuzzification</u>:- The result of the rule firing is a fuzzy set. The purpose of defuzzifiction is to obtain a scalar value of output. This is done using the center of Area/Gravity.

5-<u>Denormalization</u>:- The output value obtained after defuzzification is denormalized with the help of scalar denormalization factor.The denormalization is simply the inverse method of the normalization procedure[4]

Results :

After the extraction of single beat fetal HR from tracer, this single beat have been changed from time domain to frequency domain by Wavelet Transform. The DWT is applied to extract the DWT coefficients[7] the mother wavelets have been used Db4.

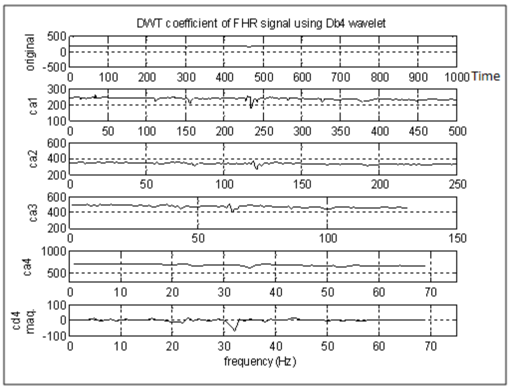


Fig. 4. The DWT coefficients of fetal HR Db4 wavelet of level 4 of sample No.1

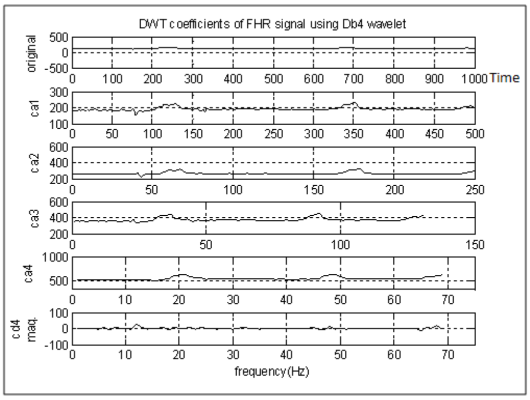


Fig. 5. The DWT coefficients of fetal HR Db4 wavelet of level 4 of sample No.2

Performance of Neural Network

In training process, the goal is to minimize the error between the actual and the desired outputs. The learning process of error BP is to allowing to run until either the MSE is less than or equal to minimum error value or else the maximum number of iteration is reached.

The accuracy of ANN evaluated for all frequency level ,since the lowest frequency have the nearest characteristic of FHR signals resulted that 70 sample recognized all and show that:

1. The final mean-square error is small (10^{-10}).
2. The test set error and the validation set error have similar characteristics.
3. No significant overfitting has occurred by iteration 0 (where the best validation performance occurs).

Table 2. Percentage correct classification for different frequency levels.

Coeff.test	**Average time of train**	**Average time of test**	**%correct**
Ca1	470.930853 sec.	0.05814 sec.	92.8%
Ca2	362.238131 sec.	0.052245sec	92.8%
Ca3	375.768014 sec.	0.05012 sec.	92 .8%
Ca4	98.228307 sec.	0.03912 sec.	100%

Figures 6- 9 shows the training state for different frequency levels in ANN program.

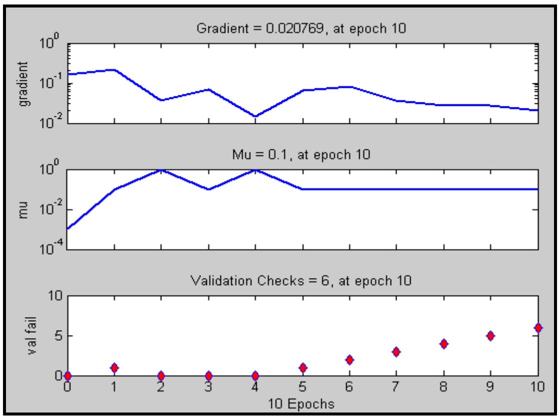


Fig. 6. The training curve for the structure of the first level (best validation performance is 0.048989 at epoch4)

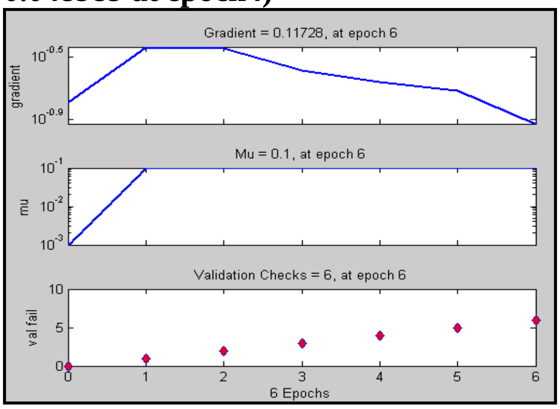


Fig. 7. The training curve for the structure of the second level (best validation performance is 0.032961 at epoch1)

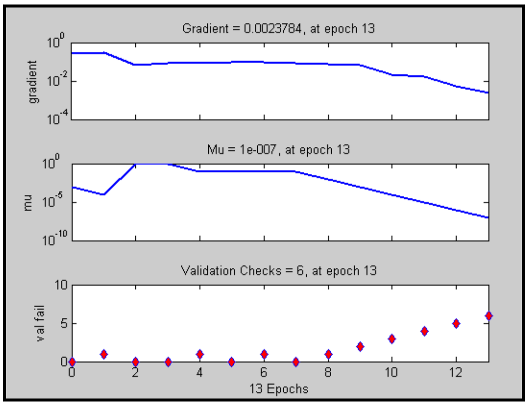


Fig. 8. The training curve for the structure of the third level (best validation performance is 0.07494 at epoch7)

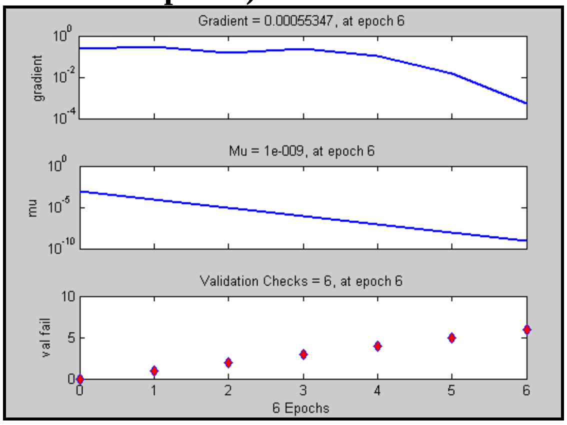


Fig. 9. The training curve for the structure of the forth level (best validation performance is 0.022625 at epoch0)

Fuzzy System Models Analysis Result

In our experiments, the heart rate signals of 70 fetus each were simulated. During the simulations, the percentage of accuracy were observed to evaluate the accuracy of our system. They created two input to fuzzy system (min and max) with five numbers of fuzzy sets into the same 70 fetus HR signals and one output to fuzzy system with the same number of set but different in values to check the effectiveness of our purposed system. All fetus HR were tested, the output was included normal , check, abnormal FHR according to fire rule of the system. All normal cases below 40% did not require to be seen by physication , all cases between 40% to 50% needed to be checked by physication and all abnormal cases up to 50% should be seen by physication.

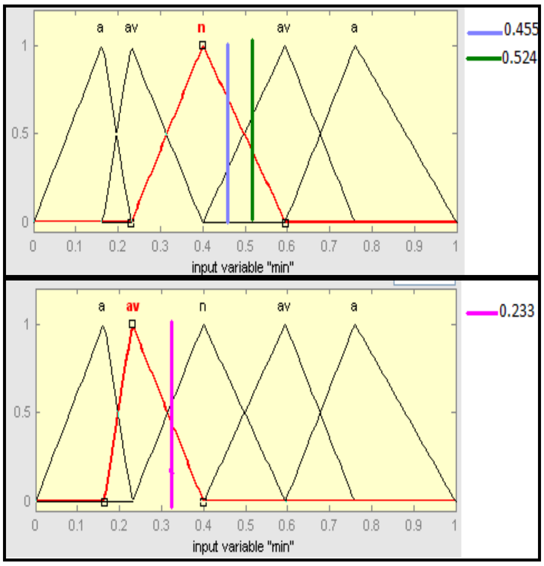


Fig. 10.a Min input membership function for normal fetus No.20,64 and67.

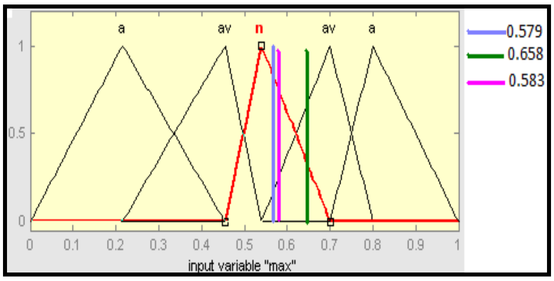


Fig. 10.b Max input membership function for normal fetus No.20,64 and 67

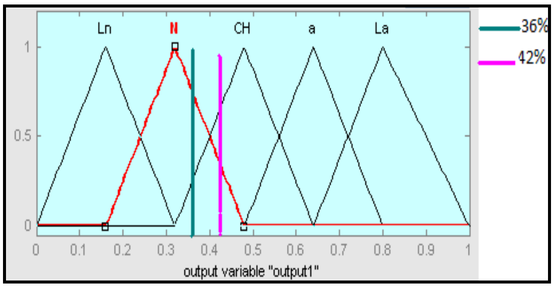


Fig. 10.c Output membership function for normal fetus No.20,64 and67.

Conclusions and Discussion

Cardiotocography (CTG) is a biophysical method for monitoring of fetal condition during pregnancy.

In present work, the conclusions have been pointed out:-

- The electronic fetal monitoring system automatically has been estimated the fetal heart rate baseline, recognized bradycardia and tachycardia.
- Classification of FHR patterns was achieved by means of DWT combined with Back Propagation Neural Networks and Fuzzy logic System.
- fuzzy system has been usedwith the two input (Min and Max) and one output using the membership functions of the Triangle type that gave lower values of the error.
- The Neural Network was excellent at recognizing patterns that for lowest frequency and that give a 92% for the others frequencies.
- The Fuzzy system was a very good at recognizing patterns that give a 90% classification for the lowest frequency and 85%-81% for the others frequencies.
- A wavelet based neural network classifier and fuzzy logic system have been proposed for FHR classification. The feature set has been carefully chosen to have enough information for good accuracy. This feature set is a subset of DWT coefficients based on 'Db4' wavelet.
- Uses fuzzy system with the two input (Min and Max) and one output using the membership functions of the Triangle type that gave lower values of the error.

so we obtained approximation result than other research like **G. Georgoulas et.al** presented an approach to automatic classification of FHR tracings belonging to hypoxic and normal newborns. The classification was performed using a set of parameters extracted form the FHR signal and two Hidden Markov Models . The results were satisfactory indicating that the FHR convey much more information than what was conventionally used .They used 36 recordings from 36 pregnant women (38-42 weeks of gestation age). The FHR recordings have various lengths, ranging from 20 minutes to more than 1 hour. scalp electrodes were used for the acquisition, a feature extraction were derived both from the time domain and the frequency domain.They divide the 36 cases into 4 non-overlapping groups containing 9 cases each (5 normal and 4 hypoxic). Each time they exclude one of them from the training process . They repeate this procedure 4 times and They average the classification performances. Various configurations of HMMs (different number of hidden states) were tested and the results managed to have a maximum overall classification rate of 83% (for seven hidden states) having at the same time high classification rates both for the normal (85%) and the abnormal cases (81%)[8] , and **G.vasios et.al** they developed an automated computerized system that assisted the early diagnosis of fetal hypoxia. They demonstrated that it was possible to distinguish between healthy and academic fetuses by way of wavelet transform analysis of fetal HR recordings and fetal pulse oximetry ($FSpO_2$).They applied Self-Organizing -Map in order to investigate the relationship between the fetal HR variability in different scales and $FSpO_2$(threshold value 30%level) for normal and academic fetuses during the second stage of labor . They were used mother wavelet Daubechies 20-tap, the decomposition was performed up to scale index 5 and SOM neural network consist of 2layers an input layer and 2 output .Data collected for 35 woman .They concluded that fetal pulse oximetry seems to be an important additional source of information.Not only the time , but also the minimum value that $FSpO_2$ reaches play an important role in the classification of patterns, especially in the cases of non-reassuring rate patterns. Performance of neural network was the sensitivity=83%,the specificity =96%,and the accuracy =91% [9].

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تصنيف الحالات غير السوية للجنين باستخدام اشارات تخطيط معدل ضربات القلب CTG

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الخلاصة:

تقدم هذه الدراسة طريقة التحليل لإشارات معدل ضربات قلب الجنين بأستعمال الشبكة العصبية الأصطناعية،المنطق المضبب وتحويل المويجة المتقطع (DWT) لغرض التحليل التلقائي بأستعمال الحاسوب الشخصي. مخطط ضربات قلب الجنين هو طريقة اولية لمراقبة الجنين ويستند تقييمَ آثاره المطبوعة على التحليلِ البصريِ للأنماطِ التي تَصِفُ تغيّرَ إشارةِ معدّل نبضات القلب. وقد أخذت بيانات معدل ضربات قلب الجنين من جهاز مراقبة الأم والجنين من نوع (operator manual P/N 15457AA REV.C from GE medical system)في مستشفى بغداد التعليمي.

استعملت شبكة متعدد الطبقات مع خوارزميه طريقة الانتشار العكسي لإشارة الخطأ في تدريب الشبكة العصبية وقد تم استعمال برنامج أل MATLAB v7.7 . تمضمنت المرحلة الأولى في النظام هو تحويل تخطيط قلب الجنين إلى متسلسلة رقمية يمكن النظام من تحليلها. بينما تم في المرحلة الثانية التحويل بأستخدام تحويل المويجة المتقطع(DWT) وذلك للحصول على صفات النظام.

تضمنت المرحلة الأخيرة من البحث إدخال المعاملات التقريبية الناتجة إلى الشبكة العصبية الصناعية والمنطق المضبب. حيث تمت مقارنة النتائج لغرض الحصول على افضل نتائج لتصنيف اشارة معدل ضربات قلب الجنين.