

Improving The Accuracy of Cardiotocogram Machine Analysis Using Artificial Neural Network (ANN)

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Abstract- *This work aims at improving the Accuracy of Cardiotocogram Machine Analysis using Artificial Neural Network (ANN). There is a need to improve the cardiotocogram machine analysis because the conventional method of analysis has a major drawback of impression and inaccuracy. This drawback, if not properly analyzed will lead to permanent fetal brain damage or death. From the literatures reviewed, it was discovered that there is a need to develop a reliable technique that will reduce the incidence of unnecessary medical intervention and fetal injury during child labor. To achieve this, artificial neural network algorithm for cardiotocogram analysis was developed. A sample of five patients were collected from the existing result of the cardiotocogram from ESUT Teaching Hospital and it was saved in Microsoft excel. The result was injected to MATLAB 2015a, where the data was trained. The result achieved a classification accuracy of 98.34% which is very good. The system was compared with the other state of the art algorithms and the result showed 2.11% better than the best existing system performance.*

Indexed Terms- *Improving, Cardiotocogram, Machine analysis, and Artificial neural network*

I. INTRODUCTION

Fetal Medicine aims to monitor and determine actions to provide fetus wellbeing. Cardiotocography (CTG) is an exam applied before or during labor to monitor simultaneously Fetal Heart Rate (FHR) and Uterine Contraction (UC) based on Doppler ultrasound and toco sensors, making it possible to identify fetal cardiovascular or neurological risky situations or pathologies (Ingemarsson et al,1998; Zong abd Jiang, 2008; Zadeh, 1983) .

According to the American Congress of Obstetricians and Gynecologists (ACOG), common problems found during the analysis of Electronic Fetal Monitoring (EFM) are poor interobserver and intra-observer diagnostics reliability and high rates of false-positives in visual interpretation (ACOG, 2005). Different digital signal processing techniques have been used to extract information from these signals: Wavelets (Magenes et al., 2000), artificial neural networks (ANN) (Magenes et al., 2000), and also the application of combined techniques of ANN with other signal processing tools, such as multi resolution Principal Component Analysis (PCA) (ACOG, 2005).

CTG is probably the most widely used technique in all obstetrics. It was introduced by Orvan Hess and Ed Hon at Yale University in 1957. Before that, the only device used was a stethoscope to determine fetal status and maternal uterine contractions. Nevertheless, CTG can be considered a gold standard examination for FHR detection (Signaini, 2003). Doppler sensors have similar accuracy to that of fetal abdominal ECG and can also be used in many different clinical situations. (Dawes et al., 1991) developed an algorithm for the FHR analysis based on low-pass frequency filters to obtain the baseline and identify accelerations and decelerations. This algorithm was used in the System 8000, a commercial software which is now discontinued. Mantel et al., (1990) improved some aspects of Dawes' algorithm, for example in the beginning of the recording and the detection of changes of the baseline.

This work presents a complete computerized CTG analysis system based on a set of artificial neural network system for Cardiotocography based monitoring, to reduce the incidence of unnecessary medical intervention and fetal injury during child labour, due to a high degree of uncertainty and imprecision in obstetric data and knowledge.

- Problem Statement

The outcome of childbirth is usually good for the fetus, but sometimes problems occur that can result in permanent fetal brain damage, other abnormalities or even death. Cardiotocogram interpretation is a difficult task and this requires clinical experience and significant expertise. Delay in the interventions and failure to intervene when necessary can lead to preventable injuries and deaths. The Digital CTG analysis has been impeded by inherent problems of imprecision and uncertainty in the clinical data and the interpretation methods used. Also, CTG does not contain sufficient information for accurate assessment of the fetal condition.

The large amount of information produced by the fetal CTG requires continuous and vigilant monitoring but this is not always practical in a busy labor ward. Continuous monitoring is a very intensive process which would lead to fatigue and eventually mistakes. Computer assistance would help to provide constant monitoring. Therefore, the need to develop a reliable artificial neural network system which will reduce the incidence of unnecessary medical intervention and fetal injury during child labor becomes imperative for this thesis

- Aim and Objectives of the Study

The aim of this work is to improve the accuracy of Cardiotocogram machine analysis using artificial neural network. The main objectives are to

- 1) Characterize the existing cardiogram machine analysis
- 2) Collect data on Cardiotocogram analysis from a hospital.
- 3) Develop an Artificial Neural Network and simulate the model in MATLAB 2015a.
- 4) Validate the proposed model with the existing model.

- Significance of the Study

- a) It will reduce the risk of intervention like Caesarean Section (CS).
- b) It will reduce high degree of imprecision and uncertainty in Clinical data.
- c) It will help clinicians to adequately monitor labor and intervene when necessary.

- Scope of the Study

This work is a simulated work which is limited to the application of artificial neural network in the development of artificial neural network model to enhance the accuracy of Cardiotocogram analysis

- Justification of the Study

The proposed ANNs have the ability to learn and model non-linear and complex relationships, which is really important because in real-life, many of the relationships between inputs and outputs are non-linear as well as complex.

II. MATERIALS AND METHODS

Materials Used.

The following materials were used to simulate the proposed system:

- MATLAB 2015a
- Microsoft excel
- Laptop (64-bit operating system),4G RAM

- Design Method

The method adopted in this work is an artificial neural network methodology to improve the accuracy of Cardiotocogram readings. Firstly, the existing system of the cardiotocogram machine was studied and analyzed. The purpose was to understand the fundamental concept of the reading analysis. It was discovered that the reading was hard and time consuming, hence due to human fatigue it may lead to error. Secondly, sample of five patients were collected from the existing result of the cardiotocogram from ESUT Teaching Hospital and it was saved in Microsoft excel. An artificial neural network algorithm was proposed. A supervised learning was used by training the data set which was accompanied by class learning. When a new data arrives, then classification of that data will be done based on the training set by generating descriptions of the classes. In addition to training set the work also have a test data set that was used to determine the effectiveness of a classification. MATLAB 2015a was used to train and classification of data set. Finally, the data used in CTG machine and ANN were compared to validate the proposed ANN model

- Characterization of the existing system and data collection

Data for this work was obtained from CTG readings at the Enugu state University of science and technology teaching Hospital Parklane, Enugu State. Five patients (pregnant women) were used for the experiment to determine the fetal heart rate of the foetus and uterine contraction of the mothers. This work concentrated on the fetal heart rate, and the features investigated included the baseline rate, baseline variability, accelerations and decelerations in heart rate. Each patient lay on top of the bed, facing up, and the clinician either placed or tied the toco-probe at the right side of the mother’s abdomen. The Cardiotocogram tracing was then monitored on the monitor, and the readings of the parameters under investigation included the baseline rate, baseline variability, accelerations and decelerations were recorded. These results were also sent to the printer to obtain a hard copy. The two machines used for monitoring the fetal heart rate are the ultrasound and Cardiotocogram machines.

The inputs and outputs of the respective ranges for data collected for baseline {110-200}, variability {6-40}, acceleration {15-30}, and deceleration {15-30} are shown in Table 1

Table 1: Simulation of the inputs and outputs of theoretical CTG features.

Baseline		Variability		Acceleration		Deceleration	
Input	Output	Input	Output	Input	Output	Input	Output
110	0.0241	6	0.00869	15	0.0156	15	0.0156
120	0.0087	10	0.05	17	0.0106	17	0.0106
130	0.0087	14	0.05	19	0.0087	19	0.0087
140	0.0087	18	0.05	20	0.0087	20	0.0087
150	0.0101	22	0.00884	21	0.0087	21	0.0087
160	0.0147	25	0.00874	22	0.0087	22	0.0087
170	0.0147	29	0.00868	23	0.0087	23	0.0087
180	0.0147	31	0.00866	24	0.0087	24	0.0087
190	0.0149	35	0.00866	25	0.0087	25	0.0087
200	0.0147	40	0.00873	30	0.05	30	0.05

The results of the measured values obtained from the five patients and their computed accuracies are shown in Table 2

Table 2: Data collect from ESUT teaching hospital

Class of patient	Baseline rate (bpm)	Average value for Baseline rate (bpm)	Baseline Variability (bpm)	Average value for Baseline Variability (bpm)	Accelerations (bpm)	Average value for Accelerations (bpm)	Decelerations (bpm)	Average value for Decelerations (bpm)	Accuracy of CTG measured values (%)
one	140, 142, 138	140	7,6,5	6	22,21,23	22	19,20,21	20	0.67
Two	144, 140, 136.	140	10,11,9	10	9,10,11	10	6,6,6	6	0.68
Three	150, 148, 152.	150	9,10,11	10	20,18,16	18	11,9,10	10	0.73
Four	150, 148, 146.	148	7,8,6	7	9,10,11	10	11,13,12	12	0.65
Five	158, 160, 162.	160	7,5,6	6	21,19,20	20	20,19,21	20	0.64

III. STRUCTURAL DESIGN OF AN ARTIFICIAL NEURAL NETWORK

The proposed model uses ANN, which depends on combining Neural Network (NN) and rough set theory. The proposed model applies the supervised learning model of the RNN and formed from three consecutive phases which are pre-processing, training and testing phases as in the following:

- 1) Pre-processing phase: where medical dataset is normalized to avoid anomaly values of features and improve the efficiency of medical data in implementation stage.
- 2) Training phase: where the ANN is trained to reach best weights helps in discovering patterns of data and reduce absolute error by using a feed forward algorithm, and back propagation algorithm to update upper and lower weights to reach a better classification of CTG data set.
- 3) Testing phase: where the trained ANN is measured against new instances of data to calculate the accuracy rates using the relation: Accuracy Rate = 1 – absolute error.

Moreover, the time consumption is determined to prove the performance of the proposed model.

The ANN structure replaced the traditional neuron by two neurons (lower neuron, upper neuron) to represent lower and upper approximations of each attribute in the CTG data set, its structure formed from 4 layers input, 2 hidden and output layers. The hidden layers have rough neurons, which overlap and exchange information between each other, While the input and output layers consists of traditional neurons as in figure 1

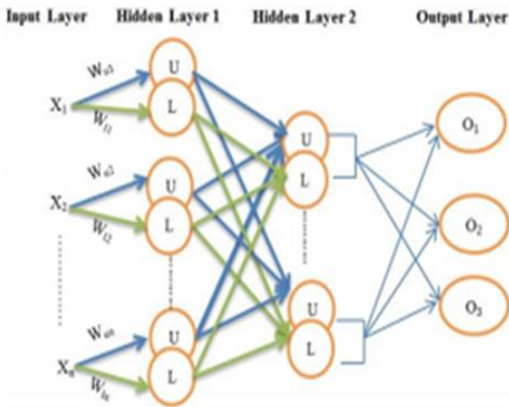


Fig. 1 Artificial Neural the Network (ANN) Structure

Input layer is composed of neuron for each data attribute. The output layer represents the three FHR classes, the hidden layers rough neurons are determined by the Baum-Haussler rule

$$N_{hn} = \frac{N_{ts} * T_e}{N_i + N_o} \tag{1}$$

Where N_{hn} is the number of hidden neurons, N_{ts} is the number of training samples, T_e is the tolerance error, N_i is the number of inputs (attributes or features), and N_o is the number of the output.

During training process, the normalized input data is multiplied by its weight and computed in sigmoid activation function.

$$f(x) = \frac{1}{1 + e^{-\lambda x}} \tag{2}$$

Proposed ANN Model for Cardiocotogram Analysis

Steps of the proposed model architecture:

Step I: preprocessing phase

1. Read features of each objects in dataset
2. Normalize all values of data by equation

$$Nor = \frac{x - min}{max - min} \tag{3}$$

Step II: Training phase

3. Initialize random (upper, lower) weights of network
4. Feed forward of attribute values and multiply in both direction ($U_w L_w$)
5. Compute ($I_U I_L$) of hidden layers by relations:

$$I_{Ln} = \sum_j^n = 1 W_{Lnj} O_{nj} \tag{4}$$

$$I_{Un} = \sum_j^n = 1 W_{Unj} O_{nj}$$

Compute ($O_U O_L$) of hidden layers by relations:

$$O_{Ln} = Min(f(I_{Ln}), f(L_{Un}))$$

$$O_{Ln} = Min(f(I_{Ln}), f(L_{Un}))$$

Check fetus according to comparing between actual output (T) and output value (O), where output represent by

$$O = O_{Ln} + O_{Un} \tag{5}$$

If output is error, then use back propagation algorithm, and compute error.

$$\Delta = T - O$$

Update (upper, lower) weights of network by derivation of activation function: new weight = old weight + ($\Delta * \eta * derivative * activation\ of(input)$) (10) where η is learning rate of model

Repeat 5, 6, 7, 8 and 8.1 until reduction error as possible as.

Step III: Testing phase

Classify new sample of objects and determine the accuracy rate of the model by using relation Accuracy = 1 - absolute error, also calculate time consumption in model processing.

MATLAB Interface to Show How the Date Was Trained

From baseline rate in figure 3.1 the input range was 110,120,130,140,150,160,170,180 while the output rate was 0.0241,0.087, 0.087, 0.087 0.0101,0.0147,0.0147,0.0147,0.0149,0.0147

Baseline rate

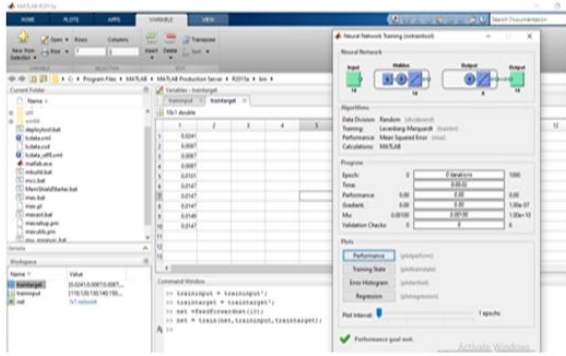


Figure 2: training tool of the ANN

```
>>traininput = traininput';
>>traintarget = traintarget';
>> net =feedforwardnet(10);
>> net = train(net,traininput,traintarget);
```



Figure 3: Regression tool of the ANN

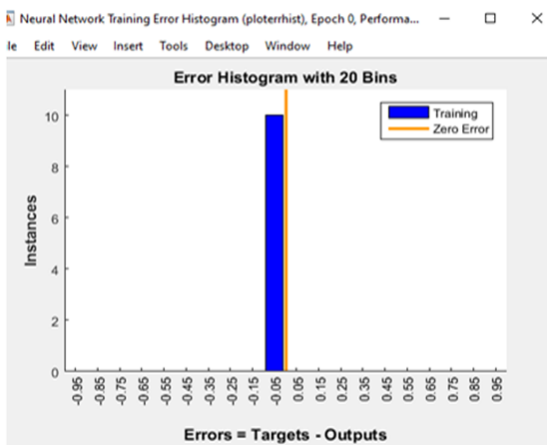


Figure 4: Error measurement tool of the ANN

Baseline Variability, in figure 4 above the input range from 6,10,14,18,22,25,29,31,35,40 and 0.00869, 0.05, 0.05, 0.00884, 0.00874, 0.00868, 0.00866, 0.00873

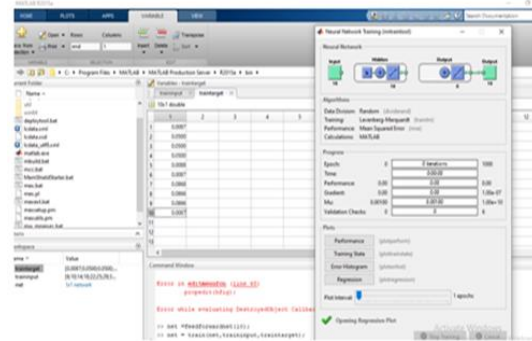


Figure 5 training tool

```
>>traininput = traininput';
>>traintarget = traintarget';
>> net =feedforwardnet(10);
>> net = train(net,traininput,traintarget);
```

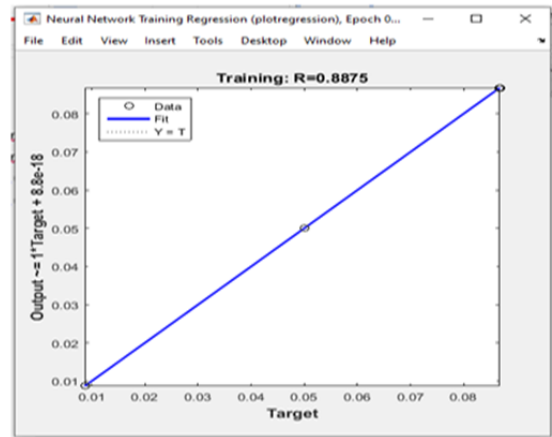


Figure 6 regression analyzer

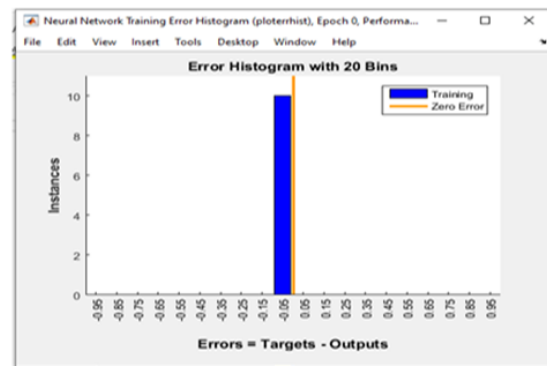


Figure 7 Error histogram tool

Acceleration in figure 1 above the input range from 15,17,19,20,21,22,23,24,25,30 output 0.0156,0.0106,0.0087,0.0087,0.0087,0.0087,0.0087,0.0087,0.0087,0.05

Deceleration in figure 10 above the input range from 15,17,19,20,21,22,23,24,25,30 output 0.0156,0.0106,0.0087,0.0087,0.0087,0.0087,0.0087,0.0087,0.0087,0.05

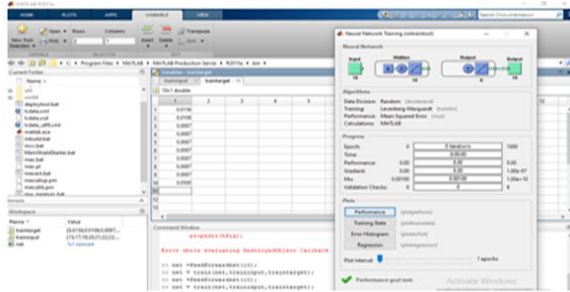


Figure 8: training tool for ANN

```
>> net = feedforwardnet(10);
>> net = train(net,traininput,traintarget);
>> net = feedforwardnet(10);
>> net = train(net,traininput,traintarget);
```

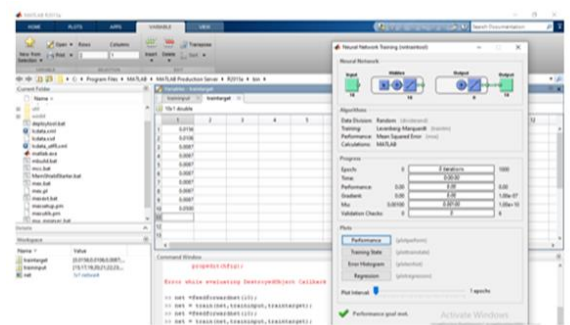


Figure 11: training tool

```
>> net = feedforwardnet(10);
>> net = train(net,traininput,traintarget);
>> net = feedforwardnet(10);
>> net = train(net,traininput,traintarget);
```

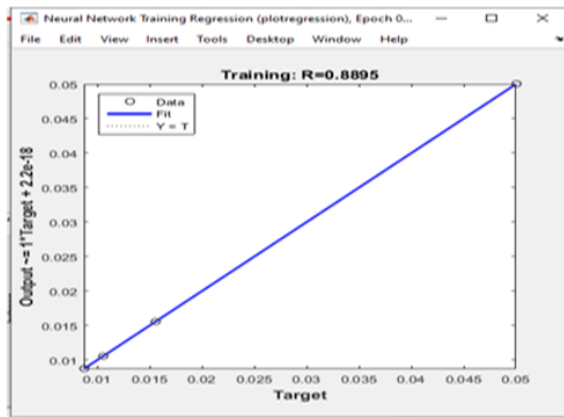


Figure 9: regression tool

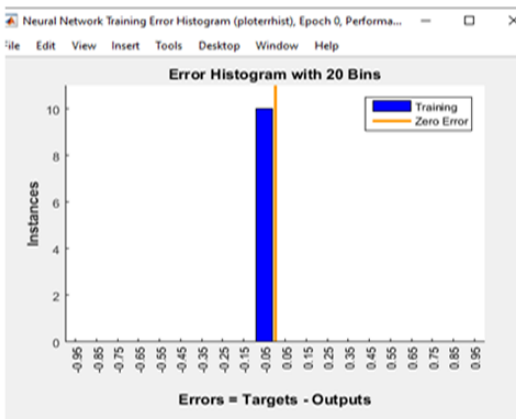


Figure 10: error histogram tool

IV. RESULTS AND DISCUSSIONS

Results Obtained from Cardiocotogram Machine

These simulation results were used to determine the optimal condition for the artificial neural network and cardiocotogram machine.

The results obtained from the measured features of the cardiocotogram machine for the five patients

The table 3 to 4 and figure 12 to 16 were tabulated from simulation file of artificial neural network

Table 3: Results obtained from Ultrasound machine

Class of patient	Baseline rate (bpm)	Baseline variability (bpm)	Accelerations (bpm)	Decelerations (bpm)
One	148	2	2	2
Two	140	2.5	2.5	2.5
Three	142	2	2	2
Four	144	2	2	2
Five	145	3	3	3

Accuracy of The Measured Values Using Cardiocotogram Machine and artificial neural network]

Figure 11 and table 4 reveals the degree of uncertainty in predicting the accuracy of Cardiogram.

To determine the degree of uncertainty between the Cardiogram machine and artificial neural network System, the accuracies against patients as tabulated and plotted in figure 11 and table 4. based on simulation. The measured results from the Cardiogram showed a strong positive correlation of $R^2=0.9723$ between the CTG accuracy and the patients while the simulated Artificial neural network system revealed a weak correlation of $R^2 =0.8895$ between the Artificial neural network accuracy and the patients. Artificial neural network system produces the best reliable accuracy from the simulation carried out.

Table 4: The Accuracies Against Patients for Cardiogram Machine

<i>Patients</i>	<i>Accuracy</i>
One	0.039
Two	0.043
Three	0.047
Four	0.048
Five	0.049

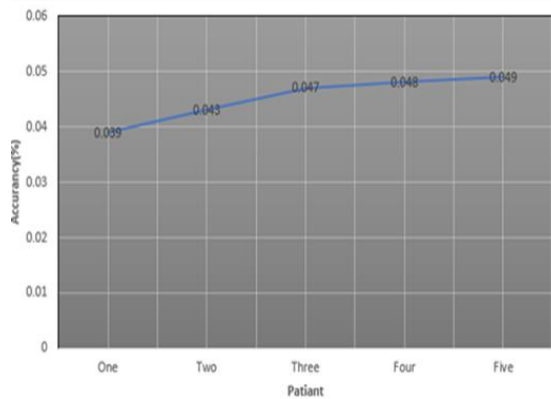


Fig 12 Graph of accuracy for Cardiogram Machine

Table 5 The Accuracies Against Patients for Cardiogram using artificial neural network

<i>Patients</i>	<i>Accuracy</i>
One	0.0137
Two	0.0214
Three	0.0214
Four	0.0214
Five	0.0147

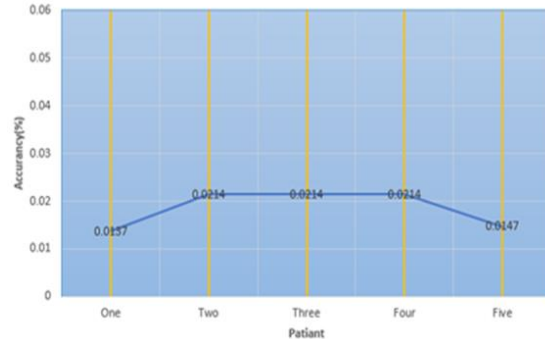


Fig 13 Graph of accuracy for artificial neural network

Determination of the Degree of Uncertainty of the Reviewer’s Values between Cardiogram Machine and Artificial Neural Network

To determine the degree of uncertainty of the Reviewer’s values between the ultrasonic machine and artificial neural network.

It was observed from the graph that the Cardiogram analysis occurred with lower accuracies than the artificial neural network. This shows that the artificial neural network produced higher classification errors during the training process compared to the measured values in the primary data from ultrasonic machine.

Table 6 Degree of Uncertainty of the Reviewer’s Values for Cardiogram Machine

Patience	Accuracy
One	0.075
Two	0.069
Three	0.051
Four	0.060
Five	0.063

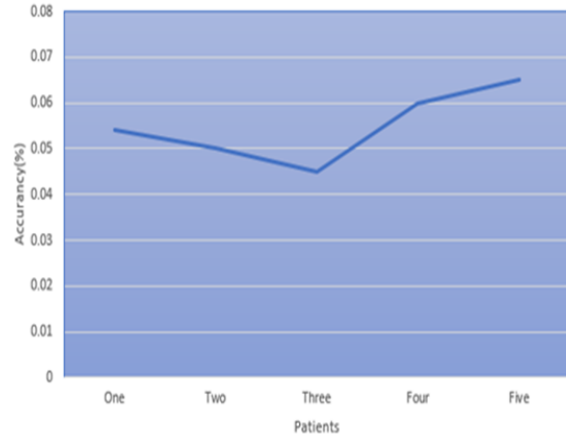


Figure 15: Degree of Uncertainty of The Reviewer’s Graph of accuracy versus patient for artificial neural network

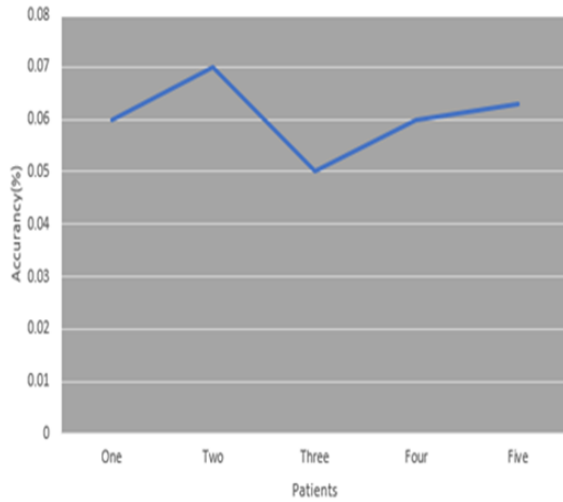


Figure 14: Degree of Uncertainty of the Reviewer’s Graph of accuracy versus patient for Cardiogram Machine

Comparison of the Average Result Between artificial neural network and Cardiogram Machine

Results obtained from the artificial neural network model and the review from expert based on ultrasonic machine were compared as shown in Table 4.5

Table 7 Degree of Uncertainty of The Reviewer’s Values for artificial neural network

Patience	Accuracy
One	0.051
Two	0.050
Three	0.049
Four	0.060
Five	0.065

Table 8: Comparison of the artificial neural network and Cardiogram Machine

Class of Patient	Cardiogram Machine	artificial neural network
	One	±5.1%
Two	±5.0%	±7.7%
Three	±4.6%	±6.0%
Four	±5.5%	±6.9%

In this work, the ultrasonic machine has provided lower classification of accuracies compared to the artificial neural network.

Figure 16 show that the ultrasonic machine has provided lower classification of accuracies compared to the artificial neural network this indicates that the artificial neural network has provided improved performance compared to the ultrasonic machine

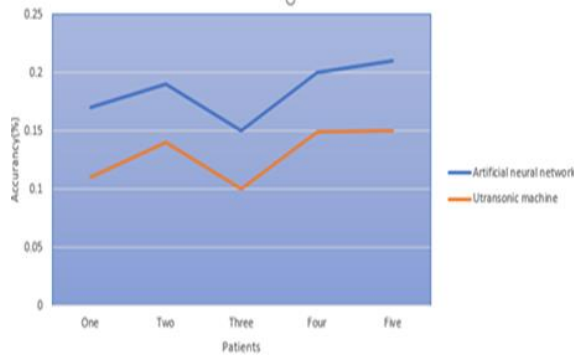


Figure 16: Accuracy versus patient for both artificial neural network and Ultrasonic machine

From the result in figure 16 it was observed that the accuracy of the artificial neural network-based machine was higher than the conventional ultrasonic machine, the implication of the result is that the use of ANN achieved better performance than the existing system currently in use.

CONCLUSION AND RECOMMENDATIONS

- Conclusion

Computerized analysis of CTG is admitted as the most promising way to tackle these drawbacks. ANN, which has a powerful connection between the input and output variables, is a mathematical model that reflects learning and generalization ability of human neural architecture (Amato et al., 2013). ANN can be employed to solve various real-world problems, such as any complex functional approximation, pattern classification or clustering, forecasting, and image completion. Therefore, ANNs are evaluated as a valuable computational model (Günther and Fritsch, 2010). ANNs consist of the input layer and the output layer, furthermore, the layer(s) between input and output layers are referred to hidden layer that may be one or more, helps to capture nonlinearity and is not directly observed. In theory, ANNs can be contained an arbitrary number of input and output variables. However, it must be noted that the number of variables and computational cost is entirely proportional (Hu and Hwang, 2001). The number of neurons per layers, training algorithms, epochs, maximum training time, performance values, gradient, and validation checks can be set before training of an ANN, so it can be expressed that ANN is very flexible and versatile tool

- Recommendations

The following was recommended

The integration of artificial neural network with a Cardiotocogram machine to facilitate the speed of testing the fetal heart rate of the foetus and also to enhance the efficiency of the clinician.

Another possible area will be to develop a technique that will provide efficient removal of power-line noise and baseline shifts using linear Finite Impulse Response filters

To investigate the readings obtained from different experts and conduct an analysis to certify the sensitivity of the Cardiotocogram machine

- Contribution to Knowledge

Training data collected in ESUT Teaching hospital and classification of such data

Simulation of ANN model was another area this research work contributed to knowledge.

V. ACKNOWLEDGEMENT

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