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CLASSIFICATION MODEL FOR CARDIOTOCOGRAM MACHINE USING FEED FORWARD NEURAL NETWORK

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Abstract

One of primary concerns during pregnancy is the challenge of accurate monitoring of Fetal Heart Rate (FHR) and interpretation of cardiogram data to help determine the condition of the baby. The aim of this study is to present a classification model for cardiotocogram machines using Feed-forward Neural Network (FNN). The dataset for this study was collected from the Kaggle repository. The data consist of 2126 fetal cardiotocogram (CTG) data with 42 attributes, span across three classes of normal, suspect and pathology. The data was processed using noise filtering, normalization and then splitted into training, testing, and validation set in the ratio of f 70:20:10. FFNN was then trained using the data and Levenberg-Marquardt as the optimization technique. The model generated was evaluated and the results reported 90.3% accuracy, 81.9% sensitivity, 82% specificity, and 80.9% precision. Comparative analysis with other state of the art algorithm was performed, with the results showing the competence of the new cardiotocogram classification model among the best. The model was recommended to improve operation and functionality of CTC machine.

Keywords: Cardiotocogram (CTG), Levenberg-Marquardt, Kaggle repository, FFNN and FHR

1. INTRODUCTION

A cardiotocogram (CTG) machine is essential equipment used in monitoring and recording fetal heart rate (FHR) and Uterine Contractions (UC) to assess fetal health and well-being (Ponsiglione et al., 2021). It is frequently used to identify fetal distress during pregnancy and childbirth. This process makes provision for prompt interventions and lowers the possibility of unfavourable newborn outcomes (Abiyev et al., 2023). In order to lower prenatal mortality and morbidity (Zarko et al., 2017), CTG is very essential, especially when fetal distress is detected early. Medical professionals can take well-informed action, such as carrying out emergency interventions, which may save the mother's and the fetus' lives (Muhammad et al., 2022). With this implication, clinical decision-making relies heavily on the appropriate interpretation of CTG data. The traditional CTG interpretation is subjective and frequently differs greatly amongst doctors, due to inconsistency and variation of diagnosis result. This variation has the potential to affect therapeutic outcomes and result in needless interventions by producing false-positive and false-negative diagnoses (Asfaw et al., 2023). Accurate analysis of FHR and UC patterns is difficult due to their intrinsic complexity and non-linearity (Rongdan et al., 2021). Despite their usefulness, current interpretation standards fall short in capturing the complexities of CTG signals, which results in limitations in both sensitivity and specificity (Sahana et al2023). The sensitivity needed to precisely identify uncommon or intricate patterns in CTG data is frequently lacking in rule-based and statistical algorithms. They might perform poorly in clinical contexts, which would limit the overall efficacy of automated CTG interpretation and its dependability in crucial situations. Current automated CTG analysis systems frequently use linear statistical techniques and rule-based algorithms. Although helpful, these techniques are ill-suited to deal with the complicated and non-linear nature of CTG data, and they could overlook minute patterns that might point to fetal discomfort. The sensitivity needed to precisely identify uncommon or intricate patterns in CTG data is frequently lacking in rule-based and statistical algorithms. They might therefore perform poorly in clinical contexts, which would reduce the reliability and overall efficacy of automated CTG interpretation. Research has shown that Artificial Neural Networks (ANN) are effective in a variety of medical applications, including image and signal analysis. Previous studies presented by different authors revealed that ANN models trained on CTG data can significantly enhance the accuracy of fetal distress detection, with higher sensitivity and specificity than conventional methods. ANN are a subset of machine learning algorithms inspired by the structure of the human brain, known for their powerful pattern recognition capabilities (Alexandros et al., 2024). ANNs are specifically suited for analyzing medical signals like CTG because they can learn from large datasets, identifying intricate patterns that traditional methods may miss. By putting into practice an ANN-based model intended to increase the accuracy of CTG analysis, this work seeks to overcome the shortcomings of conventional and rule-based CTG interpretation techniques. This study aims to develop a more dependable and consistent fetal monitoring tool by utilizing Feedforward Neural Network (FFNN) classification capabilities. By lowering the possibility of misunderstandings, providing doctors with unbiased data, and eventually enhancing patient outcomes, the incorporation of a precise, FFNN, an ANN-driven CTG analysis system, has the potential to revolutionize fetal monitoring. This automated method will be very helpful, especially in high-stress labour and delivery settings where prompt and precise assessments are vital. The arrangement of this paper is as follows: The section 1; introduces the background of the study. An overview of the relevant literature is elaborated in Section 2; the materials and method are described in Section 3; Section 4 contains the discussion and result; and the conclusion is given in Section 5.

Paper contribution:

a) Examining the previously proposed literatures on cardiotocogram.
b) Modelling of a cardiotocogram data using Feedforward Neural Network algorithm
c) Validation of the model FFNN with other existing models.

2. RELATED WORKS

Cardiotocography is mostly used in assessing the Fetal Heart Rate (FHR), and as such, several works have been carried out to optimize the use of cardiotocographs in combination with other techniques using both machine learning and deep learning models. The following literature presents the research works done by different authors. Mendis et al. (2023) carried out an extensive study on the range of computerized CTG analysis approaches to overcome the challenges of manual clinician interpretation. The author(s) presented an overview of current FHR and Uterine Contraction (UC) monitoring technologies. They took into account both public and private CTG datasets, as well as the steps involved in preprocessing these datasets. They further investigated classification algorithms such as Machine Learning (ML) classifiers (Deep Gaussian processes, logistic regression, random forest, support vector machine) and Deep learning classifiers (Long Short-Term Memory and Conventional Neural Network) used in the automation technique for fetal compromise detection. Alharbi et al. (2024) subsequently unstudied the implementation of ML and DL in addressing the challenges of fetal hypoxia using a cardiotocograph. The review provided guidance, especially for the obstetricians, on improving the accuracy of detecting suspicious fetal hypoxia more efficiently during fetal health monitoring. In the quest to proffer more solution as regards to the improvement of CTG in fetal health, Ricciardi et al. (2023) proposed a solution to the challenges of classifying suspected CTG recording using ML technique, thereby developing a machine-based labeling. The dataset used for this work consisted of 580 CTG signals for healthy fetuses from the 24th to 42nd week of gestation. A Support Vector Machine (SVM) was deployed for binary classification in order to differentiate between suspicious and normal CTG traces. The classification metrics disclosed the best accuracy of 92%, sensitivity of 92%, and specificity values of 90%. The authors further pointed out the importance of appropriate feature selection and dataset balancing in achieving an acceptable performance of the classifier. Asfew et al. (2023) focused on improving the classification performance of the CTGs by presenting three DL models for prediction of birth outcome using FHR traces recorded at the beginning of labour and for the time domain using a combination of 1D CNNs and LSTMs and a 2D CNN. These models were trained to classify newly born babies using the CTU-UHB dataset consisting of 51,449 births with 20 minutes of FHR recordings. The models were evaluated using Partial Area Under the Curve (PAUC) between 0–10% false-positive rate and sensitivity at 95% specificity. The 1D-CNN-LSTM parallel architecture outperformed the other models, achieving a PAUC of 0.20 and sensitivity of 20% at 95% specificity. Subsequently, Hirono et al. (2024) proposed the use of Doppler ultrasound (DUS) signals and binary classification using 1D-CNN in order to ascertain the fetal origin of the auto-correlated data obtained from 425 cases while considering the Maternal Heart Rate (MHR) and the Fetal Heart Rate (HFR). The model was trained using the obstetrician-labeled data from the fetus and that of the mother. The proposed model was compared to a simple mathematical method; the best performance was achieved using the proposed model, which disclosed an Area Under the Curve (AUC) of 0.98, 97% accuracy, 82.3% precision, 86.9% recall, and an 84.5% F1-score. Furthermore, Gude et al. (2022) presented a forecasting model using deep learning to predict FHR and UC in combination with the classification algorithm for predictive fetal monitoring. This hybrid algorithm was developed using random forest and support vector machines to predict 2 to 4 minutes into the future of the fetal state, while the FHR and the UC data of the patients are forecasted using a deep learning Long Short-Term Memory (LSTM) model. The classification algorithm disclosed 85% result accuracy in predicting fetal acidosis on features extracted from the cardiotocography data. The approach produced a model with the ability to ascertain the fetus condition, which can adequately guide the obstetricians in diagnosis, planning, and intervention. Kuzu et al. (2023) proposed a predictive approach based on ensemble learning for classification of fetal health into normal, suspicious, and pathology using a cardiotocography dataset of fetal movements and FHR acceleration from the Nonstress Test (NST). The proposed approach disclosed an accuracy above 99.5% on the test dataset. The observed experimental results disclosed that fetal health diagnoses can be made during NST using machine learning. Sahana et al. (2023) explore the use of a robust classification model to address the challenges of poorly interpreted fetal heart rate. The Czech Technical University and University Hospital of Brno (CTU-UHB) database consisting of 552 intrapartum records was collected using the OB Trace Vue System between 27th April and 6th August 2012. The duration of each record was 90 minutes. The use of machine learning classifiers such as SVM, Random Forest (RF), Multi-Layer-Perceptron (MLP), and bagging was deployed by the authors to classify the CTG. The model was evaluated and compared with the Area Under the Receiver Operating Characteristic Curve (ROC-AUC). The result revealed the AUC-ROC value as a high classifier. However, the SVM and RF demonstrated better performance using other parameters. While considering the suspicious cases, the SVM result was 97.4% and RF scored 98%, the sensitivity was 96.4%, and the specificity was 98%. In the second stage of labor, the SVM disclosed an accuracy of 90.6% and the RF score of 89.3%. Hence, according to the revealed results, the proposed model demonstrated its efficiency and can be incorporated into an automated decision support system.

2.1 Research gap

The traditional model such as rule-based, statistical and linear regression algorithms often performs poorly in capturing complex and nonlinear interactions between FHR and UC in CTG data. This study proposes the use of ANN based Feed forward Neural Network (FFNN) model which can adequately learn complex nonlinear mappings in CTG data features such as the FHR, UC, Maternal Heart Rate (MHR) etc. The FFNN model performs data classification which can effectively classify CTG data outcomes into normal, suspect and pathology. The FFNN has also demonstrated strength in noise and artefact handling associated with CTG data such as baseline drifts, or probe errors and noise signals) which can often mislead traditional algorithms. The FFNN model in combination with other data processing techniques such as filtering and normalization, when trained can adequately can handle such challenges. Thereby enhancing the accuracy of the CTG data during diagnoses and providing a good guide in decision- making for doctors.

3.0 MATERIAL AND METHOD

3.1 Data collection

The fetal cardiotocography data used in this work was collected from Kaggle repository. The data consist of 2126 fetal cardiotocogram (CTGs) data with 42 number of features and subsequently divided into training, testing and evaluation data. The data are presented in table 1.

Table 1: Data feature description

Feature	Data Format	Description
File-Name	String	Name of the CTG examination file
Date	Date	Date of the examination
B	Integer	Start instant of the recording
E	Integer	End instant of the recording
LBE	Integer	Baseline value assessed by a medical expert

LB	Integer	Baseline value assessed by SisPorto
AC	Integer	Number of accelerations detected by SisPorto
FM	Integer	Foetal movements detected by SisPorto
UC	Integer	Uterine contractions detected by SisPorto
ASTV	Percentage (Float)	Percentage of time with abnormal short-term variability detected by SisPorto
mSTV	Float	Mean value of short-term variability detected by SisPorto
ALTV	Percentage (Float)	Percentage of time with abnormal long-term variability detected by SisPorto
mLTV	Float	Mean value of long-term variability detected by SisPorto
DL	Integer	Number of light decelerations
DS	Integer	Number of severe decelerations
DP	Integer	Number of prolonged decelerations
DR	Integer	Number of repetitive decelerations
Width	Integer	Histogram width
Min	Integer	Lowest frequency in the histogram
Max	Integer	Highest frequency in the histogram
Nmax	Integer	Number of histogram peaks
Nzeros	Integer	Number of histogram zeros
Mode	Integer	Mode of the histogram
Mean	Float	Mean value of the histogram
Median	Float	Median value of the histogram
Variance	Float	Variance of the histogram
Tendency	Categorical (-1, 0, 1)	Histogram tendency: -1 for left asymmetric, 0 for symmetric, 1 for right asymmetric
A	Boolean	Presence of calm sleep pattern
B	Boolean	Presence of REM sleep pattern
C	Boolean	Presence of calm vigilance
D	Boolean	Presence of active vigilance
SH	Categorical (A, Susp)	Shift pattern
AD	Boolean	Accelerative/decelerative pattern indicating stress
DE	Boolean	Decelerative pattern indicating vagal stimulation
LD	Boolean	Largely decelerative pattern
FS	Boolean	Flat-sinusoidal pattern, indicates a pathological state
SUSP	Boolean	Suspect pattern
CLASS	Integer (1-10)	Class code for patterns A to SUSP
NSP	Integer (1, 2, 3)	Classification: 1 for Normal, 2 for Suspect, 3 for Pathologic

3.2 Data processing

Tocodynamometer sensors for UC and Doppler ultrasound for FHR were used in cardiotocogram (CTG) data collection while recording signals in real time during pregnancy and labor. The collected data underwent data processing through filtering using a high-pass filtering techniques to remove low-frequency noise especially in the UC signal and normalization using min-max normalization technique to handle recording inconsistencies in the FHR data. The heart rate variability, UC frequency, and acceleration or deceleration patterns were retrieved in order to ascertain the health of the fetus. The Feed Forward Neural Network (FFNN) algorithm was deployed after training for data classification into normal, suspect and pathology(distress patterns). These enhancements achieved in developing the FFNN model will aid clinicians in understanding the displayed data, thereby aid the clinicians in making well-informed decision.

3.3 Methodology

The methodology of this work began with data collection. CTG data were usually collected from the patient through the doppler ultrasound and tocodynamometer sensor, which contains primarily the FHR and the UC signals, saved in a Common Separated Values (CSV) file format. The data was processed by filtering for noise removal and feature normalization to ensure data consistency. The processed data was further apportioned in a ratio of 70:20:10 for training, testing and evaluation of the Feedforward Neural Network (FFNN) architecture in MATLAB R2022b environment while deploying the Levenberg-Marquardt technique. The FHR and UC classification accuracy of the proposed model was evaluated using Positive Predictive Value (PPV), False Dictation Rate (FDR), True Positive Rate (TPR), False Negative Result (FNR) and Receiver Operating Characteristic Curve (ROC)evaluation metrics. The validation of the proposed model was carried out using previously developed models of different authors.The FFNN modelcan be implemented within the clinical systems, assisting the medical practitioners in making informed decisions based on real-time CTG analysis. The block diagram of the model is presented in the figure 1 below.

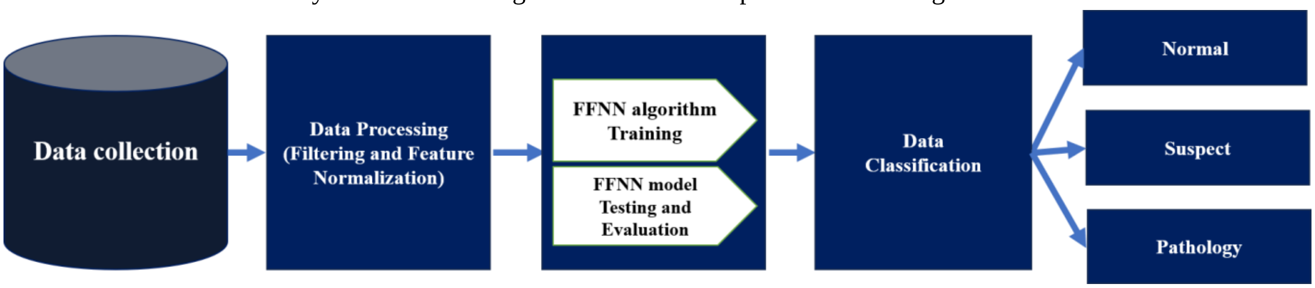

Figure 1: the block diagram of the FFNN model

3.4 How the cardiotocogram machine works

The cardiotocogram (CTG) machine uses two key sensors. The doppler ultrasound transducer sensor to measure the fetus's heart rate (FHR). This sensor uses sound waves to record the heartbeat and then convert it into an FHR in beats per minute. While the tocodynamometer sensors measure the pressure changes during contractions, which show their timing and severity. These signals are processed and displayed on the screen as continuous line graphs for both the FHR and the UC. The clinicians then analyze the various patterns, which include the variations in baseline heart rate and accelerations or decelerations and the contractions frequency. Thereby predicting possible spots of distress and prompting timely interventions during pregnancy and labor. The block diagram below illustrates the cardiotocogram machine key working modules.

Figure: 2 block diagram of the cardiotocogram machine.

1. Sensors/probe block: The cardiotocogram machine uses two sensors: the Doppler ultrasound transducer sensor, which detects the FHR, usually generated by the baby's heartbeats in the form of sound waves. While the second sensor, which is the tocodynamometer sensor, is used in detecting the uterine contractions, especially during labor.

2. Signal processing: This consists of an amplifier and filter. The amplifier enhances the generated weak signal from the sensors, and the filter removes the noise from the signals, thereby making the FHR and UC signals clearer and more readable.

3. Data processing signal analysis: In this block, the signals are examined to determine the intensity of contractions and the patterns of the FHR, such as the accelerations, decelerations and baseline heart rate.

4. Recording and Display Block: This section of the machine displays the real-time FHR and UC data on a screen, thereby aiding the clinicians in monitoring the mother and the baby's health. The paper recording also enables printing the CTG tracing data on thermal paper.

5. Alert and alarm: This enables a timely intervention of the medical professionals in case of any abnormalities in the FHR or UC patterns during labor. The entire block works together in the machine to promote safe labor, hence ensuring the wellness of both mother and child during labor and consequently childbirth.

3.5 Feed Forward Neural Network (FFNN) architecture

The FFNN architecture is modelled by constructing a one-direction data flow that takes in data from the input and passes it onto the output through multiple layers, as illustrated in figure 2 below. The data moves across four hidden layers from the input to the output. These layers consist of four neurons each with the hyperbola activation function, which works with the bias in the hidden layer's neurons. The weighted summation of the layers is computed starting from the input layer that represents the features. The SoftMax activation function is deployed to the output layer for the purpose of classification. The network detects the intricate patterns due to its non-linearity. By having a specific structured task, the end output layer can effectively carryout data classifications. FFNN errors such as prediction errors, FFNN iterative computing training errors, and modified weights can be minimized using backpropagation and enhanced control variables such as learning rate, number of neurons, and layers.

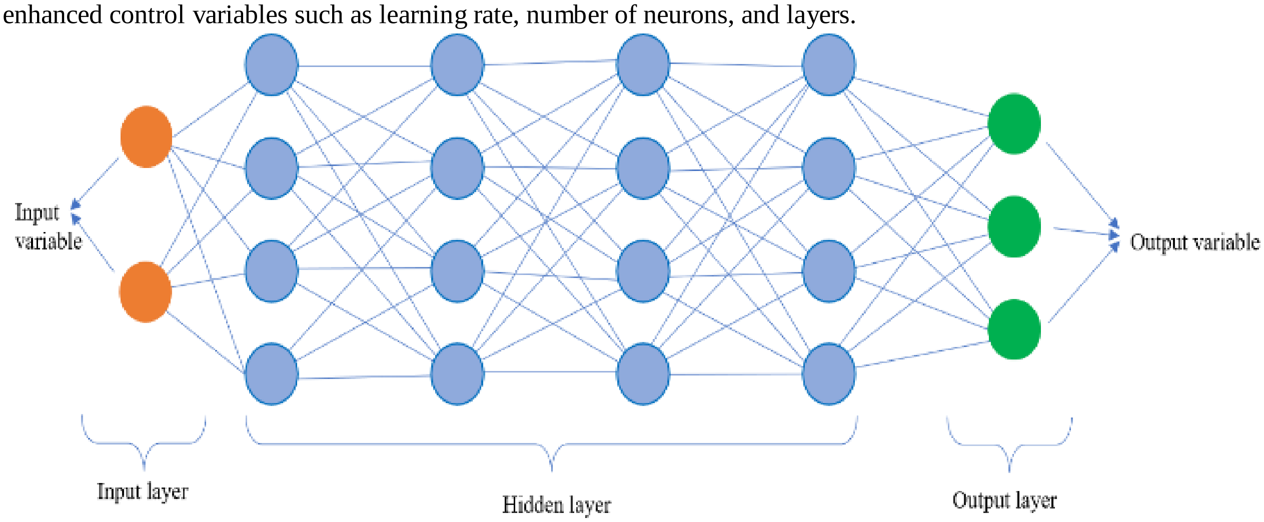

Figure 3: FFNN architecture

3.6 Mathematical model

The FFNN was modeled using four layers with four neurons was trained for data classification of cardiotocogram (CTG) data. The input features were processed through each layer to produce the final classification of the output into normal, suspect, and pathology. The mathematical model was developed considering the following FFNN structure.

Input layer: The FFNN consists of two input vectors, which pass onto the first hidden layers without computation. However, the CTG data features correspond to the number of the input features. The first hidden layer is expressed as shown in equation (1.0), followed by the tanh activation layer also given in equation (2).

$$z^{(1)} = W^{[1]}.x + b^{[1]} \tag{1.0}$$

$$a^{1} = tanh(z^{[1]}) \tag{2.0}$$

Where: $a^{(1)}$is the activation vector of the first hidden layer; The activation function equation using hyperbola $tanh$ for the nth layer is given as equation 3.0:

$$tanh(x) = \frac{e^{x} - e^{-x}}{e^{x} + e^{-x}} \tag{3.0}$$

Hidden layers: The structure of the hidden layers consist of four hidden layers with 4 neurons each, as shown in equation (3) and the $tanh$ activation function given in equation (4).

For hidden layers 2 to 4, $n = 2,3,4$

$$z^n = W^{[n]}.a^{(n-1)} + b^{[n]} \quad (4.0)$$

$$a^n = tanh(z^{[n]}) \quad (5.0)$$

Output layer: This layer involves three outputs with the SoftMax activation function which performs the classification function is given as:

$$(Z) = \frac{e^2 j}{\sum_k e^2 k} \quad (6.0)$$

The output layer is given in equation (7) as:

$$z^c = W^{[c]}.a^{[c-1]} + b^{[c]} \quad (7.0)$$

Where c is denoted as the matrix vector of the output layer

Output activation layer:

$$a^{(c)} = Softmax(z^{(c)}) \quad (8.0)$$

Hence, the single input y for the entire model is expressed as follows:

$$y = f(W^{[5]}.tanh\left(W^{[4]}.tanh\left(W^{[3]}.tanh(W^{[2]}.tanh(W^{[1]}.x + b^{[1]}\right) + b^{[2]}\right) + b^{[3]}) + b^{[4]}) + b^{[5]}) \quad (9.0)$$

Notation:

$x \in \mathbb{R}^{4xn}$ is the input vector matrix

$W^{(i)}$ and $b^{(i)}$ are the weight matrix and bias vector for the nth layers.

$z^{(i)}$ is the pre-activation vector for the nth layer.

$a^{(n)}$ is the post-activation vector for the nth hidden layer.

3.7 System Integration

The system integration for this model was developed using two flow charts. The flow chart of the CTG FFNN model presented in figure 4. The flow chart of the proposed CTG FFNN model

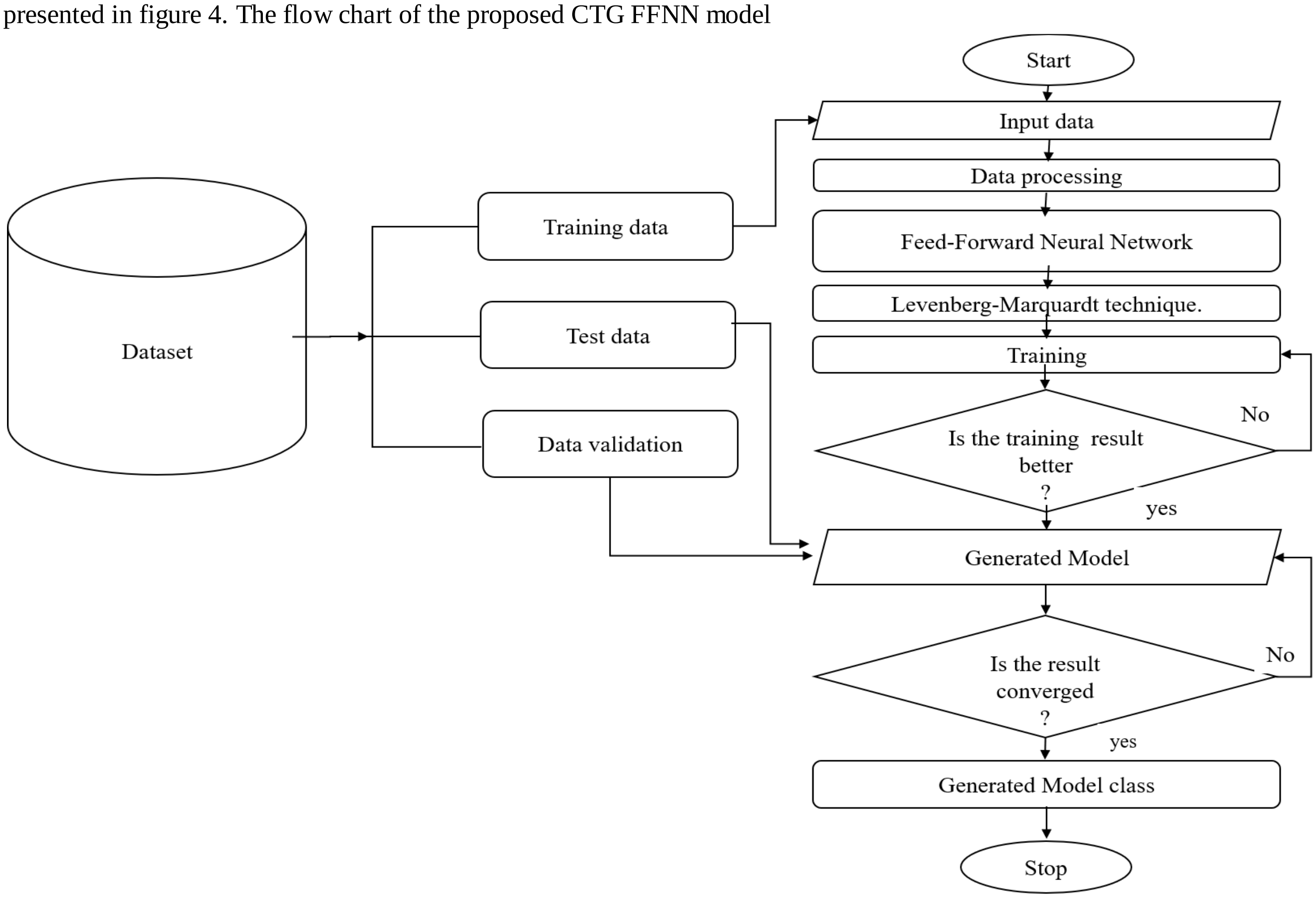

Figure 4: The flow chart of the CTG FFNN model

The CTG FFNN was modeled starting from the data collection. The dataset was divided into three sets, namely the training data, test data and validation in the ratio of 70;20;10. The Input stage receives the training data and transfers it to the data processing stage, here the received data is categorized into baseline FHR, and contraction frequency. The categorized data is further deployed to the Feedforward Neural Network (FFNN) for training using Levenberg-Marquardt technique. The training stage of the flow chart is where the FFNN algorithm is being trained and passed to the decision stage to check the generated result of the FFNN algorithm. The training decision stage passes the result to the generated result stage for testing and validation using the test and validation data. The result convergence stage ensures the improved accuracy of the FFNN generated model. The generated model class output the data classified by the model .The flow chart of the CTG machine merged with the proposed FFNN model is presented in figure 5.

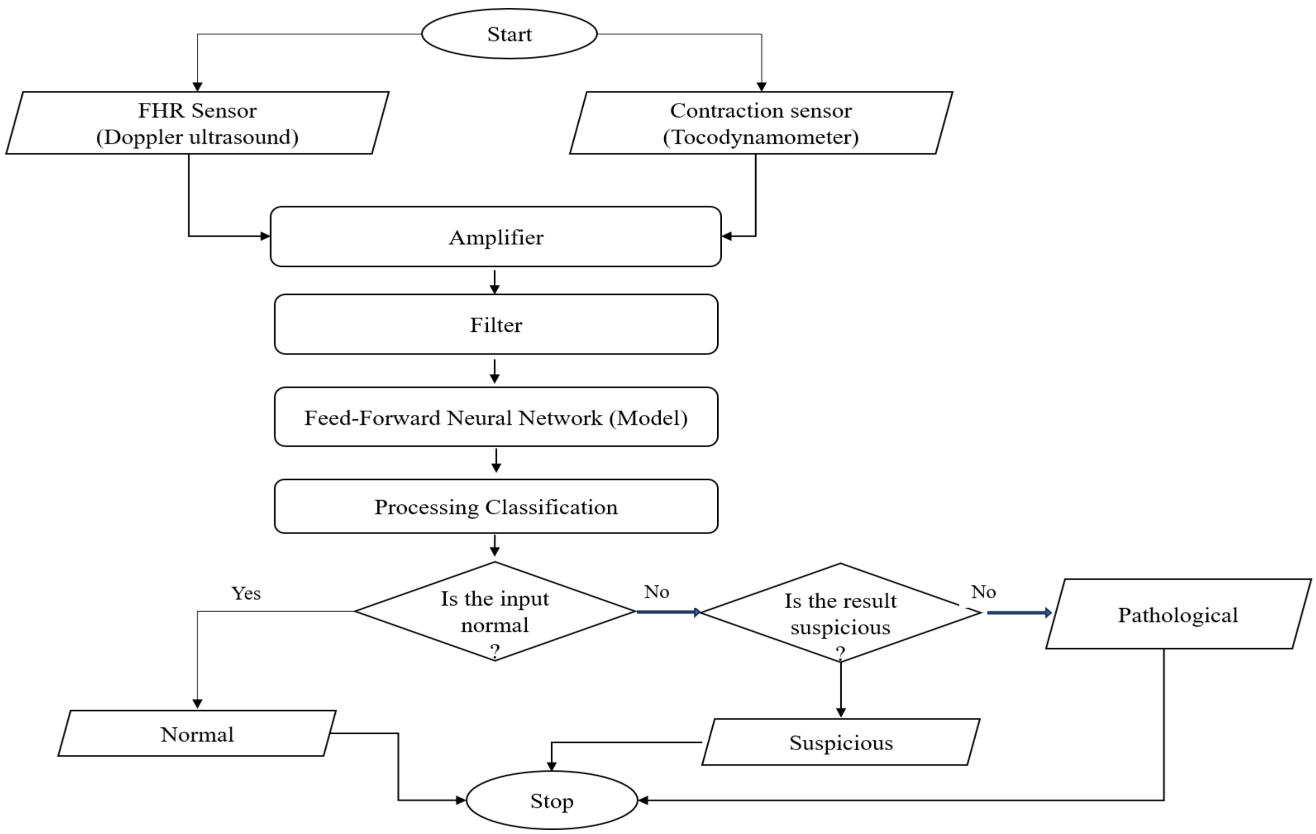

Figure 5: flow chart of the cardiotocogram machine merged with the FFNN model.

The above flow chart of the CTG machine merged with the FFNN model working process is presented in Fig 5. The system flow starts from receiving data signals from two inputs, namely the Doppler ultrasound sensor for FHR and the tocodynamometer sensor for UC. The sensors transfer the signals to the amplifiers, which magnify the sensors' signals and pass them to the filter to further process the signal by carrying out data processing using high pass filtering technique for noise removal and min-max technique normalization for data normalization. The signal (processed data) was further deployed into the FFNN model, which performs the data classification. The processing classification block input subsequently classifies the data into normal, suspicious, and pathology as the final output after evaluations in the decision block. The stop block indicates the termination of the machine process.

3.8 Evaluation Matrices

The model was evaluated using several matrixes, namely positive predictive value (PPV), False Dictation Rate (FDR), True Positive Rate (TPR), False Negative Result (FNR) and Receiver Operating Characteristic Curve (ROC).

The Positive Predictive Value (PPV): presents the proportion of true positive results among all positive predictions of the model. The high PV indicates when the system predicts a positive result. The PPV is important in ensuring that cases presented as abnormal truly require medical attention. The formula is given as

$$PPV = \frac{True\ Positives\ (TP)True\ Positives\ (TP)}{True\ Positives\ (TP)+False\ Positives\ (FP)} \quad (10.0)$$

The False Dictation rate (FDR) presents the false positive results in the positive predictions, representing the error rate of positive diagnoses. A lower FDR result is preferred in the proposed CTG model to minimize needless medical interferences and pressure on the patients.

$$FDR = \frac{False\ Positives\ (FP)}{False\ Positives\ (FP)+True\ Positives\ (TP)} \quad (11.0)$$

The True Positive Rate (TPR) presents the proportion of actual positive cases that are correctly identified by the model. It measures how effectively the model detects true cases of pathologic states. A high TPR ensures that most conditions requiring intervention are identified, reducing the risk of missing critical diagnoses.

$$TPR = \frac{True\ Positives\ (TP)}{True\ Positives\ (TP)+False\ Negatives\ (FN)} \quad (12.0)$$

The False Negative Result (FNR) in the model indicates the proportion of the actual positive cases that are incorrectly identified as negative by the model. The FNR close to zero is desirable for CTG because it ensures that very few cases requiring medical intervention are overlooked. A high FNR indicates a significant risk of missed diagnoses, potentially endangering patient safety.

$$FNR = \frac{False\ Negatives\ (FN)}{False\ Negatives\ (FN)+True\ Positives\ (TP)} \quad (13.0)$$

The Receiver Operating Characteristic (ROC) curve is the graphical representation of a model's performance across different thresholds. It plots the true positive rate (sensitivity) against the false positive rate (1-specificity). The ROC curve helps clinicians and researchers understand the trade-off between sensitivity and specificity. Adjusting the decision threshold based on the ROC curve can optimize CTG system performance according to clinical needs.

$$AUC = \int_0^1 TPR\ (FPR)\ d(FPR) \quad (14.0)$$

4.0 Discussion and Result

The proposed CTG model was trained using the CTG dataset divided in the ratio of 70:20:10 for training, testing, and validation data. The training was carried out using the Levenberg-Marquardt technique with the Tanh activation function. The hyperparameters consist of fully connected 4 layers, with size 10 and 1000 iteration limits. The training time lasted for 72.216 sec, disclosing a result accuracy of 90.3%. The results were evaluated for performance using the five following matrix: PPV, FDR, TPR, FNR, and ROC.

4.1 Positive Predictive Value (PPV) and False Dictation Rate (FDR)

The confusion matrix analysis of the PPV also known as precision and FDR for classifying the CTG data is presented in figure 6 below. The PPV depicts the true positive prediction of the given classes of the CTG data, While FDR presents the incorrect prediction in the data. The PPV matrix shows the true classes on the y-axis (True Class 1,2 and 3), and the x-axis shows the predicted classes (Predicted Class 1, 2, and 3).The class 1 in the confusion matrix of the true class 1 disclosed 95.3% correct prediction, while class 2 and 3 shows 23.0% and 9.3% are the miskenly predicted class respectively, indicating that PPV of class 1 model is correct 95.3% of the time while the FDR which is 4.7%, indicates a low rate of false positives when predicting class 1. The class 2 of the true class displayed 70.6% correctly predicted class, while class 1 and 3 shows wrongly assigned classes with 3.7% and 13.7% respectively, indicating that the PPV of class 2 is correct 70.6% of the time, while the FDR shows 29.4%, which is a higher rate of false positives. The class 3 of the true class 3 disclosed a 77.0% correct prediction while class1 and 2 were 1.0% and 6.4% misclassified respectively. This indicates that the PPV is correct 77.0% of the time and the FDR is 23.0% indicating that 23% of class 3 is wrong.

The over view of the result shows a strong precision of 95.3% (high PPV) for class 1 with a relatively low FDR of 4.7%, indicating a higher stability when predicting class 1. The class 2 disclosed a lower PPV(70.6%) and higher FDR (29.4%), this shows a relatively unreliablity in precision. Then finally, class 3 is in between good precision (77.0%) and a moderate FDR of (23.0%).

4.1 **True Positive Rate (TPR and True Negative Rate)**

The confusion matrix (left part) and the TPR and FNR (right part) for the classification model are presented in figure 7. In the confusion matrix, the Y-axis shows the true class (the input data), while the x-axis indicates the predicted classes in the model outputs. The true class 1, 94.9% of class 1, was correctly predicted, while classes 2 and 3 were 4.1% misclassified, respectively. In class 2 true class, class 2 shows 70.8% correct prediction, while classes 1 and 3 were misclassified by 20.7% and 8.5%, respectively. Then, in the class 3 true class, 80.1% of the class 3 were correctly predicted, while class 1 was 9.1% misclassified and 10.8% misclassified in class 2.

The TPR and TNR values (left part of the matrix). In the true class 1, of the class 1 cases, the model disclosed TPR of 94.9% correct identification and 5.1% FNR of missed predicted. In class 2, the model accurately identifies 70.8% and 29.2% FNR of the true class 2 cases. While in class 3 of the true class, the model correctly identifies 80.1% of TPR and FNR 19.9% missed cases in the true class 3.

4.2 Receiver Operating Characteristic Curve (ROC).

The ROC analysis in figure 7 below disclosed that the model has a strong classification performance for all three classes. Class 1 (blue) with an AUC of 0.9504, revealing the model's excellent ability to classify class 1 from other classes. The AUC in class 2 disclosed 0.9301, indicating a robust performance but slightly less than class 1, while class 3 (yellow) with an AUC of 0.9386 disclosed that the model identified a high accuracy, though it is slightly lower than class 1 and above class 2. The three classes show an AUC above 0.93, indicating a strong classification performance of the model all through classes 1 to 3. The ROC curves aid in visualizing the operating threshold, thereby allowing a closer examination of the balance between TPR and FPR.

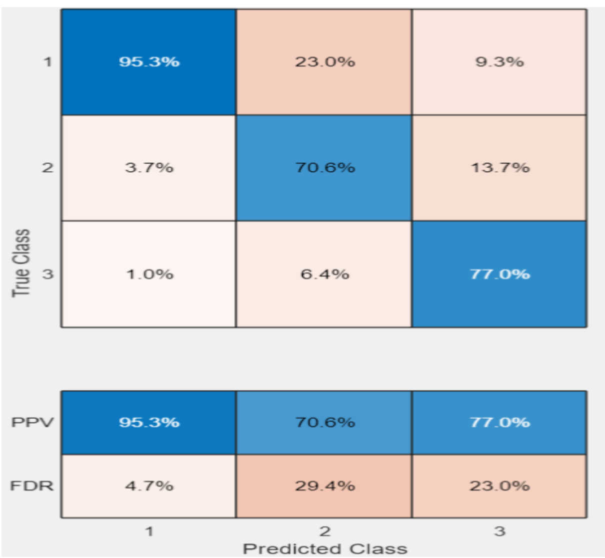

Figure 6: PPV and FDR analysis

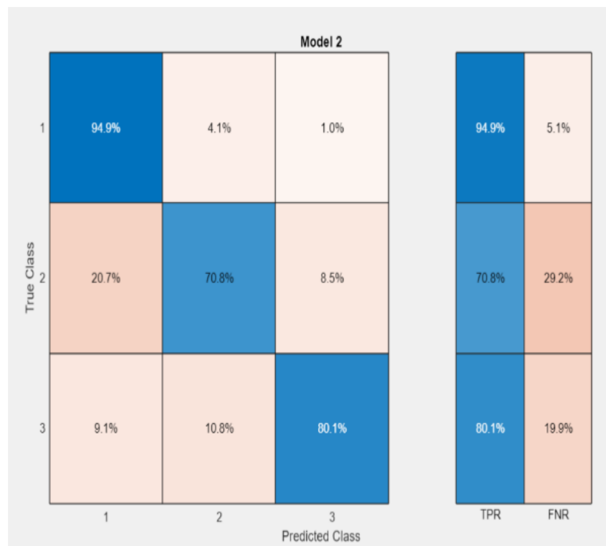

Figure 7: TPR and TNR analysis.

Table 2: Result summary for the entire 3 classes table

True class	PPV	FDR	TPR	FNR	AUC-ROC
Class 1	95.3%	4.7%	94.9%	5.1%	0.9504
Class 2	70.6%	29.4%	70.8%	29.2%	0.9301
Class 3	77.0%	23.0%	80.1%	19.9%	0.9386

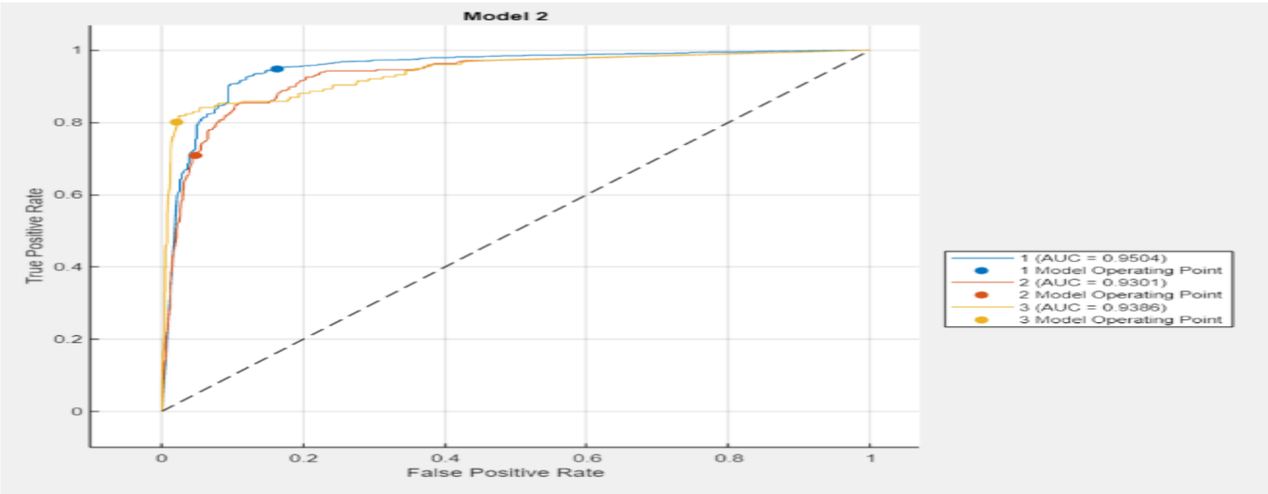

Figure 8: ROC analysis

Table 3: Evaluation metrics table of the Proposed Model

Metric	Class 1 (Normal)	Class2 (Suspect)	Class 3 (Pathological)	Ava of the 3 Classes
Positive Predictive Value (PPV) / Precision	95.3%	70.6%	77.0%	80.9%
False Discovery Rate (FDR)/ 1-Precision	4.7%	29.4%	23.0%	19%
True Positive Rate (TPR) / Sensitivity	94.9	70.8%	80.1%	81.9%
False Positive Rate (TPR) / 1-Specificity	5.1%	29.2%	19.9%	18%
AUC_ROC	0.9504	0.9301	0.9386	0.9397

The performance evaluation of the model across the three classes is shown in Table 3. The presented results in class 1 established an outstanding performance in identifying normal cases with a PPV of 95.3% and a TPR of 94.9%. The AUC-ROC of 0.9504 in class 1 reflects the model's capability in discriminating between normal and other classes, while the FDR disclosed a low rate of 4.7% and an FNR of 5.1%. In class 2 (Suspect), the performance was observed to be moderate with a PPV of 70.6% and a TPR of 70.8%. The AUC-ROC disclosed 93.01% suggesting the model's effectiveness in separating suspect cases from other classes, while FDR of 29.4, 4.7%, and an FNR of 29.2% indicated the challenges of accurately identifying these cases. The model finally disclosed well performs for class 3 (pathological) cases with a PPV of 77.0% and a TPR of 80.1%. The AUC-ROC of 0.9386 indicates strong performance, though slightly below class 1 but better than class 2, while the FDR of 23.05 and an FNR of 19.9 disclosed a moderated error rate. The result of the model demonstrated an excellent ability in classifying normal performance for normal cases (Class 1), good performance for pathological cases (Class 3), and moderate performance for suspect cases (Class 2). The AUC-ROC also disclosed high values (above 0.93) across all classes, suggesting strong overall model reliability. The proposed model can effectively improve the CTG machine's diagnostics, especially for normal and pathological cases, while suspect cases may require further model refinement.

Table 4: Comparative analysis table of recent works by different authors

Author(s)	Techniques	Result			
		Accuracy (%)	Sensitivity (%)	Specificity (%)	Precision (%)
Ricciardi et al., (2023)	ML (machine-based labeling)	92	92	90	NA
Gude et al., (2022)	NN	69.85	58.33	83.33	69.67
	RF	66.67	50.00	83.33	60.89
	SVM	72.22	66.66	85.71	67.77

Asfew et al., (2023)	Spectrogram 2D CNN	NA	95	13	1
	Spectrogram 2D CNNs + 1D-CNN-LSTM	NA	95	14	11
	Scalogram 2D CNN	NA	95	14	13
	Scalogram 2D CNNs + 1D-CNN-LSTM	NA	95	15	17
Hirono et al., (2024)	1D-CNN	97	NA	NA	82.3
Sahana et al., (2023)	MLP	92.7	92.7	96.2	92.8
	RF	96.7	96.4	98.4	96.8
	SVM	96.4	96.4	98.3	96.6
	Bagging	93.6	93.6	96.8	93.6
Okeke et al., (2022)	ANN	98.34			
Our model	FFNN	90.3	81.9	82	80.9

After training and evaluation of the FFNN model using several evaluation matrices, the model was further compared with recent works of the different authors for the purpose of validation, considering the accuracy, sensitivity, specificity, and precision results of their different works. The overall result shows that the FFNN model can compete with other models.

5.0 Conclusion

Over the years, the need for a reliable model that improved the classification efficiency of CTG machines has continued to dominate research attention in the scientific community. This work has successfully presented ANN based feed-forward neural network classification model and integrated it into a CTG machine for improved monitoring and classification of FHR. The model was designed using CTG data, applied to train FFNN, which further classifies the output data into Normal, Suspicious, and Pathology classes. To evaluate the model, several metrics were applied, with an overall result of 90.3% accuracy, 81.9% sensitivity, 82% specificity, and 80.9% precision. Finally, the FFN model demonstrated a convincing overall performance in classifying the provided CTG data, especially for Class 1 and Class 3, by having high precision, sensitivity, and AUR-ROC values. The class's outstanding performance of 95.3% precision, 94.9% sensitivity, and 0.9504 AUC-ROC demonstrated the model's reliability to successfully identify the class with minimal errors. The model performed well for class 3, with slightly lower precision (77%) and sensitivity (80.1%), as compared to class 1. However, the proposed model revealed a moderated result for class 2, by disclosing a lower precision (70.6%) and sensitivity (70.8%), with the error rate (FDR: 29.4%, FNR: 29.2%). Finally, the FFNN proposed model disclosed a viable potential in classifying the CTG data. Notwithstanding, there is a need to optimize and improve the performance of class 2 without compromising the established results of class 1 and class 3. For further improvement on the classification model especially for suspect class 2 in this study, it is recommended to adopt strategies such as rebalancing datasets, refining feature selection, or hyperparameter tuning modification to ensure an optimized classification result. However, the developed model is reliable and effective in carrying out medical diagnostics in cardiotocography and can be incorporated into a CTG machine.

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