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A Refined Artificial Neural Network Framework for Superior Fetal Health Monitoring

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Abstract: Perinatal mortality is a dismal aspect of fetal health over the world. Fetal health is a critical component of a sustainable nation. Cardiotocography (CTG) employed in the fetal health monitor to assess mother and fetal well-being during childbirth. Cardiotocograms monitor the heart rate at its baseline value during labor, ignoring the risk of perinatal before delivery. The classifier predicts CTG data, allowing obstetricians to observe and anticipate the fetus status. This classifier identifies fetal normal, suspicious and pathologic states, with the heart rate of baseline value involved indicating a difficult fetal. A CTG dataset contains 2126 recording from the UCI repository used for classification. The CTG data sets are preprocessed using Normalization and scaling techniques, and then the preprocessed input data is utilized to Artificial Neural Network (ANN) model construction for classifying the fetal health, which is normal, suspicious, and pathologic of the high risk of pregnancy during 32 and 33 weeks of observation. Further, the 5-fold cross-validation is applied to examine the proposed model is quantified by precision, recall, F-score, ROC curve generated for three classes. From the evaluation, the Tuned ANN attained accuracy as 92% outperforms the un-tuned ANN accuracy of 90%.
Keyword: Cardiotocography (CTG), Fetal health, Baseline value, Normalization and scaling techniques, Artificial Neural Network, Cross Validation

1. INTRODUCTION

Mothers have an important role in the health and fetal well-being of their children, which is why it is critical to focus on maternal health throughout physiological conditions. Almost all mothers desire a safe physiological condition with conventional delivery, as well as physically and intellectually healthy infant. Obstetric problems during labor and delivery have an unfavorable effect on fetal and mother eudemonia. Thus, Gestational care is critical for analyzing the most appropriate birth strategy and preparing the mother mentally and physically. CTGis the most often utilized diagnostic method for detecting abnormalities throughout the antepartum and intrapartum damages. It may be administered starting around 28 weeks of pregnancy; however, it is most commonly used after 38 weeks. It is used during pregnancy for pregnant women who have diabetes, high blood pressure, Rh-negative, infertility, or are elderly premipara. Cardiotocography (CTG) checks the baby's heart rate while also monitoring the fetal heart rate and uterine contraction in the world. CTG displays two lines, the upper line is a fetal heart rate record in beats per second and the bottom line is a uterine contraction from the TOCO.

The CTG is used before delivery (antenatally) and during labor to monitor the newborn for symptoms of distress.CTG uses sound waves to assess the ultrasound and determine the baby's heart rate. Doctors and midwives can assess how the baby is doing by examining several aspects of the infant's heart rate. Ultrasound is a high-frequency sound that cannot be heard but it may be transmitted (emitted) and detected by specialized devices. The CTG method allows clinicians to follow the fetus's heart rate, which involves detecting acceleration, deceleration, and variability, with the aid of uterine contraction. The usual CTG tests include locations where a baby's heart rate typically ranges between 110 and 160 beats a minute. Non-reassuringly, this is far quicker than heart rate fluctuating between161-180 or 100-109 beats a minute. It is an abnormal trace, which is about 180 beats per minute. A baby's heart rate that does not change or is abnormally low or high may indicate a concern. In most circumstances, low-risk delivery does not require CTG. The midwife will periodically monitor the baby's heart rate to ensure time that it is normal. In rare cases, the CTG is recommended for continual monitoring. The CTG dataset contains four critical features such as Base Line (BL), Acceleration (AC), Deceleration (DC), Variability, which are required to define the Fetal status as Normal, Suspicious, Pathological. The prediction problem in this study is solved using the ANN algorithm.

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2. RELATED WORKS

The CTG dataset is used from the UCI repository. [1] proposed a CART decision tree algorithm used to classify the fetal state such as Normal, Suspect and Pathologic, 5- fold cross-validation has done and precision, recall, and F-score tabulated from model The CTG dataset. [2] worked with a bagging approach and three decision tree algorithms discussed to classify fetal health from cardiotocograph data. A hybrid k-means algorithm has been processed for classifying the state of fetal health proposed by [3]. [4] has assessed a Classification Based Association (CBA), a rule-based approach to the CTG analysis of the fetal evaluation is suggested and the model is evaluated with 83% and 84% accuracy before and after feature selection for classifying the fetal health status. [5] proposed three classification model are Discriminant analysis(DA), Decision Tree(DT), Artificial Neural Network has shown the accuracy 82.1%, 86.36%, 97.78% for distress due to lack of oxygen in the uterus, and classified from CTG status, accurately predicted. Decision Tree-Based Adaptive Boosting Approach [6] processed to predict the fetal distress determination by using the CTG monitoring. PCA and AdaBoost Method proposed to select the total feature or selected features used for classifying the fetal state 93% and 98.86% of accuracy from cardiotocograph data [7]. [8] used Machine Learning Algorithm conjunctions to evaluate the distress of fetal health [8]. [9] made feature extraction and classification of fetal distress from CTG data. SVM with K-means cluster used to extract the seven features perfectly out of twenty-one and improve the classification performance 90.64% of accuracy then the classifier ensemble model and ensemble feature selection are implemented in [10]. It gives high accuracy for the ensemble model and correlation-based feature selection has been applied to improve the accuracy of the ensemble SVM model. [11] made a comparative study of SVM and Decision Tree Algorithm using the CTG dataset. [12] processed and compared the machine learning Algorithm for fetal heart rate classification then concluded ANN was superior to the other algorithm. [13] proposed a fetal state classification using the Bagging Ensemble classifier. It combines the base model which is the vote or average of the prediction. In CTG data used from UCI repository then the bagging approach used to select the best model to serve reiterating training and evaluated many times. In the last, the edge of the model pointed to the model diversity using bootstrap sampling of the training set and voting or average for the prediction. [14] gave the state of the fetal heart rate and Mainly considered kernel, penalty factor. In this work, LS-SVM is implemented as a two-parameter such as LS-SVM_1 and LS_SVM_2 and the first parameter pointed as Normal (Nr), Suspect, Pathologic(PS), second parameter shown in P and S. These parameters are optimized by the PSO and effectiveness of the proposed system is evaluated by the 10-fold cross-validation on the dataset [14]. [15] implemented a machine learning algorithm, discussing the importance of machine learning. SVM and Random forest have proposed to overcome the important issue of suspect cases when predicting fetal outcomes. SVM gave a better performance for suspect cases [15]. After discussing the literature, it is located that researches proposed in [3][7][9][10] considered only feature selection with the classification of fetal health based on the CTG data set of 21 attributes. Some authors used these total attributes for feature selection without normalization. In this work, an Artificial Neural network with 5-fold cross-validation has suggested assisting the clinical monitoring and diagnosis of the fetal status into normal, suspicious, pathologic and that dataset is pre-processed by the normalization and scaling techniques for predict the fetal status accurately then classifier used to classify it.

3. METHODS AND MATERIALS

Fetal progress may be useful sign of fetal health. Conflicting fetal development might be a significant cause of feature passing. To promote fetal wellbeing, the fetus must be examined at an early stage. The suggested framework is aimed at developing that uses familiar classification methods to study fetal movement in order to enhance the feature of determination for pregnant women with reduced fetal development. The proposed work is described in the below system architecture is illustrated in Figure 2.

CTG dataset description

In this study, the CTG dataset taken from the UCI repository is utilized to evaluate CTG recording and extract significant characteristics. The CTG dataset includes 21characteristics derived Fetal Heart Rate (FHR), Uterine Contraction (UC) signals. It contains 2126 samples, of which 1655 samples are normal cases, 295 samples are suspicious cases and 176 are pathologic cases. Professional obstetricians assessed all CTG recording, and each sample received a consensus label.

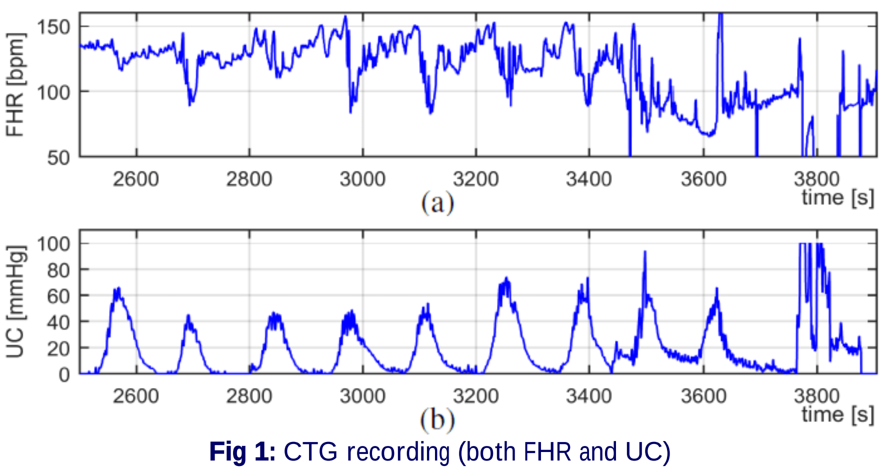

Fig 1: CTG recording (both FHR and UC)

Although the dataset allows the 10-class or 3-class classification, this study use 3-class fetal class labels (1=Normal, 2-Suspecisious, 3- Pathologic) is used for the target feature in this work. In the below figure, (a) shows the FHR rate and (b) displays the Uterine contraction.

Table 1CTG data summary

Feature and Description
BL- Base Line
AC- Acceleration
FM-Fetal Movement
UC- Uterine Contraction
DC-light Deceleration
DS-Severe Deceleration
DP-Prolonged Deceleration
ASTV-Abnormal Short Term Variability
MSTV-Mean Value of Short Term Variability
ALTV-Abnormal Long Term Variability
MLTV- Mean Value of Long Time Variability
Width-Width of the FHR histogram
Min- Minimum of FHR histogram
Max- Maximum of FHR histogram
Nmax- Histogram Peak
Nzeros- Histogram Zeros
Mode- Histogram Mode
Mean- Histogram Mean
Median- Histogram Median
Variance- Histogram Variance
MLTV- Mean Tendency
Class- FHR pattern (0-10)
Fetal State- (0-Normal, 1-Suspicious, 2-Pathologic)

4. DATA PREPROCESSING USING NORMALIZATION AND STANDARDIZATION:

Normalization is performed in data preparation when features have varied scales to put all numerical values into a similar range between 0 and 1. It rescales values based on the minimum range of each characteristic, reducing the effect of outliers.

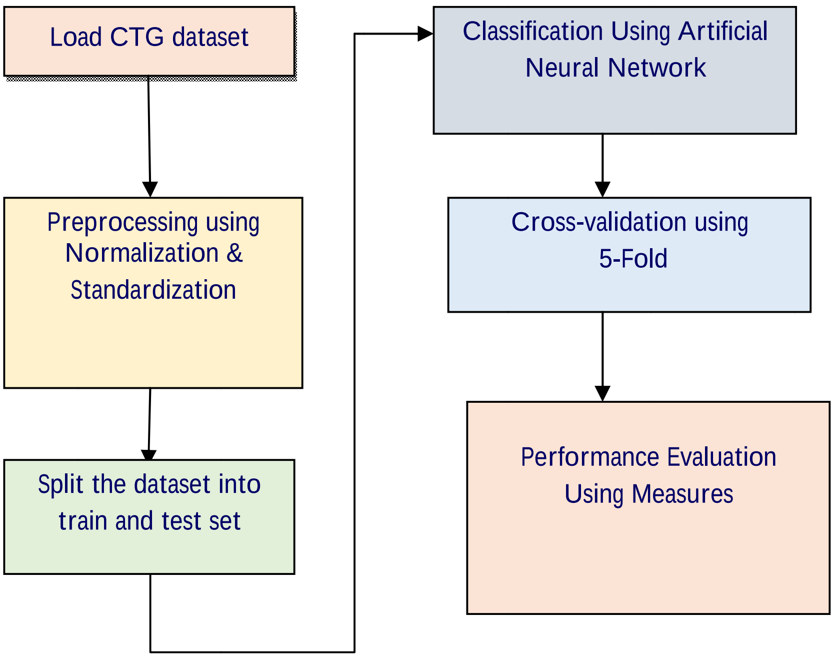

Fig 2 Flow Diagram of proposed methodology

Class values in the CTG datasets are integers, hence one-hot encoding is utilized before normalization. This transformation effectively reduces the data to an n-dimensional unit hypercube. Standardization, on the other hand, is used in frequency –based models to keep characteristics with broad ranges from dominating. It centers each feature at zero and scales its variation to one by removing the mean and dividing by the standard deviation, resulting in standardized CTG data that may be further modeled.

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5. CLASSIFICATION USING ARTIFICIAL NEURAL NETWORK

In this work, the role of artificial neural networks is as the three layers such as input layer, hidden layer, and output layer. This architecture has 1 input layer, 3 hidden layers, and 1 output layer in this classification. The input layer accepts 21 dimensions with ReLu activation function (4) and followed by hidden layer with 20,40,60 neurons (3) using sigmoid (5), and ReLu activation function (4) and the final output layer has 3 neurons (3) (class=0, class=1, class=2) with softmax functions (6), suitable for a classification problem. The model is trained with categorical-cross entropy (7). Then the output layer (1) is computed as

$$O = f(net) = f(\sum_{j=1}^{n} w_j x_j) \tag{1}$$

Where $w_j$is the model weight vector and activation function is $f(net)$. The scalar product of the weight and input vectors is given as a variable net by

$$Net = W^T x = w_1 x_1 + \cdots + w_n x_n \tag{2}$$

Where$T$ is the transpose of a matrix.The neuron is computed as an internal activity of the model by

$$v_k = \sum_{j=1}^{p} w_{kj} x_j \tag{3}$$

$$\text{Relu} f(x) = \max(0, x) \tag{4}$$

$$\text{Sigmoid function } \sigma(x) = \frac{1}{1+e^{-x}} \tag{5}$$

$$y_i(x) = \frac{e^{z_i}}{\sum_{k=1}^{k} e^{z_j}} \tag{6}$$

$$CE = -\sum_i^k t_i \log(y_i(x)) \tag{7}$$

Cross-validation using K-Fold

After determining the optimum parameter for the model, the K-fold cross-validation procedure begins by developing a customized model object based on the determined optimal parameter. The training dataset is then separated into five folds, with the model being trained and validated repeatedly on each fold to assess performance. The accuracy of all five folds is evaluated, and then mean accuracy is determined to evaluate the model's stability. Once the customized model is complete, predictions are made on the dataset, and performance measures such as accuracy, fi-score are calculated.

6. RESULT AND DISCUSSION

The cardiotocography data prediction model is processed using an Artificial Multi-class Classification Neural Network by performing, which performs cross validation on the optimized model, the best model is used to produce a tuned model and decide the classification. All experiments were performed in python version 3.7.12.To minimize the class imbalance issues in the training process using the (Figure 3) model is training accuracy. Further, the model loss is monitored during the training process for improving the accuracy of the model. Especially, the cross validation techniques are used to improve the model accuracy form the un-tuned model.

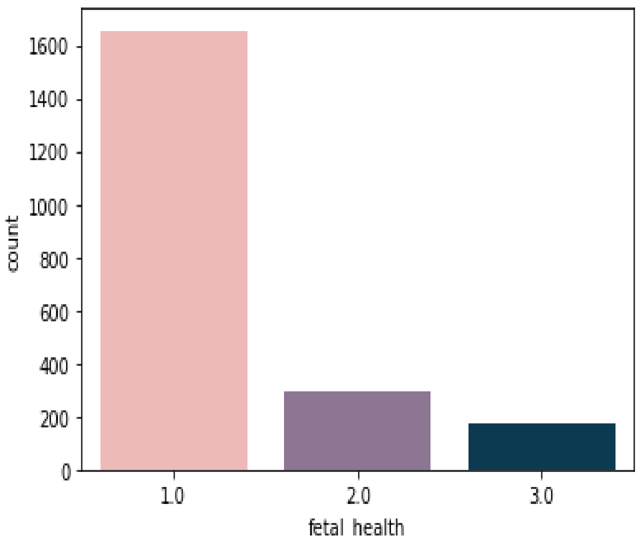

Fig 3: Class Distribution for imbalance

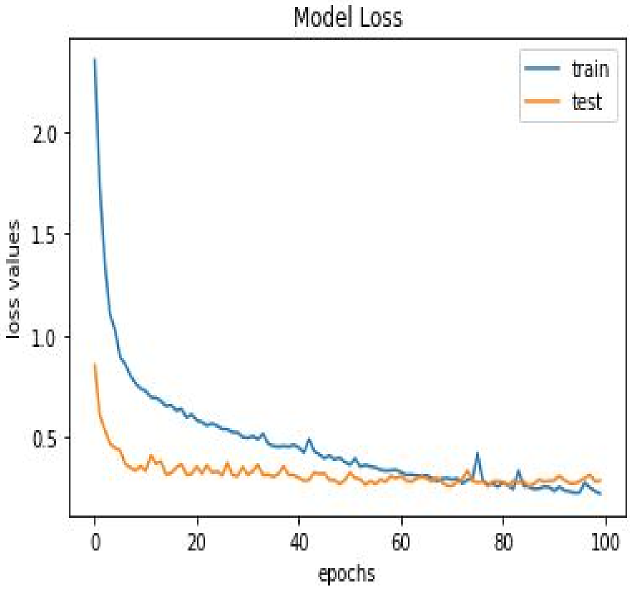

Fig 4: Untuned ANN Loss

During the training, Model loss is depicted (Figure 4) according to the model then the model is evaluated using cross validation. The 5-fold cross validation is used to evaluate the model and finally provide the best model accuracy from each dataset partition. This study discusses performance measures and evaluates reports (Table 2) of individual class accuracy, recall and f1-score for that class support. Finally, a weighted average will be calculated for the average class support.

Table 2 Performance Evaluation of Tuned ANN

Tuned Model Report	Performance Metrics			
	Precision	Recall	F1-score	Support
0	0.94	0.98	0.95	326
1	0.75	0.78	0.78	58
2	0.93	0.80	0.87	42
Macro-Avg	0.88	0.83	0.88	426
Weighted-Avg	0.91	0.94	0.93	426

Table 3. Classification comparisons of Un-tuned and Tuned ANN

Model	Accuracy	Precision	Recall	F1-weight
Untuned-ANN	90.3	90.4	89.5	90.8
Tuned ANN	92.4	90.5	90.4	92.3

The Table 3displays the F1-score, accuracy and macro-average. The macro-average is calculated as the basic arithmetic means of each class F1, as well as the macro-average precision and recall while the weighted average by multiplying each value in a dataset by a predefined weight before perform the final computation. The ROC curve (Figure 5) depicts the true positive rate and false-positive rate for the prediction model at various probability levels. It is suitable when the observations are balanced across classes.

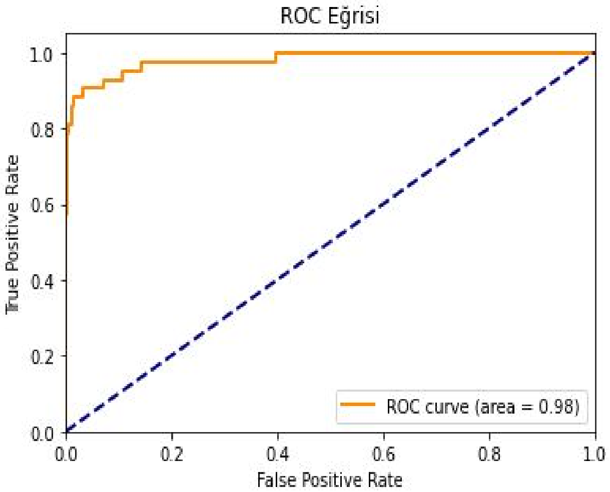

Fig 5 ROC Curve of Tuned ANN

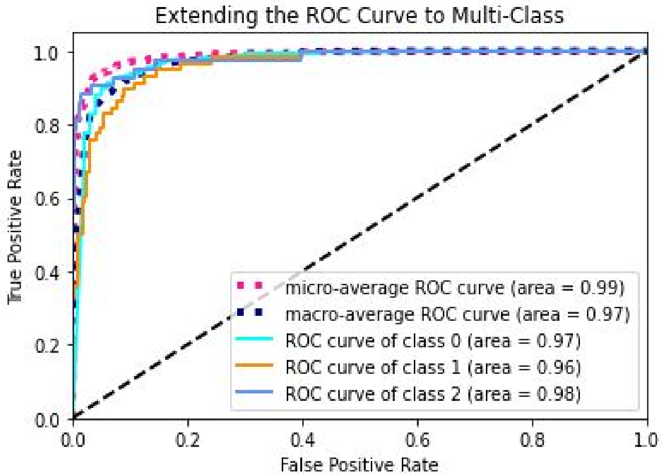

Fig 6: Extended ROC of Tuned ANN

Table 4 Confusion matrix of Tuned ANN

Confusion Matrix		Predicted class		
		0="Normal"	1="suspicious"	2="pathologic"
Actual Class	0="Normal"	317	8	1
	1="suspicious"	13	44	1
	2="pathologic"	4	5	33

This three-class ROC curve achieves unique prediction accuracy. The ROC curves for class 0 (area=0.97), class 1(area=0.96), class 2(area=0.98) presented. The micro average ROC curve binary prediction (area =0.99) and the macro-average ROC curve's multi-label classification (Figure 6) (area =0.97). This classifier is approved by micro-average and macro-average.

7. CONCLUSION

An Artificial Neural Network was built using the CTG datasets from UCI Repository, and its performance was assessed using cross validation and K-fold parameter adjustment. Initially, the untuned ANN model achieved a weighted f1-score of 90.8% and an overall accuracy of 90.3%, exhibiting baseline performance without any parameter adjustment. After doing, cross validation customized model produced better results, with a weighted f1-score of 92.3% and an accuracy of 92.4%, demonstrating the efficiency of hyprparameter tuning in improving classification performance. UN tuned model weight is 90.8 and accuracy is 90.3 obtained by using ANN without cross validation then Tuned model weight is 92.3 and accuracy is 92.4 experimented by using the cross-validation and further the ROC curve is generated for the balanced dataset.

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