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Classification of Cardiotocography Records with Naïve Bayes

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Abstract

Cardiotocography provides information about the fetal heart rate during pregnancy and childbirth, monitoring the uterine contractions and the physiological status of the fetus to identify hypoxia. Accurate information from these records can be used to estimate the pathological condition of the fetus. Thus, it allows early intervention by reporting any irreversible negative condition in the fetus. In this study, due to the importance of this subject, Naive Bayes machine learning algorithm can be used to diagnose the model developed. The result was 97.18% classification and 95.68% test success with Naive Bayes machine learning algorithm. The obtained data were presented in detail in the following sections.

Keywords: "Biomedical diagnostics, Machine learning algorithms, Fetal heart rate measurements"

1. Introduction

Fetal Heart Rate (FHR) provides visual and auditory data as well as uterine contractions [1]. The most important criterion in the evaluation of fetal health is the measurement and interpretation of fetal heart rate and uterine contraction values [2]. Fetal Heart Rate Monitoring (FHRM) is a way of controlling the fetus's state of health in the womb. Nowadays, the importance of FHRM is increasing. Turkey Statistics Institution According to the number of infant deaths in the year 2015 13654 was 13036 in 2016. The infant mortality rate, which represents the number of infant mortalities per thousand live births, was 10.2 per thousand in 2015 and 10 per thousand in 2016. In other words, 10 infant deaths per thousand live births fell in 2016 [3].

FHR can be used when there are birth pains and during labor. With FHR, doctors can provide information about the state of health of the fetus so that precaution can be taken. Particularly in hazardous pregnancies, FHR is more important [4]. In 2013, the Czech University of Technical University, " Mobile CTG – Fetal Heart Rate Assessment Using Android Platform " in their study called the heart rate of the fetus from the doppler device moved to the android platform [5].

In 2011, Chalmers University of Technology student Susanne Andersson's "Acceleration and Deceleration Detection and Baseline Estimation" in her master's thesis described the interpretation of electronic signals from any Doppler instrument using the Dawes-Redman algorithm [6]. In 2013, the Finland based software company "Unborn Heart" developed the mobile application and shows the fetus's heartbeat value to the expectant mother, but also has the ability to listen to the heartbeat sound of the fetus [7]. Fetal monitoring [8], using non-linear features for fetal heart rate classification [9], Fuzzy analysis of linear results to improve automatic fetal status assessment [10], and cardiotocogram classification for prediction of fetal risks using machine learning techniques were performed [11]. Studies representing non-visual patterns in the FHR were performed [12-15]. Blinx et al. In their study, a Decision Tree (DT), Artificial Neural Network (ANN) and Separation analysis were compared. The National security agency classifier achieved an overall accuracy of 97.78% [16]. Menai et al. Naive Bayes (NB) achieved 93.97%, 91.58% and 95.79% values for Accuracy, Sensitivity and Specificity, respectively, using the classification [17]. Karabulut et al. used an adaptive enhancer classifier that produced 95.01% accuracy [18]. Spilka et al. [19] used a Random Forest (RF) classifier and latent class analysis, producing Sensitivity and Specificity values of 72% and 78%, respectively [20]. Spilka et al. using a C4.5 decision tree, Naive Bayes and SVM, produced the best results using a 10-fold cross-validation method that obtained 73.4% for Sensitivity and 76.3% of Specificity [21]. Along with these studies, artificial intelligence techniques were used in different fields [22-23].

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This study is a classification and diagnosis of this important subject. The aim of this study is to develop an application for faster and more accurate interpretation of FHR results. In this way, errors and delays caused by the negativity will be eliminated.

2. Materials and Methods

In this section, information about the database and Naive Bayes machine learning algorithm is given.

2.1. Dataset and features

The data set consists of measurements of FHR and uterine contraction characteristics on cardiotocograms classified by obstetricians [24,25]. The 2126 fetal cardiotocogram (CTG) is automatically processed and includes measurement results of the relevant diagnostic features. CTGs were also classified with three specialist obstetricians and a consensus classification label assigned to each. The classification was made according to both morphological order (A, B, C. ...) and fetal condition (N, S, P). The data set attribute information in Table 1 shows the following [26].

Table 1. Attributes of dataset

Feature	Descriptions
LB	FHR baseline (beats per minute)
AC	# of accelerations per second
FM	# of fetal movements per second
UC	# of uterine contractions per second
DL	# of light decelerations per second
DS	# of severe decelerations per second
DP	# of prolongued decelerations per second
ASTV	percentage of time with abnormal short term variability
MSTV	mean value of short term variability
ALTV	percentage of time with abnormal long term variability
MLTV	mean value of long term variability
Width	width of FHR histogram
Min	minimum of FHR histogram
Max	Maximum of FHR histogram
Nmax	# of histogram peaks
Nzeros	# of histogram zeros
Mode	histogram mode
Mean	histogram mean
Median	histogram median
Variance	histogram variance
Tendency	histogram tendency
NSP	fetal state class code (N=normal; S=suspect; P=pathologic)

2.2. Naive Bayes Classifier

In this study, Naive Bayes machine learning algorithm was used to classify the cardiotocogram. The Naïve Bayes Classifier is a simple probabilistic classification method based on Bayes theorem. In Bayes' theorem, in cases where two (and) random events occur one after the other, the probability of the second event occurring in the event of one of these two events can be represented by the expression. With the change property, the product rule can be written in two different expressions as in Equation 1;

$$P\left(X \cap Y\right) = P\left(X \middle| Y\right) P\left(Y\right) = P\left(Y \middle| X\right) P\left(X\right) \tag{1}$$

Bayes' theorem defines the relationship between a random event that arises from a random process and conditional probabilities and marginal probabilities for another random event as in Equation 2.

$$P\left(Y\middle|X\right)=\frac{P\left(X\middle|Y\right)P\left(Y\right)}{P\left(X\right)} \tag{2}$$

The probabilities of the dependent states that are likely to occur in any problem are calculated by the Bayes equation given above. In this equation, $P\ (X)$ represents the input probability of the problem, $P\ (Y)$ represents the probability of a possible output state, and $P\ (Y \mid X)$ represents the probability of a Y output versus input X [19]. In the NB classification technique, it analyzes the relationship between dependent and independent properties to create a conditional probability from each relationship. To classify a new sample, an estimate is made by combining the effects of independent variables on the dependent variable [27].

3. Experimental Results

This section provides information about the performance of the system using Confusion Matrix (CM). It is a matrix model that provides a holistic approach to the classification performance of an intelligent system algorithm. A CM is structurally expressed as in Equation 3.

$$CM=\begin{bmatrix} TP & FP \\ FN & TN \end{bmatrix} \tag{3}$$

In this study, 9 statistical measurements were used to analyze the classification results. These measurements and formulas are shown in Figure 1. In the classification process, 75% of the dataset was used for training and 25% for testing.

Sensitivity or True Positive Rate	$TPR=\frac{TP}{TP+FN}$	Accuracy	$ACC=\frac{TP+TN}{TP+TN+FP+FN}$
Specificity or True Negative Rate	$TNR=\frac{TN}{TN+FP}$		
Precision or Positive Predictive Value	$PPV=\frac{TP}{TP+FP}$		
Negative Predictive Value	$NPV=\frac{TN}{TN+FN}$	F-Measurements	$FM=\frac{2}{\frac{1}{TPR}+\frac{1}{PPV}}$
False Positive Ratio	$FPR=\frac{FP}{TN+FP}$	Matthews Correlation Coefficient $MCC=\frac{TP\times TN-FP\times FN}{\sqrt{(TP+FP)(TP+FN)(TN+FP)(TN+FN)}}$	
False Negative Ratio	$FNR=\frac{FN}{TP+FN}$		

Figure 1. Statistical measurement methods

Table 2. shows the results of the statistical measurements obtained according to these diagnostic procedures. (For NSP fetal state class code (N=normal, Class0; S=suspect, Class1; P=pathologic, Class2)).

Table 2. Statistical measurement results

NB CLASSIFIER

	Normal	Suspicious	Pathological
Normal	87	0	0
Suspicious	0	414	22
Pathological	0	1	8

	TP	FP	FN	TN
Normal	87	0	0	445
Suspicious	414	22	1	95
Pathological	8	1	22	501

	TPR	SPC	PPV	NPV	FPR	FNR	ACC	MCC	FM
Normal	1	1	1	1	0	0	1	1	1
Suspicious	1	0,81	0,95	0,99	0,19	0,01	0,96	0,87	0,97
Pathological	0,27	0,99	0,89	0,96	0,73	0,04	0,96	0,47	0,41

It is also possible to see a graphical summary of the results obtained in Figure 2.

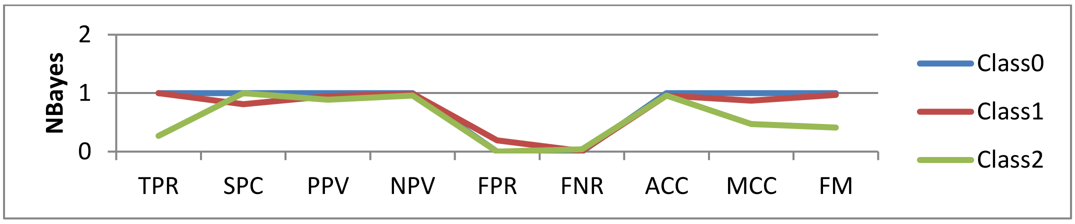

Figure 2. Graphical summary of the results obtained

4. Conclusions

CTG recordings are widely used in pregnancy, because CTG provides important information about the physiological health of the fetus. In this study, a classification process was performed to enable the diagnosis to be given to CTG records automatically. With this study, any discomfort in the fetus can be detected instantly with the diagnostic results to be given automatically. Thus, health problems during pregnancy can be determined in advance by taking the necessary measures. With the proposed classification model, 97.18% and 95.68% of the tests were achieved (For N=normal; S=suspect; P=pathologic).

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