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A Novel Hybrid Model for Automated Analysis Of Cardiotocograms Using Machine Learning Algorithms

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Abstract: In this study, a new hybrid model was presented for the prediction of fetal state from fetal heart rate (FHR) and the uterine contraction (UC) signals obtained from cardiotocogram (CTG) recordings. CTG monitoring of FHR and uterine contractions during pregnancy and delivery provides information on the physiological status of the fetus to identify hypoxia. The precise information obtained from these records provides some ideas for interpreting the pathological condition of the fetus. Thus, with early intervention, it allows to prevent any negative situation that will occur in the fetus in the future. In this study, due to the importance of this subject, a new hybrid model was developed which can perform high rate accurate diagnosis using Machine Learning (ML) algorithms. In the hybrid model, 4 different ML algorithms (k Nearest Neighbors (k-NN), Decision Tree (DT), Naive Bayes (NB) and Support Vector Machine (SVM)) were used. While the diagnosis without the hybrid model was low, the improved hybrid model increased the accuracy by 34%. As a result of this hybrid model, 100% success was achieved for classification, test success, Accuracy, Sensitivity and Specificity with NB and DT ML algorithms.

Keywords: Biomedical diagnostics, Machine Learning algorithms, Fetal heart rate measurement.

1. Introduction

The FHR detection module is used to detect the heart sound of the unborn baby. FHR detection module: The transmitter and receiver, called Tx and Rx, consist of ultrasonic sensors and a modulator and demodulator circuit controlling these ultrasonic sensors. FHR is a method used to control the fetus's state of health in the womb. FHR is also used when there are birth pains and during labor. The FHR can provide information on the health status of the fetus to doctors and provide precautionary measures. Particularly in dangerous pregnancies, FHR is more important [1]. Ultrasonic sensors are mainly used to convert the applied electrical signal to an audio signal or to convert the sound signal impinging on the sensor to an electrical signal. The signal is passed through a series of electronic filters so that the heart sound signal detected from the Rx ultrasonic sensor can be removed from the accompanying electrical noise. The cleaned signal is the electrical signal of the heart sound reflected by the movements of the heart and detected by ultrasonic sensors. This electrical signal corresponds to an electrical signal value of very small amplitude to be detected by the microprocessor. The electronic amplifier passes through the circuit stage to raise the electrical signal to an electrical signal level that can be detected by the microprocessor. Thus, the electrical signal is increased to a level that can be detected by the microprocessor. At the same time, by means of a headphone connection on the prototype circuit, it reaches a heart sound level, that is, an electrical signal, which can be heard by a headset used by the user. They carried the heart rate of the fetus from the doppler device to the android platform in their study called "Mobile – FHR Assessment Using Android Platform" [2]. 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 [3]. Finland-based software company Odosoft born "UnbornHeart" developed the mobile application. It has the feature of listening to the heart rate of the fetus and the heartbeat sound of the fetus to the expectant mother [4]. The most important criterion in the evaluation of fetal health is the measurement and interpretation of FHR and UC values. These measurements can be made in clinical or hospital environment with advanced technology and high cost Non-Stress Test (NST) devices. In order to apply NST measurement, the pregnant individual must make an appointment with the health institutions in advance, reach the clinic or hospital environment and connect to the NST device for at least 20 minutes. Depending on the status of the pregnancy and the risk group, these procedures should be repeated periodically until the end of pregnancy.

Several studies have been carried out using ML algorithms related to FHR. Cardiotocogram classification [5], fetal monitoring [6], using nonlinear features for FHR classification [7], Fuzzy analysis of birth outcome characteristics to better automate fetal status assessment, classification of cardiotocogram data to predict fetal risks [8–9]. CTG has taken a pivotal role in the development of objective measures as a function of CTG signals [10], particularly within the machine learning community [11-21], studies representing non-visual patterns found in FHR [22-25]. Blinx et al. compared DT, Neural Network and Discriminant Analysis. The ANN classifier achieves an overall accuracy of 97.78% [26].

In this important issue, this study was carried out so that the classification and diagnosis process can be performed automatically. The aim of this study is to develop a hybrid model for faster and more accurate interpretation of FHR results. In this

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way, errors and delays caused by the negativity will be eliminated.

2. Material and Methods

MLAs can be defined as brains that allow machines to learn, making them smarter. Exposing these algorithms to new data and experiences on a regular basis; It allows great things to be accomplished in various tasks related to classification, predictive modeling and analysis of data.

The learning process begins with inputting training data such as examples, direct experience, instructions, observations into the chosen algorithm to look for patterns in the data. To test whether this algorithm works correctly, new input data is added to the machine learning algorithm. The prediction and results are then checked.

2.1. ML Algorithms

k-NN is an algorithm that uses training datasets to find the k closest data points in some dataset. k-NN is a supervised MLA used for both regression and classification problems. This algorithm first stores and defines the distance between all inputs in the data, choosing the closest input to the query and outputs.

The DT algorithm is a type of supervised machine learning. It is used to solve regression and classification problems. The goal is to leverage a decision tree to move from observations to processing results.

NB algorithm, which calculates the probability of an item falling into a certain category using the conditional probability rule, is known as supervised MLA.

In the SVM algorithm, data is classified according to the degree of polarity that can go beyond the X/Y estimation. SVM is categorized among supervised MLAs and is primarily used for classification and regression analysis. The algorithm works by creating models that assign new instances and data to a category.

2.2. Dataset and Features

The dataset contains information including measurements of FHR and UC features in cardiotocograms classified by obstetricians [27]. Records of 2126 fetal cardiotocograms (CTGs) were automatically processed and the measurement of diagnostic features required was recorded. Classification in the database was performed according to both morphological pattern (A, B, C....) and fetal status (N, S, P). As a result, the dataset can be used in any study that will be used for 10-class or 3-class experiments. Dataset attribute information shows following in Figure 1 [28].

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)

Figure 1. Dataset information

3. Experimental Results

The structure of the developed hybrid model is as shown in Figure 2. Different hybrid models were tried during the studies, but this model provided the exact diagnosis rate. In the proposed hybrid model, operations are carried out with the machine learning algorithm, which always achieves the highest accuracy, and the next step is taken.

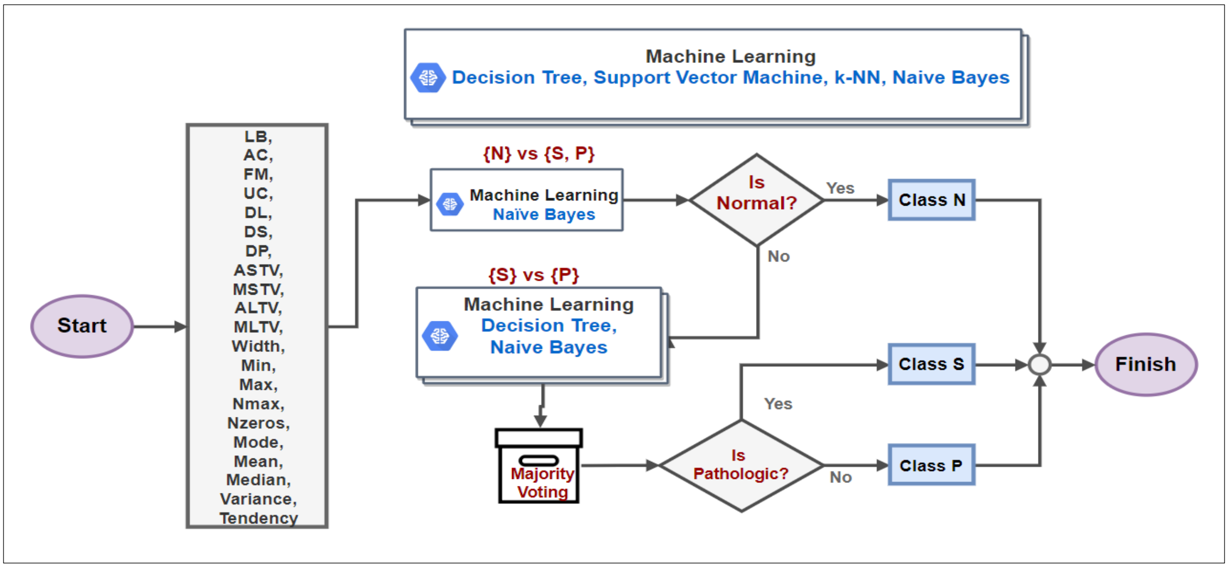


Figure 2. Proposed hybrid model

The confusion matrix shows the current state of the data and the number of correct and incorrect predictions of our classification model. The statistical measurements used in this study are shown in the Figure 3.

65% of the data in the database was used for training and 35% for the test. The classification and test results, which were initially performed without any hybrid model, are as follows in Table 1, Table 2 and Table 3. The statistical results obtained from the k-NN ML algorithm without the hybrid model are shown in Table 2 (1, 2, 3, 4, 5, 6, 7, 8, 9 = TPR, SPC, PPV, NPV, FPR, FNR, ACC, MCC, FM for all tables).

Sensitivity or True Positive Rate	$TPR=\frac{TP}{TP+FN}$	Dice Similarity Coefficient	$DSC=\frac{2TP}{2TP+FP+FN}$
Specificity or True Negative Rate	$TNR=\frac{TN}{TN+FP}$	Accuracy	$ACC=\frac{TP+TN}{TP+TN+FP+FN}$
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 3. Statistical measurements.

Table 1. k-NN ML algorithm statistical results

	Pathologic	Normal	Suspect		TP	FP	FN	TN
Pathologic	23	64	3	**Pathologic**	23	67	7	660
Normal	6	531	89	**Normal**	531	95	87	44
Suspect	1	23	17	**Suspect**	17	24	92	624

	1	2	3	4	5	6	7	8	9
Pathologic	0.77	0.91	0.26	0.99	0.09	0.01	0.9	0.41	0.38
Normal	0.86	0.32	0.85	0.34	0.68	0.66	0.76	0.18	0.85
Suspect	0.16	0.96	0.41	0.87	0.04	0.13	0.85	0.18	0.23

It is also shown graphically in Figure 4.

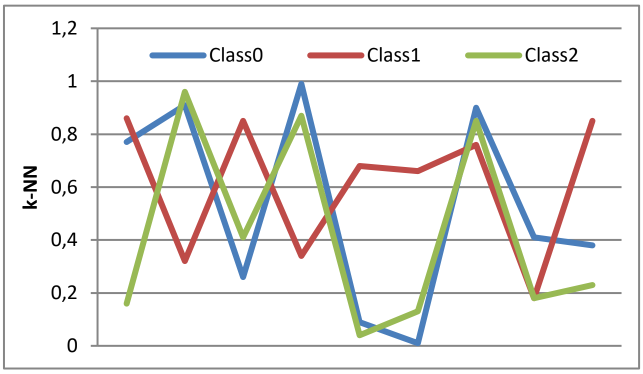


Figure 4. k-NN ML algorithm statistical results

The statistical results obtained from the DT ML algorithm without the hybrid model are shown in Table 2.

Table 2. Statistical results of DT ML algorithm

	Pathologic	Normal	Suspect		TP	FP	FN	TN
Pathologic	90	0	0	**Pathologic**	90	0	0	667
Normal	0	480	146	**Normal**	480	146	10	121
Suspect	0	10	31	**Suspect**	31	10	146	570

	1	2	3	4	5	6	7	8	9
Pathologic	1	1	1	1	0	0	1	1	1
Normal	0.98	0.45	0.77	0.92	0.55	0.08	0.79	0.55	0.86
Suspect	0.18	0.98	0.76	0.8	0.02	0.2	0.79	0.3	0.28

It is also shown graphically in Figure 5.

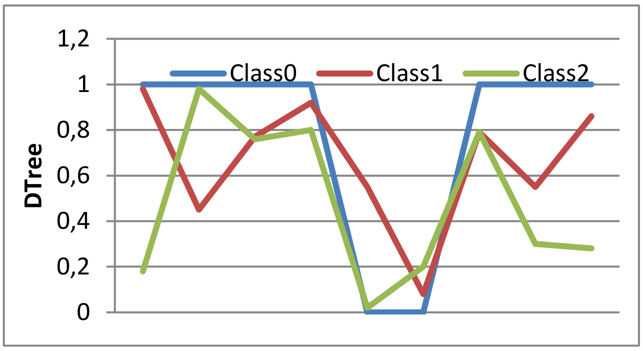


Figure 5. DT ML algorithm statistical results

The statistical results obtained from the NB ML algorithm without the hybrid model are shown in Table 3.

Table 3. NB ML algorithm statistical results

	Pathologic	Normal	Suspect		TP	FP	FN	TN
Pathologic	90	0	0	**Pathologic**	90	0	0	667
Normal	0	613	13	**Normal**	613	13	3	128
Suspect	0	3	38	**Suspect**	38	3	13	703

	1	2	3	4	5	6	7	8	9
Pathologic	1	1	1	1	0	0	1	1	1
Normal	1	0.91	0.98	0.98	0.09	0.02	0.98	0.93	0.99
Suspect	0.75	1	0.93	0.98	0	0.02	0.98	0.82	0.83

It is also shown graphically in Figure 6.

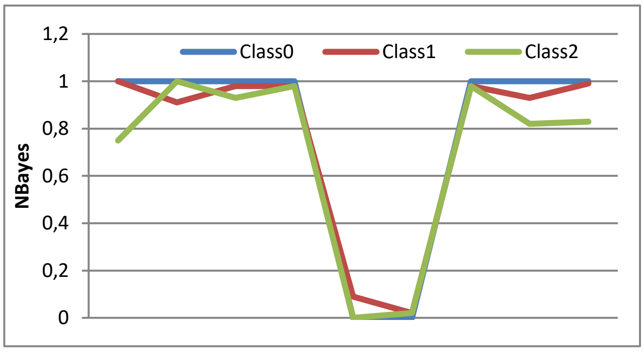


Figure 6. NB ML algorithm statistical results

The statistical results obtained from the SVM ML algorithm without the hybrid model are shown in Table 4.

Table 4. Statistical results of SVM ML algorithm

	Pathologic	Normal	Suspect		TP	FP	FN	TN
Pathologic	15	75	0	**Pathologic**	15	75	0	667
Normal	0	578	48	**Normal**	578	48	101	30
Suspect	0	26	15	**Suspect**	15	26	48	668

	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**
Pathologic	1	0.9	0.17	1	0.1	0	0.9	0.39	0.29
Normal	0.85	0.38	0.92	0.23	0.62	0.77	0.8	0.19	0.89
Suspect	0.24	0.96	0.37	0.93	0.04	0.07	0.9	0.24	0.29

It is also shown graphically in Figure 7.

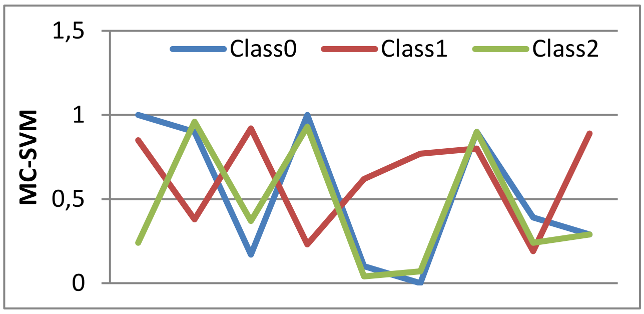


Figure 7. SVM ML algorithm statistical results

Table 5. k-NN algorithm statistical results

	Suspect	Normal		TP	FP	FN	TN
Suspect	23	70	**Suspect**	23	70	2	39
Normal	2	39	**Normal**	39	2	70	23

	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**
Suspect	0.92	0.36	0.25	0.95	0.64	0.05	0.46	0.23	0.39
Normal	0.36	0.92	0.95	0.25	0.08	0.75	0.46	0.23	0.52

The training and test scores obtained from the hybrid model ML algorithms are given below Table 5, Table 6, Table 7, respectively. The statistical results obtained from the k-NN after the generated hybrid model are shown in Table 5.
It is also shown graphically in Figure 8.

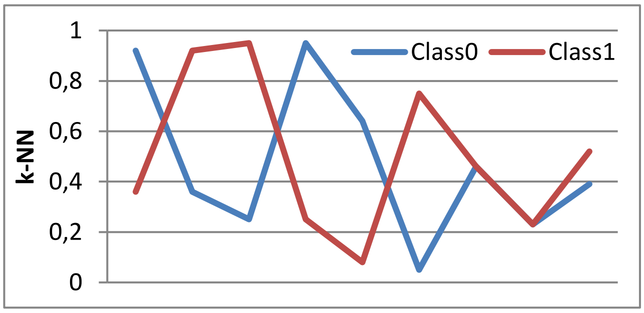


Figure 8. k-NN ML algorithm statistical results

The statistical results obtained from the DT after the generated hybrid model are shown in Table 6.

Table 6. DT algorithm statistical results

	Suspect	Normal		TP	FP	FN	TN
Suspect	93	0	**Suspect**	93	0	0	41
Normal	0	41	**Normal**	41	0	0	93

	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**
Suspect	1	1	1	1	0	0	1	1	1
Normal	1	1	1	1	0	0	1	1	1

It is also shown graphically in Figure 9.

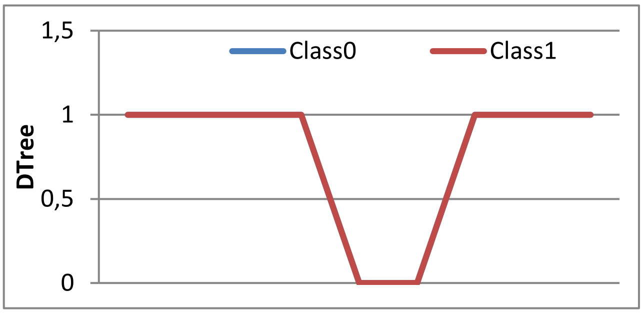


Figure 9. DT ML algorithm statistical results

The statistical results obtained after the generated hybrid model NB are shown in Table 7.

Table 7. NB algorithm statistical results

	Suspect	Normal		TP	FP	FN	TN
Suspect	93	0	**Suspect**	93	0	0	41
Normal	0	41	**Normal**	41	0	0	93

	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**
Suspect	1	1	1	1	0	0	1	1	1
Normal	1	1	1	1	0	0	1	1	1

It is also shown graphically in Figure 10.

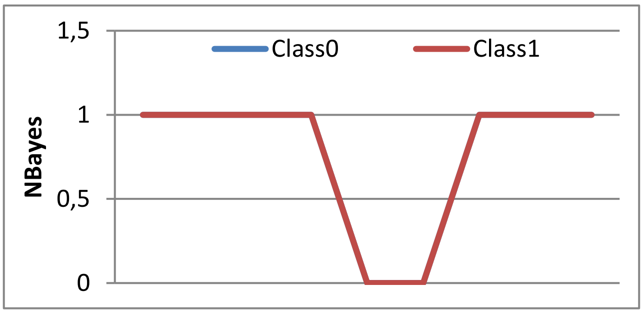


Figure 10. NB ML algorithm statistical results

The statistical results obtained from the SVM after the hybrid model generated are as shown in Table 8.

Table 8. SVM algorithm statistical results

	Suspect	**Normal**		**TP**	**FP**	**FN**	**TN**
Suspect	6	87	**Suspect**	6	87	0	41
Normal	0	41	**Normal**	41	0	87	6

	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**
Suspect	1	0.32	0.06	1	0.68	0	0.35	0.14	0.12
Normal	0.32	1	1	0.06	0	0.94	0.35	0.14	0.49

It is also shown graphically in Figure 11.

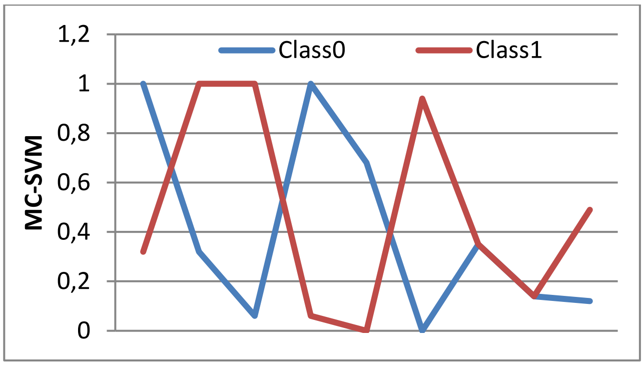
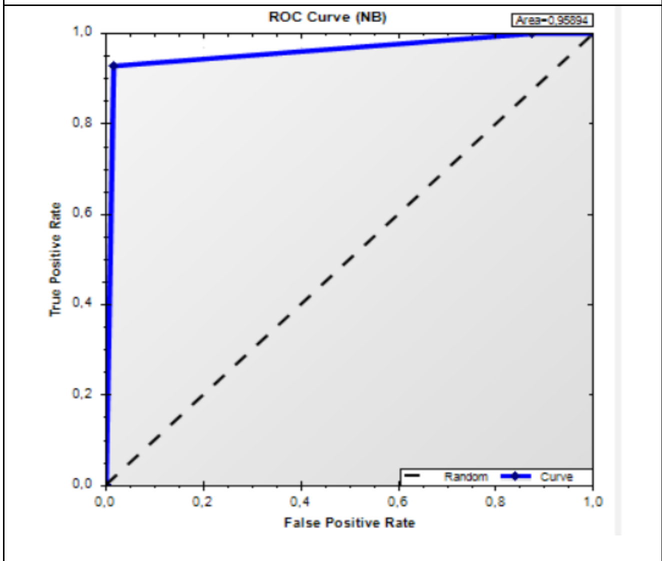
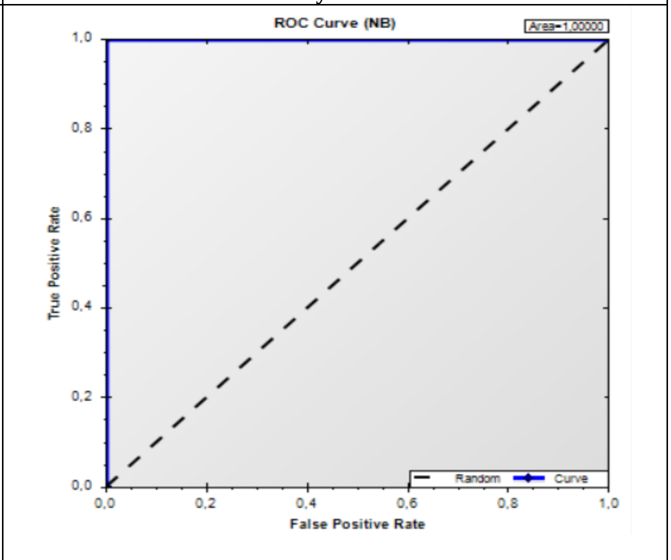
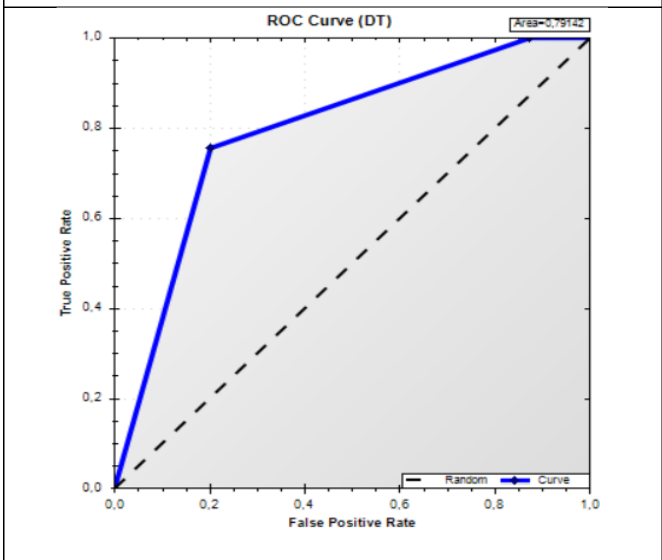
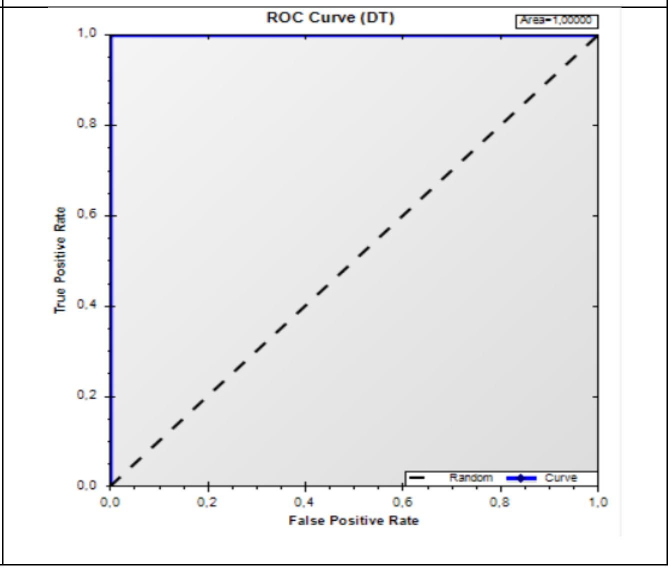


Figure 11. SVM ML algorithm statistical results

ROC curves obtained from MLA as a result of the application of normal and hybrid models are given in Table 9.

Table 9. ROC curve results

Normal	**Hybrid**
	
	

When looking at the Table 9, it is seen that the ROC curve values of the proposed hybrid result increase. Accuracy values obtained as normal and hyrid results are shown in Table 10.

Table 10. Accuracy values obtained from normal and hybrid models

	Normal		**Hybrid**	
	Train score	**Test score**	**Train score**	**Test score**
k-NN	1	0.74636	1	0.47014
DT	1	0.79395	1	1
NB	0.97808	0.97886	0.994065	1
SVM	0.92037	0.771466	0.9020771	0.440298

Accuracy values increased as a result of the proposed Hybrid model. The training and test data obtained after the normal classification (without hybrid model), the first stage (with hybrid model) and the final stage (with hybrid model) are as shown in Table 11.

Table 11. Step-by-step classification results (hybrid model)

Normal classification result				
	k-NN	**DT**	**NB**	**SVM**
Train Score	%100	%100	%97.81	%84.08
Test Score	%75.43	%79.39	%97.89	%80.32
Final classification result				
	k-NN	**DT**	**NB**	**SVM**
Train Score	%100	%100	%99.41	%77,15
Test Score	%46.27	%100	%100	%35,07

Looking at the Table s above, it will be seen that the hybrid model has achieved its goal by increasing the classification and test results at each step. The proposed hybrid model reached better results than other studies in the literature. In Table 12, comparisons of other methods and the proposed hybrid model are given.

Table 12. Comparison with other method

	Other Methods (%)							
	Romano et al. [10]	**Blinx et al. [26]**	**Karabulut and Ibrikci [29]**	**Spilka et al. [30]**	**Spilka et al. [31]**	**Paul et al. [32]**	**Ayres et al. [27]**	**Proposed Hybrid Method (%)**
Accuracy	77	-	93.97	95.01	-	-	-	100
Sensitivity	93	-	91.58	-	72	73.4	90	100
Specificity	82	-	95.79	-	78	76.3	96	100
Overall classifier	-	97.78	-	-	-	-	87	100
Train Score	-	-	-	-	-	-	-	100
Test Score	-	-	-	-	-	-	-	100

4. . Conclusions

CTG recordings are widely used in pregnancy today because CTG provides important information about the physiological health of the fetus. In this study, a hybrid model was proposed, which allows automatic, rapid and complete diagnosis of CTG recordings. With this model, any discomfort in the fetus can be detected instantly with the diagnostic results to be given automatically. In this way, the necessary precautions can be taken by determining the negativities in pregnancy. While the average classification rates were 95.4725% training and 83.2575% test results on average, with this proposed hybrid model, this average value was obtained as 98.3925% training and 94.4175% test results. With the hybrid model created in the study, a 34% improvement was achieved for accurate diagnosis. Sensitivity and Specificity ratios were obtained as 100% with the proposed hybrid model. In general, the classification results have increased and reached a level that can be fully diagnosed.

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