International Journal of Engineering and Advanced Technology (IJEAT)
ISSN: 2249-8958 (Online), Volume-9 Issue-3, February 2020

Enhanced Optimal Feature Selection Techniques for Fetal Risk Prediction using Machine Learning Algorithms

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***Abstract**: Cardiotocography (CTG) records fetal heart rate (FHR) and uterine contractions (UC) simultaneously. The CTG, which is one of the most common diagnostic techniques used during pregnancy and before delivery to evaluate maternal and fetal well-being. Doctors can understand the state of the fetus by observing the Cardiotocography trace patterns. There are several techniques for interpreting a typical cardiotocography data based on signal processing and computer programming. Only a few decades after cardiotocography has been implemented into clinical practice, the predictive potential of these approaches remains controversial and still unreliable This paper presents MRMR feature selection algorithms with four classification for Fetal risk prediction using python.*

Keywords: Fetal heart rate, cardiotocography, uterine contractions, machine learning, MRMR, python.

I. INTRODUCTION

The innovative engineering methods have played an important role in the area of medicine, to help doctors achieve the desired outcomes effectively. The medical sector can't work efficiently, survive and improve its existence without engineering technology intervention, If traced back, that could be illustrated. Clinical studies are aiming to understand better the inner behavior of the human body over the decades. an area of medicine that needs immediate treatment from technical techniques is problems being faced by females during their pregnancy due to biological conditions deformity.

About 795 women dying from preventable sources of pregnancy and childbirth, of which 98% are in developing countries. Maternal deaths worldwide plummeted by 45% after 1990, the global maternal mortality ratio (no of deaths per 100000 live birth) decreased by just 2.460% per year between 1990 and 2015. According to some gynaecologists, every trimester is described as about 14 weeks, which adds to about 42 weeks of pregnancy. Around 20 million women worldwide suffer ill health every year as a result of pregnancy.

Revised Manuscript Received on February 05, 2020.

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In 1990, about 377,000 women died as a result of pregnancy complication, which dropped to 293,000 in 2013. Among those 288000 women have died during the delivery procedure andmost of the deaths where in low facilities settings and majority of them could have been saved. people who have suffered from problems while giving birth or after the procedure was performed. A professional practitioner's treatment before, during and after childbirth can save the live of pregnant women and newborn infants. Most maternal deaths are escapable, as the mechanisms for avoiding or treating complications.

Fetal heart rate

In the utero period, the general FHR fluctuates between 120-155 BPM. It is detectable sonographically from about 6 weeks and the range varies all through development, rising to about 170 bpm at 70 days and then to about 130 bpm at term. Although myocardium begins to contract rhythm 20 days after giving birth (from inspontaneity depolarizing myocardial pace maker cells in the embryonic heart), about 6 weeks of sonography gestation is first noticeable. Typically, the FHR then beats between 100 and 120 per minute (bpm).

FHR gradually fluctuates in the next 14-21days and becomes:

5-6 Weeks ~110 bpm (mean)

~170 bpm over 9-10 weeks

There after a drop in FHR becomes average:

~151 bpm to 98 days

~142 bpm to 140 dayss

~131 bpm per term

Although the heartrate in the healthy fetus is normally normal, a beat-to-beat variation of about 5 to 14 beats per minute may be permitted.

Fetal heart monitoring

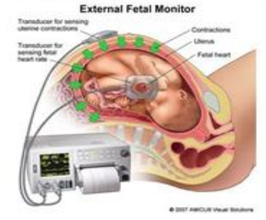
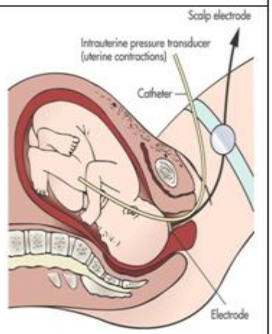
Fetal cardiac monitoring measures your baby's heart rate (fetus). This allows your health care provider to see how the child is healthy. Your health care provider will perform a fetal heart rate test in the later stages of pregnancy. In fetuses the normal heart rate varies from 110 to 160 bpm. It may range from 5-25 beats per minute. As your baby reacts to uterine conditions the fetal heart rate will change. An irregular fetal heart rate mean that baby isn't getting sufficient oxygen or other problem.

A. External fetal heart monitoring

We use a device to hear through patient belly (abdomen) and record your baby heartbeat. One type of display is an ultrasonic Doppler system. It's often used for monitoring the baby's heart pulse during prenatal visits. It also be used during labor to monitor fetal heart rate.

The health care provider may also regularly monitor the baby's heart pulse during conception and childbirth.
To do this, your belly is fastened to the ultrasonic probe (transducer). It sends in a machine the sound of your baby's heart. The pattern and rate of heart rate for your baby is shown on a computer and written on paper.

Table1: Types of Fetal Monitoring Techniques.

TYPES	DEFINATION	DIAGRAM
External monitoring	External fetal heart rate monitoring uses a device to detect or record fetal heart beat through the abdomen of the mother. The most specific type of external monitor is a fetoscope (a kind of stethoscope).	
Internal monitoring	An electrode is placed along the scalp of the baby and it passes through the cervix from the baby.the heart rate and the contractions of the baby are monitored during labour by the healthcare supplier.	

B. Internal fetal heart monitoring

We insert a wire (electrode) that is placed on the scalp of the infant. The wire is going through your cervix from the infant. The monitor is linked. This method gives better readings, because it doesn't affect things like movement. But this can be achieved if the fluid-filled sac that protects baby during the pregnancy has separated and opened the cervix (amniotic sac).. If the external monitoring does not give a good reading, the provider may use internal monitoring. And your doctor may use this tool to take a closer look at your baby during labour.
The healthcare provider will monitor uterine contraction and heart rate of the baby during labour. Your provider should remember How often contractions do you experience & how long each lasts. Because the heart rate and the contraction are fetal registered simultaneously, these findings can be interpreted and compared together.
Doctor can check pressure inside the uterus while doing internal fetal heart monitoring. To do so, doctor will put a tube (catheter) through the cervix and into uterus. The catheter shall forward uterine pressure reading to a monitor.

Need of fetal heart monitoring

Fetal heart rate monitoring is helpful if the patient have a high-risk pregnancy. If patient have diabetes or high bp, a high risk for the child. It is also high risk if the baby doesn't grow or develop as it should. Fetal heart rate monitoring can be used to check whether the child is affected by premature laboratory medicines. These are medications that help keep the work from getting started too early. Other research may also use fetal heart rate monitoring including:

A. **Nonstress test :** When the baby moves, this monitors the fetal heart rate.
B. **Contraction stress test :** It, along with uterine contractions, monitors fetal heart rate. Medicine or other approaches are used to initiate contractions.
C. **A biophysical profile :** This is combination of nonstress test with ultrasound.

Risks of fetal monitoring

For that study, radiation is not used. The transducer usually does not cause any pain.You can consider the elastic belts which slightly uncomfortable keep the transducers in place. These can be modified according to need.
During certain forms of fetal heart rate monitoring you have to lie still. At sleep, you may need to stay in bed. Patient may have some discomfort with internal testing when electrode is inserted into uterus. Internal monitoring risk include infection & bruise of the scalp or other part of the baby's body.
Note: If you are HIV-positive you shouldn't have internal fetal heart rate monitoring. This is because you might pass the infection on to your kids.
Based on your particular health condition you may have other risks. Make sure to discuss any issues you may have with your provider prior to the instructions.
Certain things may or mayn't make the results of fetal heart rate monitoring less accurate. These include:

- Maternal obesity
- Baby position
- Too much fluid with amniotics (polyhydramnios)

Table2: Types of Fetal Diseases.

	TYPE-1	TYPE-2	TYPE-3
NAME	**Fetal Bradycardia**	**Fetal Tachycardia**	**Fetal Bradyarrhythmia(s)**
DEFINITION	Fetal bradycardia refers to an abnormally low heart rate in the fetus, a potentially alarming outcome. A constant heart rate below 100 beats per minute (bpm) during the first trimester is generally considered bradycardic.	Fetal tachycardia is an anomalous increase in heart rate in the fetal. If the heart rate above 160-180 beats per minute and ranges from 170-220 bpm (high tachyarrhythmias).	Fetal bradyarrhythmia refers to an abnormally low heart rate of the fetus (less than 100-110 beats per minute 3,7) and is also irregular.
CAUSES	poor uterine perfusion	maternal fever	NILL

	□ maternal hypotension □ umbilical cord prolapse □ rapid fetal descent	□ Dehydration □ maternal ketosis □ preterm fetus □ maternal thyrotoxicosis	
SYMPTOMS	□ An abnormally fast heart rate. □ Abrupt decreases in heart rate. □ Late returns to the baseline heart rate after a contraction.	□ An abnormally slow heart rate	NILL
HEART RATE	below 100 beats per minute (bpm)	above 160-180 beats per minute (bpm)	less than 100-110 beats per minute.

Cardiotocography Classification

The National Institute of Child Health and Human Development is implementing CTG's framework for assessing FHR and uterine contraction trends. Listed below are only a few of the most important features for CTG data classification.

Baseline: The mean value of the Fetal Heart Rate data is defined as the baseline ranging from 100 to 160 bpm for a 10 min period without acceleration or decelerations.

Variability: The variation spectrum in the FHR excluding the acceleration or deceleration is described as Variation. Depending on the time, this can be either short or long term.

Accelerations and Decelerations: Acceleration is defined as an increase in FHR of more than 15 bpm from baseline and lasting at least 15 seconds or higher. Acceleration is defined as a drop in FHR exceding 15 bpm from baseline and lasting at least 15 seconds or more. Drop in Fetal Heart Rate is characterized as early deceleration shortly after the onset of a Uterine contraction with peaks of deceleration and contraction facing one another. It is a clue to a healthy fetus.

Category I FHR tracings provide baseline FHR with mild variation ranging from110 to 160. They lack variable and late decelerations, with early decelerations and accelerations possible.

Category II Tracings are those which can not be classified as either Category I or Category III. Such readings include: low or lack of variability, repeated decelerations, accelerations even after fetal activity, recurrent variable decelerations with no baseline variability.

Category III FHR levels are not common, and the risk of hypoxia and acidemia is higher. These either have repeated late decelerations or no variation in baseline, or sinusoidal pattern. Such readings are exceptional.

Normal Fetal Heart Rate Chart By Week

The fetal heart rate varies according to fetal gestational age. It begins at a slower rate may increases every day until around 12th week it stabilizes. The normal heart rate is between 120 and 160bpm around this gestation period. The chart below gives you an idea of how week by week the fetal heart rate varies.

Tables3: Fetal heart rate chart by week.

FETAL AGE (by weeks)	NORMAK FHR (BPM)
5	80-103
6	103-126
7	126-149
8	149-172
9	155-195(avg 175)
12	120-180(avg 150)
After 12	120-160(avg 140)

II. LITERATURE REVIEW

ANN approach for prediction of hypertension disease has been favoured in the studies. ANN's high cost of computation and long learning speeds enforce expanding the concept to deep learning network. Low computational costs and the classification of learning levels are therefore important for such problem. To enhance fetal risk prediction SVM hybrid response approaches were discussed with the other attribute reduction tool (Subha V *et al.* 2017).

This paper simultaneously studies the enhancement of Cardiotocogram data classification accuracy in the selection of features and classifiers based on ensemble learning. In the selection of features, two subset filtering techniques (Correlation-based Feature Selection; Consistency-based Filter) and two filter-based feature ranking techniques (Relief; Information Gain) are considered, while the Support Vector Machine classification technique is used in the classification (Silwattananusarn *et al.*2016).

Comparing the predictive accuracy of normal and pathological classifications (99.78 per cent), the findings performed much better than previous work[20] and were 99.2 per cent accurate when using Random Forests (Nagendra *et al*.2017).

Classification confusion matrix with minimum error of misclassification (0.184383) using pruned decision tree to analyze cardiotocogram data to determine fetal distress (Permanasari *et al*.2017).

CTG monitoring is useful for obstetricians in identifying fetal situations and in deciding on medical intervention during pregnancy and delivery before permanent baby damage (Zhang *et al*.2017).

When validated, potential applications for this approach could include the use of lay doctors and nurses in remote critical care of pregnant women at high risk of severe perinatal outcome based on CTG tests, for clarity and further management.(Hoodbhoy *et al.*2019).

The study work analyzes the same data and found that ANN achieves overall accuracy as 92.42%. The results from the CTG classification obtained in the paper suggest that the most accurate results are obtained from the decision tree-based algorithm (J48) with 0.0408 as MAE, 0.8716 as kappa statistics and 94.33 per cent as accurate with the highest precision metric value. Classification of Random Forest and Regression was near J48 (Bhatnagar *et al.*2016).

Pre-processing of fetal heart monitoring data, sequential removal of fetal heart rate data for dataset removal with a high proportion of deletions, back to back missing values, linear interpolation, smooth denotation and then modification of the data structure to obtain three different data formats (Tang *et al.*2018).

Fetal distress assessed by discriminatory analysis, decision tree, and artificial neural network; results show that the accuracy of DT, ANN and DA is 86.36%, 97.78% and 82.1% respectively. The authors suggested using the classification techniques to fit into different attributes and apply feature techniques in the data processing pre-processing phase (Huang *et al.*2012).

The effect on classifiers of using AdaBoost ensemble is investigated for the perfect determination of the fetal distress from the results of CTG. The most prominent result is the AdaBoost decision-based algorithm with 0.034 MAE, 0.861 kappa statistics and 95.01 percent accuracy, meaning 2126 samples will be perfectly predicted by 2020. These findings are a further improved next step, after the related literature studies (Karabulut *et al.*2014).

The application of the algorithm to the different stages of the pregnancy data provide an objective measure of the fetal health condition assessed in the author (Ersen *et al.*2013).

(Sundar C *et al.*2012) examined the output analysis of a CTG dataset based neural network classification model. The performance of the classification method, which was based on supervised machine learning, provided significant results. The classifier based on ANN was able to identify normal, suspicious and pathological conditions with very good accuracy from the nature of CTG data. ANN based classifier delivered excellent Rand Index, F-Score, Recall and Precision performance. It was able to identify with almost equal accuracy the normal and the pathological condition. Compared with other two classes, the performance in identifying the Suspicious CTG pattern was poor.

(Pooja Sharma *et al.*2012) A decisiontree algorithm and an existing C4.5 algorithm are proposed and implemented for the comparative study and performance analysis.

A Support Vector Machine algorithm was developed in com bination with empirical mode of decomposition to achieve h igh compliance with Fetal Heart Rate data prediction with e xpert clinical interpretation(krupa *et al.*2011).

(Kalpesh *et al.*2013) developed a system that uses data mining concepts to predict students performance from their previous performances. We have applied classification algorithms ID 3 and C4.5 to student data and estimated the overall and individual performances of newly admitted students in future exams.

(Yugal *et al.*2012) focus on basic data mining classification techniques such as the BayesNet, NavieBayes, NavieBayes Uptable, Multilayer Perceptron, Voted Perceptron and J48 (C4.5) classifiers. These algorithms are used to classify the dataset, and their performance is analyzed by means of absolute error, root mean square error and the time taken to construct the model.

The decision tree C4.5 algorithm used by (Hamidah *et al.*2010) to create the rules for classifying human talent data. The rules produced are evaluated using the unidentified data to approximate the precision of the prediction results.

Other author, however, argued the importance of hybrid data mining algorithms to a pregnant women's build model, prevention of health risks caused by inconsistencies in parameters during pregnancy. The C4.5 algorithm delivered exact performance of 98 per cent (Lakshmi *et al* . 2016).

My aid in better predicting fetal growth during pregnancy is the proper dataset consisting of the correct number of parameters and applying the hybrid approaches. Similarly, eight machine learning algorithms have been documented using weka tools over the CTG dataset in other studies. The exact prediction response of all algorithms was analyzed for validation by partitioning the dataset into ten equal size. The performance of the classifier model, the highest precise classification was scored 99.2 percent. Feedforward NN solved ANN drawbacks with non-linear functions which composed a number of weighing inputs, hidden layers followed by initiation function, a bias that provides output for the next layers (Kalyani *et al.*2018).

Table4: Related data

S.NO	AUTHOR	ALGORITHMS	ACCURACY
1	Subha V(2017)	Naïve Bayes Algorithm, Decision Tree, Multi-layer Perceptron(MLP),Radial Basis Function Networks (RBF)	NB: 82.1 DT: 92.9 MLP: 91.9 RBF:86.0
2	Silwattananusarn (2016)	SVM	98.49
3	Nagendra (2017)	SVM, Random Forests	99.78(SVM)
4	Permanasari (2017)	AdaBoost, Decision Tree, ANN	97.78(ANN)
5	Zhang (2017)	Adaboost, SVM	Adaboost(98.6)

6	Hoodbhoy (2019)	MLP, Decision Tree, Random Forest, Logistic Regression, SVM, KNN	97(SVM)
7	Bhatnagar (2016)	Naïve Bayesian Classifier, Decision Tree, Random Forest, JRIP,,MultiLayer Perceptron, ANN	92.42(ANN)
8	Tang (2018)	SVM, Random Forest, MKNet, MKRNN	94.7(SVM)
9	Huang (2012)	DA, DT, ANN	97.78(ANN)
10	Karabulut (2014)	Naïve Bayes, Radical Basis Function, SVM, Neural Network, DT	DT with AdaBoost(95.014) DT without AdaBoost(92.427)
11	Ersen YJlmaz (2013)	LS-SVM	91.62.
12	Sundar C (2012)	ANN	97.24.
13	Pooja Sharma (2012)	Decision Tree	77.23
14	Niranjana Krupa (2011)	ANN,SVM	86
15	Kalpesh Adhatrao (2013)	ID3,C4.5	75.14
16	Yugal Kumar (2012)	Naïve Bayes	97.28
17	Lakshmi .B.N (2015)	Decision tree	98
18	Hamidah Jantan (2010)	SVM,AIS,C4.5	77
19	Kalyani (2015)	RF,C4.5,SVM, CART,ANN, K-NN	98.67
20	Daniel LaFreniere (2016)	ANN	82
21	Subha V (2015)	SVM with GA	91.35

Methodology:

Minimum Redundancy Maximum Relevance technique is used for selecting the features which has high correlation with the class and low correlation with other features in the dataset. The selected features are then classified using the following algorithms: Navies Bayes, Decision Tree, Random Forest , Support Vector Machine.
Figure 1 depicts the System Architecture Diagram

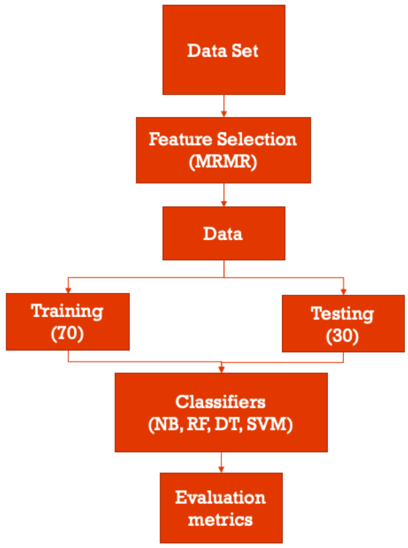


Fig. 1 System Architecture

Result analysis

The performance of the proposed work is analyzed using the following metrics: accuracy, precision, recall and F-score. Table 5 representsthe comprasion between the classifiers terms of accuracy which is figured in fig.2

Table5: Comparison results of classifiers with regard to Accuracy

Accuracy in %			
Classifiiers	No . of . features-20	No .of . features-25	No .of . features-30
Naives Bayes	88	90	98
Random Forest	96	97	98
Decision Tree	95	97	98
SVM	95	94	98

Fig. 2 Comparison results of classifiers with regard to Accuracy

Table 6 representsthe comprasion between the classifiers terms of accuracy which is figured in fig.3

Table6: Comparison results of classifiers with regard to Precision

Precision in %			
Classifiiers	No . of . features -20	No .of . features-25	No .of . features-30
Naives Bayes	73.6	76.6	97
Random Forest	88.3	94	95
Decision Tree	86	93.6	94.6
SVM	83.6	83.6	97.3

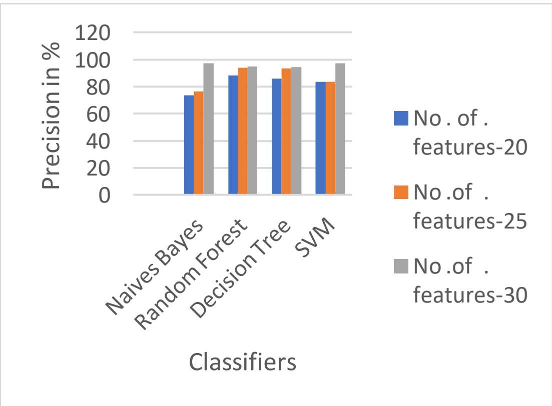


Fig. 3 Comparison results of classifiers with regard to Precision

Table 7 representsthe comprasion between the classifiers terms of accuracy which is figured in fig.4

Table7: Comparison results of classifiers with regard to Sensitivity

Sensitivity in %			
Classifiiers	No . of . features -20	No .of . features-25	No .of . features-30
Naives Bayes	83.3	85.6	94
Random Forest	91	95.3	95
Decision Tree	90.6	95	96.6
SVM	85.6	88	97.6

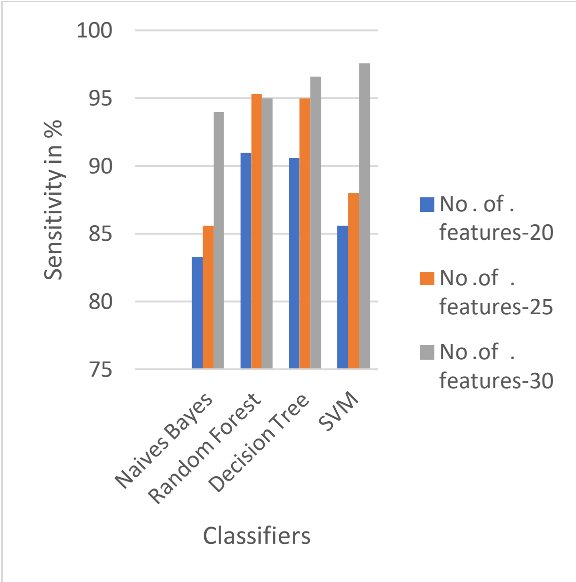


Fig. 4 Comparison results of classifiers with regard to Sensitivity

Table 8 representsthe comprasion between the classifiers terms of accuracy which is figured in fig.5

Table8: Comparison results of classifiers with regard to F-score

F-score in %			
Classifiiers	No . of . features-20	No .of . features-25	No .of . features-30
Naives Bayes	75.3	79.3	95.66
Random Forest	89.3	94.3	95.3
Decision Tree	88	94.3	96
SVM	84.3	84.6	97.6

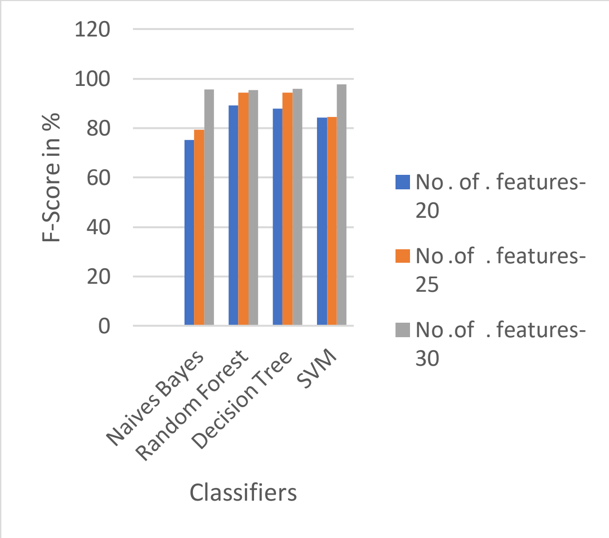


Fig. 5 Comparison results of classifiers with regard to F-score

III. CONCLUSIONS

Thus the paper examines the Fetal Risk Prediction using MRMR Feature Selection algorithm on four different Classifiers SVM Classifier with high F-score(97.6), sensitivity(97.6) , Precision(97.3).SVM Classifier have got the maximum metrics percentage for MRMR Feature selection algorithm.

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