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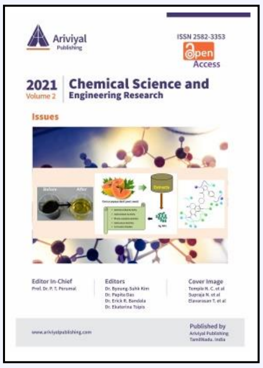

Performance Analysis of Various Supervised Classifiers for Predicting Preterm Delivery using Multi-channel Uterine EMG Signals

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Abstract: Prediction of premature labour is of great significance in preventing infant deaths, or the consequent health risks globally. The enormous global burden on both families and society calls for preventive and predictive measures. The uterine Electromyography signals also called as Electrohysterogram (EHG) signals, has been very promising in studying the uterine contractions. Therefore, use of uterine EMG signals can prove to be a marker in diagnosing Preterm birth. In this study, the TPEHG DB (Term-Preterm Electrohysterogram Database) dataset with 300 records (262 term and 38 preterm records) are used. The raw uterine EMG signal is initiallypre-processedandthen various linear, non-linear and statistical features are extracted. The extracted features are applied to different machine learning classifiers. Further, Bayesian Hyper parameter Optimization technique was employed on these classifiers to improve their classification accuracy. Support vector machine (SVM) classifier with Bayesian Hyper parameter Optimization technique, tested using 10-fold cross-validation on 38 preterm records provided 96.667% accuracy.

Keywords: Uterine Electromyography; Premature labour; Bayesian Hyper parameter Optimization; Support vector machine

1. Introduction

Premature labour (pregnancy duration < 37 weeks) is one of the most significant public wellbeing issues, which is the supporter of new born child dismalness and mortality. Nearly 7% of all births are preterm.[1,2] Determining preterm labour can be very useful in providing the necessary treatment.[3] Over the past decade, examination of uterine EMG signals has been used for analysis of preterm labour. Untimely labour expectation is a firmly troublesome undertaking because of the unpredictable uterine contractions. Uterine Electromyography signals determine the uterine contractions which are recorded non-invasively using bio potential electrodes.[4] The recent researches in this area show that uterine electromyography signals are very useful to separate true and premature delivery records.

In[5] linear and the nonlinear features were compared for classification of signals. Consequently, the nonlinear feature such as sample entropy accuracy was higher than the accuracy of linear features such as root mean square value.

Approximation entropy and the time reversibility features were used to differentiate between the term and preterm contractions.[6] True and premature labour contractions were analysed using wavelet transform.[7]

In AR and wavelet[8] analysis were used for extracting the features and then unsupervised statistical classification was performed based on Fisher's Exact Test. Pyramid algorithm based Discrete Wavelet Transform (DWT) was employed to differentiate EHG Signal for true labour and preterm labour signals.[9] Cepstral analysis was used to determine premature labour.[10]

Preterm labour detection using uterine EMG signals have been presented in most of the recent studies. This paper focuses on using linear, non-linear and statistical features to classify records. The following linear features are chosen: Root mean square, peak frequency, median frequency, waveform length, zero crossings. Non-linear feature like sample entropy and statistical features including mean absolute value, variance and standard deviation were extracted from uterine EMG signals. Then these three types of features are applied to four different classifiers which are Classification and Regression Tree (CART), Naive Bayes, k-Nearest Neighbour (KNN) and Support Vector Machine (SVM). Further, Bayesian Optimization technique is employed in order to increase the overall classification accuracy. Finally, comparison of these four different classifiers' accuracies with and without Bayesian Optimization technique is performed.

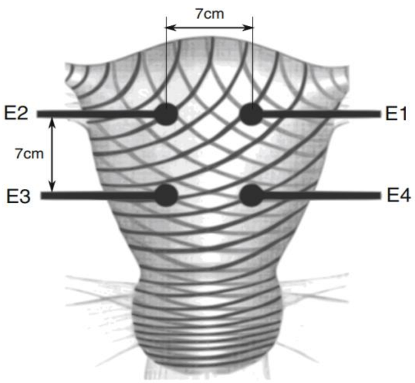

Fig. 1. Electrode placement on the abdomen

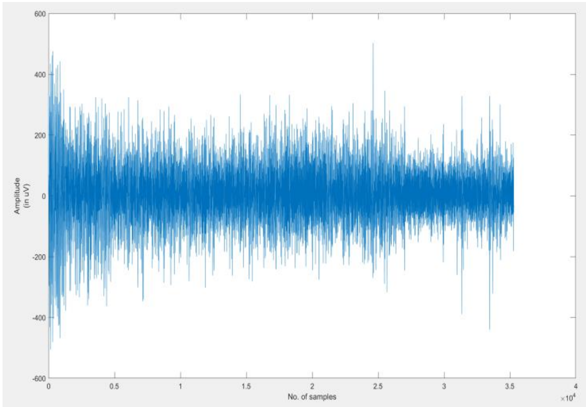

Fig. 2. EHG Signal (Term Record)

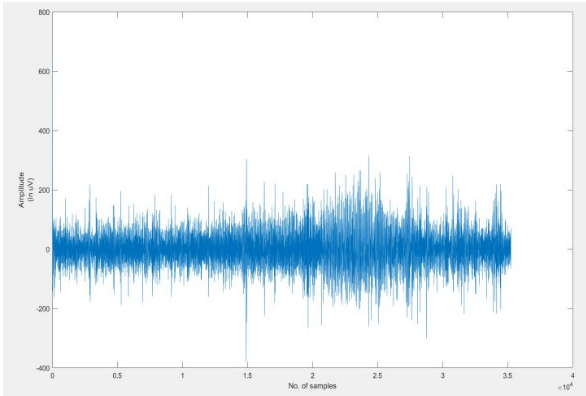

Fig. 3. EHG Signal (Preterm Record)

The contents of this paper are structured as: Section II explains the Methodology i.e., the dataset, pre-processing, feature extraction and classifiers used. Section III presents the results and discussion. The final conclusion is presented in section IV.

2. Methodology

2.1. Uterine EMG Dataset Description

In this work, the TPEHG (Term-Preterm Electrohysterogram) dataset is used. It consists of 300 uterine EMG records. These records were performed at the Department of Obstetrics and Gynaecology, Medical Centre Ljubljana, Ljubljana.[5] Each record was taken for about 30 minutes with sampling frequency of 20 Hz and consists of three channels with four electrodes as shown in Fig. 1.

The scanning system with 16-bit resolution and ±2.5mV amplitude range was used. Each record was obtained by placing four $AgCl_2$ electrodes on the abdominal surface forming three channels.

1. The first electrode (E1) was placed 3.5 cm towards left and 3.5 cm over the navel;
2. The second electrode (E2) was placed 3.5 cm towards right and 3.5 cm over the navel;
3. The third electrode (E3) was placed 3.5 cm towards right and 3.5 cm under the navel;
4. The fourth electrode (E4) was placed 3.5 cm towards left and 3.5 cm under the navel.

First channel: S1 = E2 – E1
Second channel: S2 = E2 - E3
Third channel: S3 = E4 - E3

The signals were filtered before sampling using a three-pole analog Butterworth filter with a bandwidth ranging from 0 – 5 Hz. Out of these 300 records, 262 records were taken during pregnancies which resulted in term delivery (gestation duration at delivery >37 weeks). Further these 262 records were classified according to the week of gestation in which the uterine EMG signal was recorded. 143 records were taken before the 26^{th} gestational week. 119 records were taken during or after the 26^{th} gestational week.

The remaining 38 records were taken during pregnancies which ended in premature birth (gestation duration at delivery ≤ 37 weeks). In these 38 records, the records obtained before the 26^{th} gestational week was 19 and the records obtained during or after the 26^{th} gestational week were 19.

2.2. Pre-processing

The uterine EMG signal with lower frequencies consists of noise due to breathing and stretching of skin. Hence, the signals are first pre-processed using Butterworth digital filters with different frequency bands like 0.08 – 4 Hz,[11] 0.05 – 4 Hz,[13] 0.2 – 4 Hz.[12] To remove the transient effects of the filters, 90 seconds of beginning and end part of the records was removed.

The drawback of Butterworth digital filter is phase-shifting, which is problematic when high-pass filtering is used. This drawback can be eliminated by filtering the entire signal twice in different directions, forward and backward obtaining a zero-phase shift filtered signal. Thus, a four pole Butterworth filter is used with bandwidth range 0.3 Hz – 4 Hz. The pre-processed uterine EMG signal for both Term and Preterm record is shown in Fig. 2 and Fig. 3.

2.3. Feature Extraction

The most important part of the pattern recognition is the feature extraction. The features extracted must be effective as the accuracy of classification depends on these features. This research work includes 6 linear, 1 non-linear and 3 statistical feature that includes the features of both time-domain and frequency-domain extracted from the uterine electromyography (EHG) signals to differentiate between true and premature record.

2.3.1. Root Mean Square (RMS) Value

It is calculated as the square root of mean of the square of all the samples in a signal. It is given by equation (1)

$$RMS = \sqrt{\frac{1}{N}\sum_{i=0}^{N-1} x(i)^2} \quad (1)$$

Where, N = sample size, $x(i)$ = input signal

2.3.2. Peak Frequency

The frequency at which the maximum peak occurs is called as the peak frequency. The peak frequency $fmax$ is calculated by equation (2)

$$fmax = arg\left(\frac{f_s}{N} max_{i=0}^{N-1} P(i)\right) \quad (2)$$

Where f_s = sampling frequency, N = sample size, P = frequency power spectrum

2.3.3. Median Frequency

It is the frequency at which half of the total power within the epoch is reached. It is given by equation (3)

$$f_m = i_m \frac{f_s}{N}, \sum_{i=0}^{i=i_m} P(i) = \sum_{i=i_m}^{i=N-1} P(i) \quad (3)$$

Where f_s = sampling frequency, N = sample size, P = frequency power spectrum

2.3.4. Waveform Length

Waveform length (WL) is the cumulative length of the wave over a period of time. It is given by

$$WL = \sum_{n=1}^{N-1} |x_{n+1} - x_n| \quad (4)$$

Where x_n = input signal, N = sample size

2.3.5. Zero Crossings

Zero crossing (ZC) is the number of times; the amplitude of the waveform crosses the zero y-axis. It is formulated as in equation (5)

$$ZC = \sum_{n=1}^{N-1}[sgn(x_n * x_{n+1}) \cap |x_n - x_{n+1}| > threshold] \quad (5)$$

Where x_n = input signal, N = sample size

2.3.6. Peak Location

It is the sample number at which the signal exhibits maximum amplitude.

2.3.7. Sample Entropy

Sample entropy is used for estimating the complexity of the time series signal. The main advantage of using sample entropy is that it is independent of the length of the data and makes the implementation trouble-free. It is given by equation (6)

$$SampEn = \begin{cases} -\log(c_m)/C_{(m-1):c_m \neq 0 \wedge c_{(m-1)}} \\ -\log\left(\frac{N-m}{N-m-1}\right) : c_m = 0 \vee c_{(m-1)}=0 \end{cases} \neq 0 \quad (6)$$

Where N = sample size

2.3.8. Mean Absolute Value (MAV)

It is calculated by taking the average of the absolute value of the signal as given by equation (7)

$$MAV = \frac{1}{N}\sum_{n=1}^{N} |x_n| \quad (7)$$

Where x_n = input signal, N = sample size

2.3.9. Variance

The variance is the mean value of the square of the deviation of that variable. It is calculated by equation (8)

$$VAR = \frac{1}{N-1}\sum_{n=1}^{N} x_n^2 \quad (8)$$

Where x_n = input signal, N = sample size

2.3.10. Standard Deviation

The standard deviation SD of a signal is formulated as by equation (9)

$$SD = \sqrt{\frac{1}{N-1}\sum_{n=1}^{N} x_n^2} \quad (9)$$

Where x_n = input signal, N = sample size

2.4. Machine Learning Classifiers

The classification was performed using supervised Machine learning algorithms such as Classification and Regression Tree (CART), k nearest neighbour (KNN), Naïve Bayes and Support Vector machine (SVM). CART is a decision tree that employs low cost and complexity approach. It combines a decision tree inducer for discrete classes, as well as a structure for inducing regression trees. CART involves many techniques, such as the surrogate device for dealing with missing values and the way of handling nominal attributes.[15] KNN classifier with k=5 was used for its high success rate and low complexity, but since the dataset size is finite, it is not assured for the convergence to get the optimal solution.[16] The Naïve Bayes algorithm which uses Bayes theorem performs well even if there is a small amount of dataset. The Support vector machine (SVM) algorithm which works on the principle of structural risk minimization for predicting the data correctly has a very outstanding record for the classification of uterine EMG signal. To minimize training error different kernel functions are used. In this work the radial basis kernel function (RBF) is used in the design of SVM.

Table 1. Features of uterine EMG signals of Term Record (Values expressed as Mean±Standard Deviation

Feature name	Channels of Term Record		
	CH1	CH2	CH3
Root mean square(mV)	94.8±56.4	78.4±47.8	72.2±47.3
Peak frequency (Hz)	0.53±0.41	0.39±0.15	0.46±0.34
Median frequency (Hz)	0.23±0.11	0.173±0.06	0.21±0.09
Waveform length(µm)	833360± 296383	547000± 259666	566000± 174386
Zero crossings	5093.8± 1272.9	3920±1154	4888± 1222
Maximum Peak location	2126± 1248	1671±1043	2023± 1192
Sample entropy	1.76±0.28	1.46±0.31	1.74±0.27
Mean absolute value	59.83±26	50.7±25.8	42±17.39
Variance	12180± 22113	8450± 14278	7451± 1573
Standard deviation	94.8±56.4	78.4±47.8	72.2±47.3

Table 2. Features of uterine EMG signals of Preterm Record

Feature name	Channels of Preterm Record		
	CH1	CH2	CH3
Root mean square(mV)	84.5±35.5	74.2±31.4	65.9±28
Peak frequency (Hz)	0.45±0.28	0.37±0.05	0.40±0.19
Median frequency (Hz)	0.19±0.07	0.17±0.05	0.16±0.04
Waveform length(µm)	770000± 275619	534000± 209551	528000± 185919
Zero crossings	4903± 1226	3874± 1174	4481± 1134
Maximum Peak location	2090± 1261	1489± 1002	1863± 1164
Sample entropy	1.64±0.36	1.42±0.36	1.59±0.27
Mean absolute value	57.3±25.5	50±23.2	42.8±17.9
Variance	8390± 7434	6470± 6065	5120± 4646
Standard deviation	84.5±35.5	74.2±31.4	65.9±28

2.5. Bayesian Hyper parameter Optimization Technique

The main idea of Bayesian Hyper parameter Optimization is to build a probabilistic model of the required objective function and then use it in selecting the most favourable hyper parameter to estimate the true objective function. This optimization technique is efficient as it chooses the next hyper parameter in an informed way. By evaluating hyper parameters that are more efficient from past results, a better model can be created with a reduced number of iterations with the Bayesian method.

3. Results and Discussions

To classify the term and preterm labour records, various linear, non-linear and statistical features have been extracted and applied to the four aforementioned classifiers:

Table 1 shows the Mean ± Standard Deviation values of all the features of the 262 Term uterine EMG records. The above features are extracted in the frequency range of 0.3 – 4 Hz. From the table, it can be inferred that all the feature values for channel 1 are higher than the other two channels. Root mean square, mean absolute value, variance and standard deviation values of channel 2 are higher than that of channel 3. For the remaining features, channel 3 is dominating over channel 2.

Table 3. Classification Results without Bayesian Optimization

Classifier name	10-fold cross validation			
	CH	Sp (%)	Se (%)	Overall accuracy (%)
CART	CH1	90.38	12.5	80
	CH2	90.38	25	81.67
	CH3	84.62	25	76.67
KNN	CH1	94.23	58	81.67
	CH2	100	12.5	88.33
	CH3	98	67	85
Naive Bayes	CH1	96.15	25	83.33
	CH2	96.15	12.5	85
	CH3	94.23	12.5	83.33
SVM	CH1	100	75	88.33
	CH2	100	75	88.33
	CH3	100	75	88.33

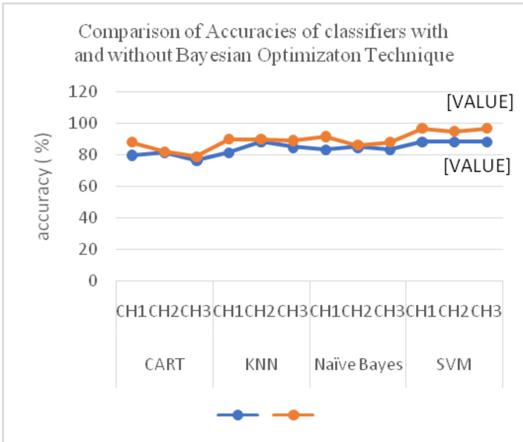

Fig. 4. Comparison of Accuracies of Classifiers

Table 2 presents mean ± SD values of all the features of 38 Preterm uterine EMG records. Similar to Term records, these features are also extracted in the frequency range of 0.3 – 4 Hz. From the table 2, it can be seen that all the feature values for channel 1 are higher than the other two channels. The Root mean square, mean absolute value, variance and standard deviation, waveform length values, median frequency values of channel 2 are higher than that of channel 3. For the remaining features, channel 3 is dominating over channel 2.

On comparing the feature values of both the Term and Preterm records, there is a huge difference in Root mean square, peak frequency, variance and standard deviation. However, median frequency values can also be used as an effective feature to represent frequency domain characteristics. Sample entropy values are as expected with values for Preterm records being lower than the Term records. The zero crossing values for channel 1 are effective than for channel 2 and channel 3. Even though the differences in values among all the features are noticeable, they are dispersed.

Table 3 indicates that the algorithm CART provided the lowest specificity (Sp), sensitivity (Se) and accuracy for all the three channelswhen compared with the other three classifiers. KNN and Naïve Bayes algorithm provided good specificity of 94.23, 100, 98 and

Table 4. Classification Results with Bayesian Optimization

Classifier name	10-fold cross validation	
	Channel	Overall accuracy (%)
CART	CH1	88
	CH2	82
	CH3	79
KNN	CH1	90
	CH2	90
	CH3	89
Naïve Bayes	CH1	91.667
	CH2	86.22
	CH3	88
SVM	CH1	96.667
	CH2	95
	CH3	96.667

96.15, 96.15, 94.23. The sensitivity values of KNN and naïve Bayes algorithm are slightly better than CART i.e., 58, 12.5, 67 and 25, 12.5, 12.5. SVM provided the best accuracy (88.33), specificity (100) and sensitivity (75) when compared to the other classifiers used.

Table 4 indicates the accuracies of algorithms implemented with the Bayesian Hyper parameter Optimization technique. The CART algorithm obtained the accuracy of 88%, 82% and 79% for the three channels. The K nearest neighbour algorithm provided the accuracy of 90% for channel 1 and channel 2 and 89% for channel 3. Naïve Bayes performed slightly low than the KNN algorithm with an accuracy of 91.667%, 86.22% and 88%. Finally, SVM had given the best and highest accuracy of 96.667%, 95% and 96.667% for the three channels.

Fig. 4 gives the comparison of both the implementation methods i.e., the four classifiers implemented with and without Bayesian Optimization. The accuracy of SVM for all the three channels is higher followed by KNN and Naive Bayes. Naïve Bayes and KNN showed good accuracies for channel 1. The CART algorithm performed the lowest compared to others.

4. Conclusions

The main objective of this research is to classify between term and preterm signals. Hence, different linear, non-linear and statistical features were extracted and applied to four different classifiers CART, KNN, Naïve Bayes and SVM. Further to improve the classification accuracy, the same classifiers were implemented with Bayesian Optimization technique. From the results obtained, it can be stated that the accuracy of channel 1 of the classifiers is high. Hence, the use of channel 1 can be more efficient for determining the true and premature labour. To obtain the highest classification accuracy, Support Vector machine (SVM) algorithm can be used as it provides the best classification accuracy among the four classifiers used.

Conflicts of Interest

The authors declare no conflict of interest.

References

1 Karlsson B.; Terrien J.; Gudmundsson V.; Steingrimsdottir T.; Marque C. Abdominal EHG on a 4 by 4 Grid: Mapping and Presenting the Propagation of Uterine Contractions. In 11th Mediterranean Conference on Medical and Biomedical Engineering and Computing 2007, 139-143. Springer, Berlin, Heidelberg. [CrossRef]

2 Verdenik I.; Pajntar M.; Leskošek B. Uterine Electrical Activity as Predictor of Preterm Birth in Women with Preterm Contractions. *Eur. J. Obstet. Gynecol. Reprod. Biol*., 2001, **95**, 149-153. [CrossRef]

3 Rabotti C.; Mischi M.; Oei S.G.; Bergmans J.W. Noninvasive Estimation of the Electrohysterographic Action-potential Onduction Velocity. *IEEE Trans. Biomed. Eng*., 2010, **57**, 2178-2187. [CrossRef]

4 Baghamoradi S.M.S.; Naji M.; Aryadoost H. Evaluation of Cepstral Analysis of EHG Signals to Prediction of Preterm Labour. In December 2011 18th Iranian Conference of Biomedical Engineering (ICBME), 81-83. IEEE. [CrossRef]

5 Fele-zorz G.; Kavsek G.; Novak-Antolic Z.; Jager F. A Comparison of Various Linear and Non-linear Signal Processing Techniques to Separate Uterine EMG Records of Term and Pre-term Delivery Groups. *Med. Biol. Eng. Comput*., 2008, **46**, 911-922. [CrossRef]

6 Hassan M.; Terrien J.; Alexandersson A.; Marque C.; Karlsson B. Nonlinearity of EHG Signals used to distinguish Active Labor from Normal Pregnancy Contractions. In January 2010 Annual International Conference of the IEEE Engineering in Medicine and Biology, 2387-2390. IEEE. [CrossRef]

7 Hassan M.; Terrien J.; Karlsson B.; Marque C. Interactions between Uterine EMG at Different Sites Investigated using Wavelet Analysis: Comparison of Pregnancy and labor Contractions. *EURASIP J. Adv. Signal Process*., 2010, 1-9. [Link]

8 Diab M.; Marque C.; Khalil M. Modeling and Classification for Uterine EMG Signals using Autoregressive Model. 2006. [CrossRef]

9 Arora S.; Garg G. A Novel Scheme to Classify EHG Signal for Term and Pre-term Pregnancy Analysis. *Int. J. Comput. Appl*., 2012, **51**. [Link]

10 Far D.T.; Beiranvand M.; Shahbakhti M. Prediction of Preterm Labor from EHG Signals using Statistical and Non-Linear Features. In November *2015 8th Biomedical Engineering International Conference (BMEiCON)* 1-5. IEEE. [CrossRef]

11 Verdenik I.; Pajntar M.; Leskosek B. Uterine Electrical Activity as Pedictor of Preterm Birth in Women with Preterm Contractions. *Eur. J. Obstet. Gynecol. Reprod. Biol*., 2001, **95**, 149-153. [CrossRef]

12 Maul H.; Maner W.L.; Olson G.; Saade G.R.; Garfield R.E. Non-invasive Transabdominal Uterine Electromyography Correlates with the Strength of Intrauterine Pressure and is Predictive of Labor and Delivery. *J. Matern-Fetal Neonatal Med*., 2004, **15**, 297-301. [CrossRef]

13 Maner W.L.; Garfield R.E. Identification of Human Term and Preterm Labor using Atificial Neural Networks on Uterine Electromyography Data. *Ann. Biomed. Eng*., 2007, **35**, 465-473. [CrossRef]

14 Song Y.Y.; Ying L.U. Decision Tree Methods: Applications for Classification and Prediction. *Shanghai Arch. Psychiatry*, 2015, **27**, 130. [CrossRef]

15 Denoeux T. A K-nearest Neighbor Classification Rule Based on Dempster-Shafer Theory. In Classic works of the Dempster-Shafer Theory of Belief Functions, 2008, 737-760. Springer, Berlin, Heidelberg. [CrossRef]

16 Kumar R. Optimized Feature Selection for the Classification of Uterine Magnetomyography Signals for the Detection of Term Delivery. *Biomed. Signal Process. Control*, 2020, **58**, 101880. [CrossRef]