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# Classification of Uterine Electrohysterography (EHG) Signals using Machine Learning method

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## ABSTRACT

In this paper, Uterine Electrohysterography (EHG) is a valuable diagnostic tool for monitoring uterine contractions during pregnancy and assessing uterine health. In this study, we explore the application of machine learning methods to classify EHG signals, aiming to enhance the accuracy and efficiency of uterine contraction analysis. Our research begins with the collection of a comprehensive dataset of EHG signals, meticulously labeled to denote different uterine conditions, including normal contractions, preterm contractions, and other relevant categories. These signals are subjected to preprocessing steps, including noise removal, segmentation, and feature extraction, to create a suitable input for machine learning models. Several machine learning algorithms, such as Support Vector Machines (SVM), are evaluated for their effectiveness in classifying EHG signals. We conduct rigorous model selection and hyperparameter tuning using a validation dataset to optimize classification performance. The performance of the selected model(s) is assessed using a separate test dataset, with standard classification metrics such as accuracy, precision, recall, and F1-score. Interpretability techniques are applied to provide insights into the model's decision-making process. Furthermore, this research addresses ethical considerations, ensuring that data collection and model predictions adhere to ethical standards and do not perpetuate biases. Compliance with healthcare regulations, such as HIPAA, is a paramount concern in the deployment of this technology. In conclusion, this study contributes to the development of a robust and accurate classification system for EHG signals, with potential applications in pregnancy monitoring and uterine health assessment. The successful integration of machine learning into EHG analysis holds promise for improving prenatal care and diagnostic capabilities in obstetrics.

**KEYWORDSEHG, Electrohysterography (EHG) Uterine contractions, Machine learning Signal classification, Feature extraction Support Vector Machines (SVM)**

## 1 Introduction

Uterine Electrohysterography (EHG) is a vital technique employed in obstetrics to monitor uterine contractions during pregnancy and assess uterine health. This non-invasive method records electrical activity associated with uterine muscle contractions, providing valuable insights into the progression of pregnancy and the early detection of potential complications. Accurate classification and analysis of EHG signals hold great promise for enhancing prenatal care and improving diagnostic capabilities in obstetrics. Traditional methods of EHG analysis involve manual examination and interpretation by healthcare professionals, which can be time-consuming and subject to interobserver variability. In recent years, the advent of machine learning has opened new avenues for automating the classification of EHG signals, offering the potential for more consistent and efficient analysis. This research endeavors to explore the application of machine learning techniques to classify EHG signals accurately. The primary objectives are to: Develop a comprehensive dataset of EHG signals, meticulously annotated to encompass a range of

uterine conditions, including normal contractions, preterm contractions, and other relevant categories. Implement data preprocessing steps, including noise removal, signal segmentation, and feature extraction, to prepare the EHG data for machine learning model input. Evaluate a variety of machine learning algorithms, such as Support Vector Machines (SVM), to determine their efficacy in classifying EHG signals. Conduct rigorous model selection and hyperparameter tuning, using a validation dataset to optimize classification performance. Assess the chosen model(s) using a separate test dataset, employing standard classification metrics like accuracy, precision, recall, and F1-score. Interpretability techniques will be applied to gain insights into the model's decision-making process. Address ethical considerations in data collection and model predictions, ensuring that the study adheres to ethical standards and does not perpetuate biases. Compliance with healthcare regulations, such as HIPAA, will be a top priority in the deployment of this technology.

The outcomes of this research have the potential to significantly impact obstetrics and prenatal care. An accurate and automated classification system for EHG signals can lead to more timely interventions in cases of preterm contractions, enhance the monitoring of high-risk pregnancies, and provide valuable insights into uterine health. Furthermore, the successful integration of machine learning into EHG analysis aligns with the broader trend of leveraging artificial intelligence in healthcare for improved patient outcomes and enhanced clinical decision support.

## II. Literature Review

Biomedicine is the application of engineering principles to biology and medicine to improve the quality and effectiveness of patient care. Although the studies on the field are based on many years, studies using machine learning algorithms of EHG signals have gained intensity in recent years.

Khalil and Duchene et al. (2000)[5], presented a sequential detection/classification approach applied to uterine EMG in their study. They stated that the dynamic cumulative sum (DCS) algorithm gave successful results. Euliano et al. (2013)[10], compared TOCO, EHG, and alternative invasive intrauterine pressure catheter (IUPC) methods. The study was conducted with data from 73 subjects and EHG gave better results than other methods in terms of Contractions Consistency Index (CCI). Alexandersson et al. (2015)[4], created a database to provide public access to 16-electrode EHG data in his study. In the study, 122 EHG signals belonging to the years 2008-2010 were recorded in Iceland. These records showed that EHG data, a pregnant woman's body mass index, age, and obstetric history can influence the frequency components of contractions.

Ye-Lin et al. (2014)[20], extracted 11 features from EHG signals. These properties are spectral, temporal, and nonlinear. They investigated the classification performance with these 11 extracted features. 2-fold cross-validation, repeated 50 times, was applied across 3 classifiers, including Linear Discriminant Analysis (LDA), Quadratic Discriminant Analysis (QDA), and SVM with RBF kernel function. As a result of the study, the QDA classifier gave the best classification performance with 92.2% success. Ahmed et al. (2017)[2], determined that the multivariate multiscale fuzzy entropy (MMFE) algorithm is superior to the multivariate multiscale entropy (MMSE) in both synthetic and real EHG signals. Chen and Hao (2017)[16], presented a new method for feature extraction and classification of EHG signals based on Hilbert-Huang transform (HHT) and extreme learning machine (ELM).

The study of Idowu (2017)[13], included the records of 262 women who gave birth in the normal period and 38 women who gave birth prematurely. Innovative signal processing techniques and the application of machine learning algorithms in the analysis of EHG signals are important in estimating the risk of preterm birth. In his study, Levenberg-Marquardt trained Feed Forward Neural Network, Radial Basic Function Neural Network,

and Random Neural Network classifiers were used. As a result, 91% sensitivity and 84% specificity values were obtained. The average error rate is 12%. Acharya et al. (2017)[1], made a new proposal for automatic prediction of pregnant women who will give birth prematurely by using EHG signals. Eight different features were extracted in the study. These extracted features were analyzed with the vector machine (SVM) classifier for automatic differentiation and as a result, 96.25%, 95.08% sensitivity, and 97.33% specificity were obtained.

Muszynski et al.(2019), examined the estimation of the risk of preterm birth by analyzing electrical parameters from EHG. The results obtained make it possible to improve the estimation of the risk of preterm birth relative to routinely used instruments. Degbedzui and Yüksel (2020)[9], proposed a new method for diagnosing preterm labor without treatment based on the classification of Electrohysterography (EHG) signals. By constructing elements of a feature vector representing the time-varying spectral content of the EHG signal, the centroid frequencies of the frames were calculated. It has been shown that the proposed approach outperforms other methods and can be used effectively in the classification of EHG signals for term- preterm diagnosis.

Zardoshti et al. (Zardoshti Wheeler 1993)[14] evaluated a number of features commonly used when dealing with EHG signals. These included integrated absolute value, zero crossings and auto-regression coefficient. However, despite their good discriminant capabilities, a precise frequency threshold for accurate contraction and delivery classification, over different patients, could not be determined. Fergus et al. (2013) [15], conducted a broad study of techniques for analysing the features of the EHG signal where, features such as peak frequency, median frequency, root mean square and sample entropy, performed particularly well when discriminating between term and preterm records, with several of the classification models used to validate the approach reporting very good results.

However, it is in Electromyography (EMG) that we find some new and interesting works. In one such study, Lucovnik et al. (Lucovnik, Maner, et al. 2011)[16] investigated whether uterine EMG could be used to evaluate Propagation Velocity (PV). In this study, the electrical signals of the uterus were measured both in labour and non-labour patients who delivered at term and prematurely. The results indicate that, the combination of Power Spectrum (PS) and PV peak frequency parameters yielded the best predictive results in identifying true preterm labour. However, only one dimension of propagation is considered at a time, which is based on the estimation of time delays between spikes (Lucovnik, Maner, et al. 2011). In comparison, Lange et al. (2014) [17] estimate the PV of the entire EHG bursts that occurs during a contraction. This has been achieved by calculating the bursts corresponding to a full contraction event. The results illustrate that the estimated average propagation velocity is 2.18 (60.68) cm/s. No single preferred direction of propagation was found (Lange et al. 2014).

**III. Proposed Framework Architecture**

In order to conduct our experiments using the TPEHG dataset, the proposed methodological framework is presented in Figure 4.2. These phases consist of raw EHG signals (data collection), signal pre-processing, feature extraction, oversampling with the synthetic minority over-sampling technique (SMOTE), generating test and training models, feature selection, classification, combining classifiers, validation, and the presentation of results. The remainder of the chapter will provide a more in-depth discussion of each of these processes within the proposed methodological framework

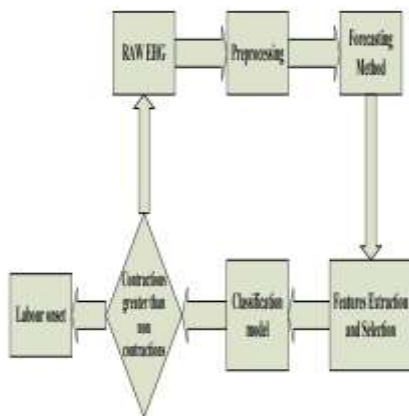


Figure.1: Methodology Phases

**IV.Results Discussion**

**a) Pre-processing and filtering**

In both databases the original EHG was processed and filtered. In the top plot of Figure 4.4 an original EHG signal is represented. There is a significant variation in the EHG signal in the beginning of the recording due to equipment electronic startup transient. The following baseline fluctuation can be explained as a normal response of the skin/electrode interface. The abrupt signal feature present in the end of the recording also represents the equipment electronic transient when it is switched off. In the Icelandic database 200 samples were removed from the beginning and the end of the signal and in the TPEHG database the first 2000 samples and the last 200 samples were removed from the original signal. This was to remove the abrupt variations seen at the beginning and the end of the signal as depicted in Figure 4.4. Next, the first value of the signal was subtracted to the whole EHG signal and decimation was applied.. In the TPEHG database the original signal sampling was 20 Hz and a decimation factor of 5 was applied resulting in a new sampling rate of 4 Hz. The signal was posteriorly filtered between 0.1 Hz to 1 Hz by a Butterworth & Lynn filtering method.

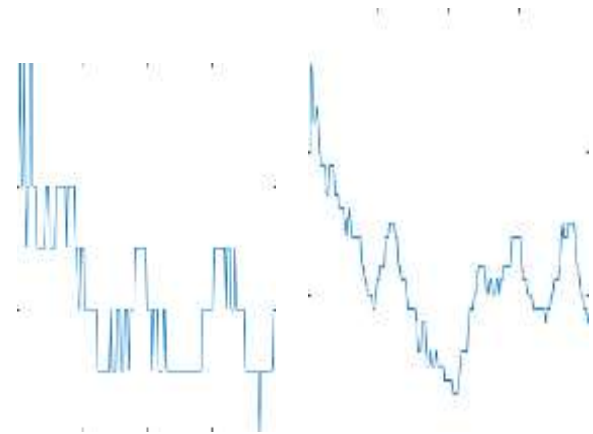


Figure 2 A original EHG Term Figure 5.2 an original EHG Preterm signal

Table 5.1 SNR of Term & Preterm Signal using Butterworth and Lynn Filter

	Term	Preterm
Butterworth Filter	6.2793	6.761
Lynn Filter	14.887	24.0148

From the observe table Snr of Lynn Filter better as compared to Butterworth Filter

To extract features from the given EHG signal have used function .These features are used as inputs to the SVM to train them and classify them later. MATLAB offered a classification application which give us a good opportunity to try as many as we want Classify

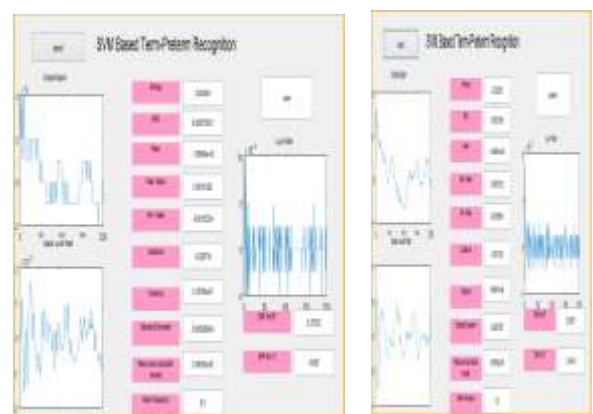


Figure 5. EHG Recognition Term using SVM

As we see in the pictures above, that our classifier behave correctly and recognize the term and Preterm EHG ."SVM Classifier" case is for what the classifier expect .

**V. Conclusion**



The study of which EHG characteristics should be considered in the classification process was one of the main focuses of this work and one of its biggest obstacles. To approach this problem, a number of features reported as useful from other works were considered and feature selection methods were employed to filter out ambiguous or less relevant features.

The development of medical information systems has played an important role in the biomedical domain. This has led to the extensive use of Artificial Intelligence (AI) techniques for extracting biological patterns in data. Furthermore, data pre-processing and validation techniques have also been used extensively to analyse such datasets for classification problems. In this thesis, the main aim was to classify between term and preterm records through the use of different types of classification algorithm and their combination to classify term and preterm records contained in the TPEHG dataset. A more conservative filter was used in comparison to many other studies (between 0.34 and 1Hz) to focus only on the electrical activity generated in the myometrium.

The results demonstrate that combining classifiers with high sensitivity, specificity and AUC values can lead to better classification.. These results are encouraging and suggest that the approach, posited in this thesis, is a line of enquiry worth pursuing. The results of this thesis also encourage more extensive use of SVM given that models produce more accurate results compare to other machine learning algorithms currently used. This study has shown the benefits of using EHG classification to determine whether delivery will be preterm or term through the process decision based diagnostic tools to support mid-wife nurses, gynaecologists in obstetric care to make the correct decision when treating patients.

Another future work that will be considered is the use of deep learning. Deep learning is a term associated with machine learning approaches that embrace the use of a succession of intermediate feature representations, of increasing abstraction, which jointly give rise to a final solution . The motivation and development of the deep learning paradigm was inspired significantly by the layered architecture of neurons present in the visual and auditory mechanisms present in biological systems, especially given the efficacy of biological systems to respond to such sensory pathways

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