

# Quantitative Analysis of Electrohysterogram Features for Pregnancy Monitoring

<sup>1</sup>Sandeep Gupta, <sup>2\*</sup>Vibha Aggarwal, <sup>3</sup>Manjeet Singh Patterh, <sup>4</sup>Lovepreet Singh

<sup>1</sup>College of Engineering and Management, Punjabi University Neighbourhood Campus, Punjab, India

<sup>2,4</sup>University College, Barnala, Punjab, India

<sup>3</sup>Department of Electronics and Communication Engineering, Punjabi University, Patiala, Punjab, India

\*Corresponding Author: Vibha Aggarwal, E-mail: [vibha\\_ec@pbi.ac.in](mailto:vibha_ec@pbi.ac.in)

Authors E-mail: [sandeeprple@pbi.ac.in](mailto:sandeeprple@pbi.ac.in), [mppattar@pbi.ac.in](mailto:mppattar@pbi.ac.in), [lovepreetrupal@gmail.com](mailto:lovepreetrupal@gmail.com)

**Abstract** - Electrohysterogram (EHG) signals have emerged as a valuable tool for analyzing uterine activity and predicting pregnancy outcomes. This study investigates key statistical features extracted from EHG signals and examines their significance in differentiating pregnancy cases. A comprehensive statistical analysis, including analysis of variance (ANOVA) and Tukey's post-hoc test, was conducted on twelve extracted features. Results indicate that six features—standard deviation, root mean square (RMS), entropy, spectral entropy, Higuchi fractal dimension (HFD), and approximate entropy (ApEn)—exhibited significant differences among the cases. These findings highlight the potential of these features in distinguishing pregnancy conditions and improving predictive models for preterm birth risk.

**Keywords:** Electrohysterogram (EHG), analysis of variance (ANOVA), Higuchi fractal dimension (HFD), approximate entropy (ApEn).

## I. INTRODUCTION

Uterine contractions play a crucial role throughout pregnancy, and the ability to monitor them effectively is needed to ensure positive expected outcomes. Electrohysterography (EHG) provides a non-invasive method for capturing electrical signals that reflect these uterine contractions. The information contained within these EHG signals holds significant potential for various aspects of pregnancy management, particularly in the context of predicting preterm birth. [1-3]

A thorough analysis of EHG features can provide valuable insights into the underlying physiological processes associated with uterine activity. By extracting and examining various characteristics from the EHG signals, researchers aim to identify patterns and indicators that are indicative of different pregnancy states and potential complications, most notably the risk of premature delivery. This study focuses on analysing a range of statistical EHG features, including measures of central tendency such as the mean, measures of

variability like the variance, and other statistical descriptors. These features are calculated from the EHG signals and then used to differentiate between different pregnancy cases based on factors such as gestational age and pregnancy outcome. To determine which of these statistical EHG features are most relevant for distinguishing between different groups, statistical tests such as T-tests and Analysis of Variance (ANOVA) will be employed. These tests will help identify significant differences in feature values across various gestational ages and between different outcomes, specifically comparing term births and preterm births. The goal is to pinpoint the features that exhibit the most discriminatory power. Subsequently, machine learning techniques, specifically Support Vector Machines (SVM) and Random Forest plots, will be utilized to construct predictive models. These models will be trained on the extracted EHG features and then tested on their ability to accurately predict pregnancy outcomes. The ultimate aim of this study is to improve obstetric care by developing more reliable and accurate methods for identifying women at risk of preterm birth, allowing for timely interventions, and ultimately contributing to better health outcomes for both mothers and their babies. Pregnancy monitoring using wearable devices has gained significant attention in recent years, enabling continuous data collection and enhanced surveillance of maternal and foetal health [1]. While previous studies have explored the potential of EHG features in pregnancy monitoring, a comprehensive statistical analysis is necessary to identify the most informative and discriminative features [2][3].

In this study, we aim to conduct a thorough investigation of a range of statistical features extracted from EHG signals and examine their significance in differentiating between normal pregnancies, preterm births, and other pregnancy conditions. Existing research has explored the application of wearable devices in pregnancy monitoring, highlighting their potential for early detection of pregnancy complications. The analysis of EHG signals has been a particular focus, as they provide insights into uterine activity and can be used to predict preterm birth. [3]. Several studies have explored the use of

EHG features, such as root mean square (RMS), spectral entropy, and Higuchi fractal dimension (HFD), in analyzing and predicting pregnancy outcomes. For example, one study found that total harmonic distortion in EHG signals was informative in determining fetomaternal health. [4] Additionally, a study on the early prediction of preeclampsia concluded that a combination of biomarkers and clinical risk factors can improve the prediction of preterm and early-onset preeclampsia. Furthermore, recent advancements in wearable technology have enabled the continuous monitoring of various biometrics during pregnancy, including physical activity and sleep patterns. [1][3]. Another study demonstrated the potential of wearable devices in continuous pregnancy monitoring and the development of decision support tools for early detection of abnormalities. However, a comprehensive statistical analysis of a broader range of EHG features is necessary to identify the most significant and discriminative features for pregnancy monitoring. In [5], authors gave a review of EHG signal analysis while highlighting the data imbalance challenges. In [6], authors analysed that how gestational age, placental position, age, BMI, gravidity, and previous C-section influence EHG features and conclude that BMI and placental position affect EHG features through a low-pass filtering effect, while entropy features do not show significant variation with gestational age. In [7] [8], term delivery and preterm birth, as well as deliveries occurring within or beyond 24 hours were distinguished with EHG signals. Foetal phonocardiography analysis has been done for statistical features with gestational age (categorised as pre, early and full term) weight, and height of the pregnant ladies [9].

## II. METHODOLOGY

The study was conducted using a dataset of EHG signals collected from pregnant women at various stages of gestation. The dataset included information on gestational age, pregnancy outcomes, and other relevant clinical variables. The dataset is categorized into six cases: early caesarean, early induced, early induced caesarean, later caesarean, later induced, and later induced caesarean. The signals were pre-processed and segmented for feature extraction. Total 12 features classified as time-domain, frequency-domain, and nonlinear features were extracted from the EHG signals. ANOVA test was conducted to find the significant differences among selected features. then obtained Significant features ( $p < 0.05$ ) underwent Tukey's post-hoc test for pairwise differences.

## III. RESULTS AND DISCUSSION

The complexity and strength of the EHG signal, as measured by metrics like HFD, Approximate Entropy (ApEn),

spectral entropy, and RMS amplitude, are known to change and evolve as a pregnancy progresses through its various stages. It has been observed that reduced complexity and alterations in the power spectrum of the EHG signal might be indicative of negative outcomes. These changes can potentially reflect underlying issues such as suboptimal uterine function, or aberrant contractility, suggesting that the uterine contractions are not occurring in a normal way. Time-frequency analysis, shows how the signal's frequency content changes over time, and nonlinear dynamics make deeper insights into the complex nature of the EHG signal.

The statistical analysis revealed that the following features exhibited significant differences ( $p < 0.05$ ):

- Standard Deviation ( $p = 0.0235$ )
- Root Mean Square (RMS) ( $p = 0.0237$ )
- Entropy ( $p = 0.0464$ )
- Spectral Entropy ( $p = 0.0218$ )
- Higuchi Fractal Dimension (HFD) ( $p < 0.0001$ )
- Approximate Entropy (ApEn) ( $p = 0.0002$ )

These features were able to differentiate between term pregnancies, preterm deliveries, and other adverse outcomes like preeclampsia and intrauterine growth restriction.

Figure 1 shows boxplots to compare the distribution of statistically significant features across six pregnancy cases. Each box represents the interquartile range (IQR), with the median shown by a central line. Non-overlapping boxes suggest significant differences between some pregnancy cases, particularly in features like HFD and ApEn.

Figure 2 presents Tukey's post-hoc test, illustrating mean differences between pregnancy groups for each significant feature. The plots show mean differences (x-axis) and confidence intervals (vertical lines). These results demonstrate the strong discriminatory power of spectral entropy and HFD, as evidenced by confidence intervals not crossing zero, indicating statistically significant differences between groups. This visualization clearly highlights the magnitude and direction of feature-specific differences, emphasizing the biomarker potential of spectral entropy and HFD in pregnancy studies.

Figure 3 shows the Feature correlation matrix that indicates the relationships among the analysed EHG features. HFD and ApEn, known for capturing signal complexity and irregularity, were among the most significant features, indicating potential nonlinearity in uterine electrical activity. Spectral entropy and RMS, related to signal power and frequency distribution, also exhibited significant differences, reinforcing their importance in EHG analysis.

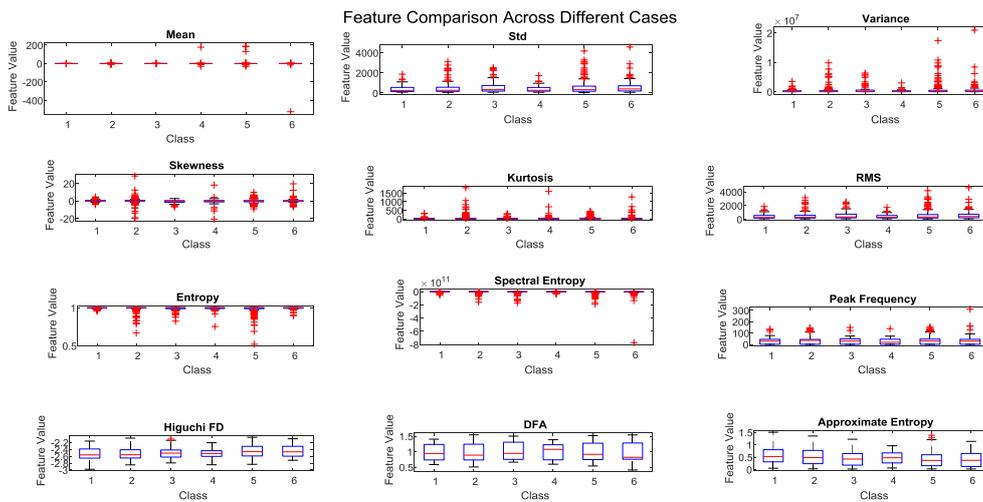


Figure 1: Boxplots of Significant Features

Tukey Post-Hoc Test Results for Significant Features

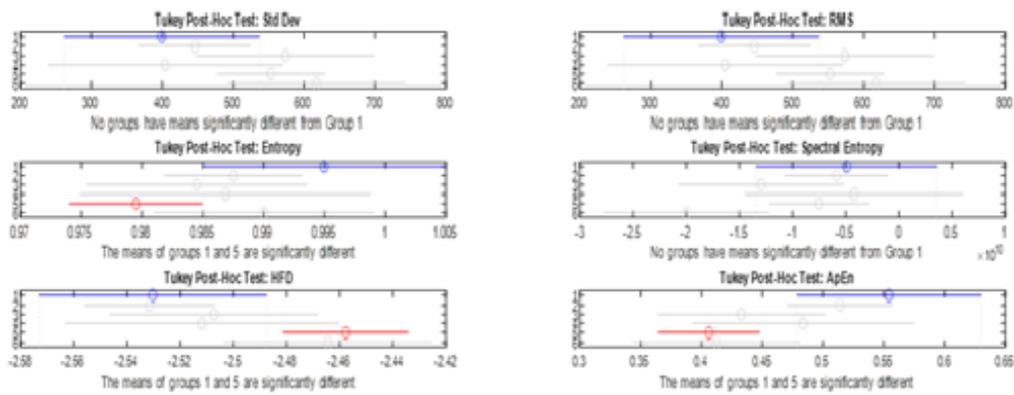


Figure 2: Tukey's Post-Hoc Test for Significant Features

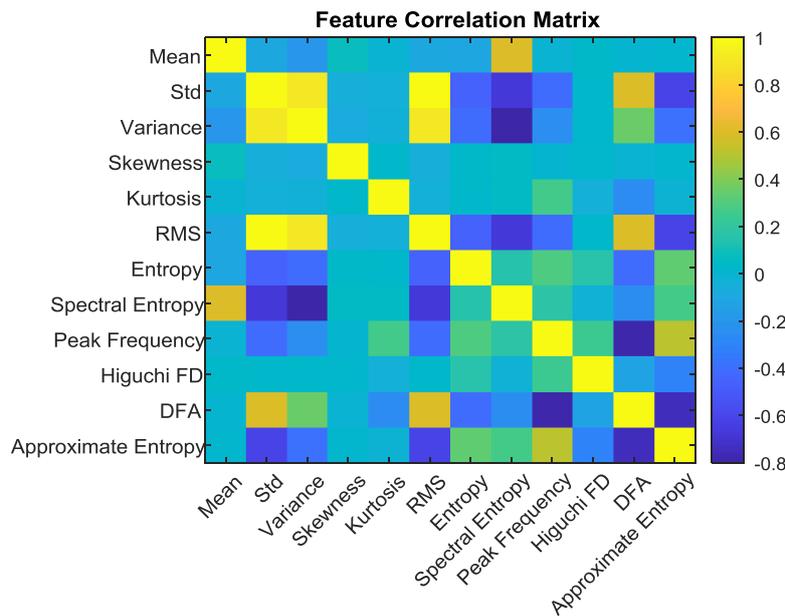


Figure 3: Feature Correlation Matrix for selected Features

#### IV. CONCLUSION

The results of this comprehensive statistical analysis of EHG features highlight the potential of using wearable monitoring and advanced signal processing techniques for enhanced pregnancy surveillance. The identification of key discriminatory features, such as HFD, ApEn, and Spectral Entropy, can aid in the development of robust predictive models for early detection of pregnancy complications and improved clinical decision-making. Further research is needed to validate these findings in larger cohorts and explore the integration of EHG analysis with other wearable data to provide a holistic view of maternal and fetal well-being.

#### REFERENCES

- [1] L. K. Bruce, D. González, S. Dasgupta, and B. L. Smarr, "Biometrics of complete human pregnancy recorded by wearable devices," Aug. 12, 2024, *Nature Portfolio*. doi: 10.1038/s41746-024-01183-9.
- [2] A.Kumar and P. B. Jaju, "Admission test cardiocography in labour as a predictor of foetal outcome in high risk pregnancies," Mar. 06, 2019, *Medip Academy*. doi: 10.18203/2320-1770.ijrcog20190981.
- [3] N. G. Ravindra et al., "Deep representation learning identifies associations between physical activity and sleep patterns during pregnancy and prematurity," Sep. 28, 2023, *Nature Portfolio*. doi: 10.1038/s41746-023-00911-x.
- [4] A.Gayasen, S. K. Dua, A. Sengupta, and D. Nagchoudhuri, "Effect of non-linearity in predicting doppler waveforms through a novel model," Sep. 18, 2003, *BioMed Central*. doi: 10.1186/1475-925x-2-16.
- [5] Jinshan Xu, Zhenqin Chen, Hangxiao Lou, Guojiang Shen, Alain Pumir, "Review on EHG signal analysis and its application in preterm diagnosis," *Biomedical Signal Processing and Control*, Volume 71, Part B, 2022, doi.org/10.1016/j.bspc.2021.103231.
- [6] Martim Almeida, Helena Mouriño, Arnaldo G. Batista, Sara Russo, Filipa Esgalhado, Catarina R. Palma dos Reis, Fátima Serrano, Manuel Ortigueira, "Electrohysterography extracted features dependency on anthropometric and pregnancy factors", *Biomedical Signal Processing and Control*, Volume 75, 2022, doi.org/10.1016/j.bspc.2022.103556.
- [7] Zhang Y, Hao D, Yang L, Zhou X, Ye-Lin Y, Yang Y. Assessment of Features between Multichannel Electrohysterogram for Differentiation of Labors. *Sensors*. 2022; 22(9):3352. doi.org/10.3390/s22093352.
- [8] Jager, F. An open dataset with electrohysterogram records of pregnancies ending in induced and cesarean section delivery. *Sci Data* 10, 669 (2023). doi.org/10.1038/s41597-023-02581-6.
- [9] S. Gupta, V. Aggarwal. MS Patterh, L. Singh, "Analysis of Foetal Phonocardiography and Clinical Outcomes: A Data-Driven Analysis Using IISc Database", *International Research Journal of Modernization in Engineering Technology and Science*, Volume:07, Issue:03, March-2025, pp-7864-7867. doi.10.56726/IRJMETS70309.

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