BioData Mining

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Enhanced labor pain monitoring using machine learning and ECG waveform analysis for uterine contraction-induced pain

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Abstract

Objectives: This study aims to develop an innovative approach for monitoring and assessing labor pain through ECG waveform analysis, utilizing machine learning techniques to monitor pain resulting from uterine contractions.

Methods: The study was conducted at National Taiwan University Hospital between January and July 2020. We collected a dataset of 6010 ECG samples from women preparing for natural spontaneous delivery (NSD). The ECG data was used to develop an ECG waveform-based Nociception Monitoring Index (NoM). The dataset was divided into training (80%) and validation (20%) sets. Multiple machine learning models, including LightGBM, XGBoost, SnapLogisticRegression, and SnapDecisionTree, were developed and evaluated. Hyperparameter optimization was performed using grid search and five-fold cross-validation to enhance model performance.

Results: The LightGBM model demonstrated superior performance with an AUC of 0.96 and an accuracy of 90%, making it the optimal model for monitoring labor pain based on ECG data. Other models, such as XGBoost and SnapLogisticRegression, also showed strong performance, with AUC values ranging from 0.88 to 0.95.

Conclusions: This study demonstrates that the integration of machine learning algorithms with ECG data significantly enhances the accuracy and reliability of labor pain monitoring. Specifically, the LightGBM model exhibits exceptional precision and robustness in continuous pain monitoring during labor, with potential applicability extending to broader healthcare settings.

Trial registration: ClinicalTrials.gov Identifier: NCT04461704.

Keywords: Artificial Intelligence (AI), Electrocardiography (ECG), Labor Pain, Nociception Assessment, Uterine Contractions, Clinical Decision-Making, Machine Learning, Pain Monitoring, Healthcare Technology, Predictive Analytics

Introduction

Pain assessment is still a subjective task that requires accurate and objective techniques. The inadequacies of current pain measurement methods have an impact on medication management and patient care [1–7]. Physiological reactions are important markers because pain activates autonomic pathways [3–6]. Physiological metrics like heart rate variability have been the main focus of research on nociception assessment [7–9]. Reductions in the amplitude of photoplethysmogram waveforms [10–14] and decreased variability in high-frequency heart rate bands [15–18] are noteworthy discoveries. Furthermore, variations in skin conductance level and fluctuation count, which are indicators of changes in electrogalvanic skin properties, indicate pain during and after surgery [8, 19–21]. A multi-parametric strategy that incorporates different nociception-related measures consistently performs better than single-parameter evaluations [22–25].

Studies that currently exist on nociception primarily assess physiological variables, such as heart rate variability [7–9]. Reduced high-frequency power in heart rate variability [10–13], decreased photoplethysmography waveform amplitude [14–18], and changes in electrogalvanic skin properties [8, 19–21] have all been linked to nociception. The superiority of a multi-parametric approach over individual measurements is becoming more and more clear [22–25].

Under general anesthesia, perception of pain is influenced by a variety of factors. Reductions in high-frequency heart rate variability [15–18] and photoplethysmography waveform amplitude [10–14] have been associated with nociceptive responses. Changes in the electrogalvanic skin properties, as determined by the skin conductance level and fluctuation counts, are indicative of both intra- and post-operative pain [8, 19–21]. A combined analysis of these parameters yields a more comprehensive noception assessment than single-parameter evaluations [22–25].

Recent research highlights the increasing accuracy of multi-parameter nociception assessment as a result of advancements in statistical modeling and data analysis [26] Deep learning approaches are very helpful to medical AI, particularly when developing algorithms for physiological waveform analysis [27–29]. Initiatives like PhysioNet and the Computers in Cardiology Challenges have made it easier to create predictive tools for acute hypotensive episodes [30]. The development of reliable machine-learning algorithms for the analysis of ECG data with a focus on single-parameter pain assessment is hampered by the variability of pain in terms of its onset, duration, and intensity.

ECG is a perfect monitoring tool because labor pain during natural spontaneous delivery (NSD) is periodic and has a predictable onset and duration [31, 32]. Myocardial electrical activity is reflected in ECG signals, which offer useful information in the frequency and time domains [33, 34]. This study utilized fast Fourier transform to analyze ECG waveform data from pregnant women undergoing normal spontaneous delivery (NSD) during both labor and non-labor periods. The Nociception Monitoring Index (NoM) exhibited significant variations during labor pain intervals, highlighting its potential utility for real-time monitoring and assessment of labor pain intensity.

Methods

Data sources and study population

To provide a comprehensive overview of our research methodology, we have outlined the key workflow steps involved in the development and validation of our ECG-based labor pain prediction model: 1.Data Collection: ECG waveform data were gathered from women preparing for normal spontaneous delivery (NSD). 2.Feature Selection: Critical ECG features correlated with labor pain were selected to enhance model performance (see Supplemental Figs. 1–8). 3.Data Splitting: The collected data were split into training and validation sets to ensure unbiased model evaluation. 4.Model Development: Machine learning models were developed using the selected features to monitor labor pain. 5.Model Evaluation: The performance of these models was evaluated using metrics such as AUC, accuracy, and precision. 6.Model Optimization: Hyperparameter optimization was conducted through grid search and cross-validation to improve model performance. 7.Prediction and Validation: The final model was validated using the optimized parameters to ensure accurate labor pain prediction (see Fig. 1). This structured workflow ensures a systematic approach to model development and validation, enhancing the reliability and interpretability of the results.Our cross-sectional study, which focused on women getting ready for natural spontaneous delivery (NSD), was carried out at the Taiwan University Hospital (NTUH) from January to July 2020. Our research protocol was very strict and registered on ClinicalTrials.gov (number NCT04461704) in order to facilitate detailed data collection for in-depth statistical analysis. With the protocol identified as NSD-TW-01_Protocol_V1.1_20200317, the Taiwan University Hospital Research Ethics Committee awarded ethical approval (approval number 201910058RSC). All participants provided informed consent, in accordance with strict ethical guidelines. Women who were 20 years of age or older, in labor for more than 4 h, and who were categorized as having Physical Status I–II (American Society of Anesthesiologists) were eligible to participate in the study. Complete clinical records were necessary for eligibility. Participants who used epidural anesthesia, had certain medical conditions, were taking certain medications, or had a BMI of more than 40 kg/m^2 were excluded from the study. The investigator retained the right to withdraw a participant from the study if there were adverse events (AEs), protocol violations, cesarean sections, labor complications, or voluntary withdrawal. Twelve individuals made up the final cohort, which produced a dataset with 6,010 ECG data points. Optimizing the NoM algorithm was a major focus of our study. Considerable optimization and visualisation were required for this (see Supplemental Figs. 1–8). We used an 80:20 split to separate the dataset into subsets for training and validation in order to validate the algorithm.

Feature selection

A thorough feature selection process was essential to creating an accurate ECG-Based Monitoring of Labor Pain model. Our large dataset contained a variety of attributes, including ECG frequency domain data from different frequency bins and maternal demographics (e.g., Gravida & Para, Age, Gestational Age, Body Height, Body Weight,

(See figure on next page.)

Fig. 1 Workflow Diagram for ECG-Based Labor Pain Monitoring. This figure illustrates the methodological workflow employed in this study for monitoring labor pain using ECG waveform analysis. The process consists of seven key steps: 1) Data Collection: Gathering ECG data from women pre-paring for natural spontaneous delivery (NSD); 2) Feature Selection: Identifying critical ECG features correlated with labor pain; 3) Data Splitting: Dividing the data into training and validation sets; 4) Model Development: Building machine learning models using the selected features; 5) Model Evaluation: Assessing model performance with metrics such as AUC, accuracy, and precision; 6) Model Optimization: Tuning model parameters through grid search and cross-validation; 7) Monitoring and Validation: Conducting final predictions and validating the optimized model's performance to ensure accurate and reliable labor pain monitoring

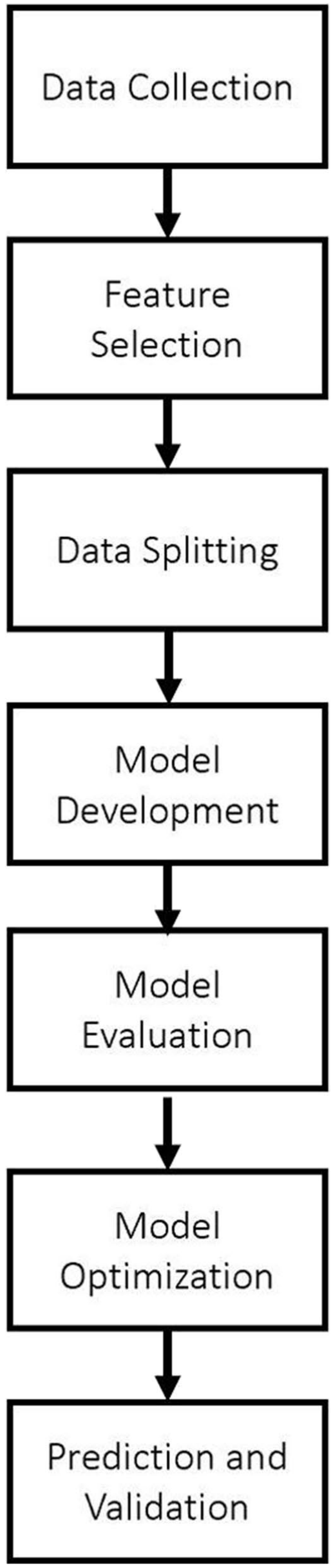


Fig. 1 (See legend on previous page.)

and BMI). By concentrating on the most illuminating attributes, the feature selection process aimed to improve the monitoring model. The performance and interpretability of the model were intended to be enhanced by this method. We identified a subset of critical attributes by carefully analyzing each attribute's effect on the NoM in both training and testing datasets. These characteristics were essential to the model since they showed strong correlations with the Nociception Index. Their ability to accurately convey important details pertinent to determining nociception levels during labor pain was the basis for their selection. This careful selection procedure made sure that our model could accurately and efficiently monitor labor pain using ECG data.

Class definition

During the first stage of our study, we created a systematic classification system to categorize the different levels of labor pain that parturient women felt during giving birth. With this framework, instances are classified into two distinct groups: "Labor Pain" (coded as 1) and "No Labor Pain" (coded as 0). This binary classification system is used. The analysis of the NoM, which is derived from ECG data, serves as the foundation for this classification. Supplemental Figs. 1 through 8 provide specific details on the NoM computation and its function in the classification process. A more targeted and effective assessment is made possible by this binary categorization, which reduces the complex nature of labor pain into a form that is manageable for computational analysis. This makes it possible to distinguish clearly between labor pain and non-labor pain, as shown by the Nociception Index that is derived from the ECG. This simple yet powerful method is essential to our effort to precisely track and evaluate labor pain using ECG data analysis.

Data cleaning and machine learning model development

In developing our ECG-Based Monitoring of Labor Pain models, we employed the Auto AI feature within Watson Studio [35–37]. This advanced tool was instrumental in streamlining our data analysis process, aiding in crucial tasks such as data transformation, algorithm selection, and parameter optimization. Auto AI not only provided various model options but also ranked them, enabling us to choose the most effective model based on empirical results [38–40]. To evaluate the efficacy of these models, we partitioned our data into two segments: 80% for training and 20% for testing. This split was crucial for both testing the models under real-world conditions and assessing their overall performance. Our exploration included four distinct machine learning models: LightGBM [41–43], XGBoost Classifier [44–46], SnapDecisionTreeClassifier, and SnapLogisticRegression [39, 40, 47]. A key aspect of enhancing the performance and efficiency of these models was the strategic selection of the most relevant features from our dataset. This feature selection was integral to optimizing the models' ability to accurately monitor and assess labor pain through ECG data.

Model evaluation

Our machine learning models' Area Under the Curve (AUC) values were the primary metric used to assess their performance. One commonly accepted indicator of a model's capacity for discrimination is its AUC. In addition to AUC, we used a number of other metrics to provide a thorough evaluation. These comprised the log loss, average precision, recall, accuracy, precision, and F1 score. By applying each of these metrics to the testing dataset, a comprehensive assessment of the models within the framework of ECG-Based Monitoring of Labor Pain was made possible. We applied SHapley Additive explanations (SHAP) analysis to obtain more profound insights into the predictive factors and improve our comprehension of ECG-Based Monitoring of Labor Pain. We were able to determine the relative significance of various features within our developed Nociception Index thanks to this sophisticated analytical technique. Through the identification of important factors and their effects on labor pain monitoring, SHAP analysis has provided invaluable insights. This knowledge is essential for developing focused interventions that are customized to each patient's needs, moving the field closer to more individualized and successful ECG-based labor pain monitoring techniques.

Hyperparameter optimization

We used a rigorous approach to hyperparameter optimization in our quest to improve the performance of the machine learning models for ECG-Based Monitoring of Labor Pain. Our approach is consistent with previous studies where ECG data has been systematically applied using machine learning models and five-fold cross-validation to ensure robustness and generalizability of the classifiers. For instance, Desai et al. [48] employed similar methods in their decision support system for arrhythmia beat classification, and Desai et al. [49] further validated these techniques in their automated diagnosis of tachycardia beats. These studies underscore the efficacy of cross-validation in achieving reliable diagnostic performance in ECG-based applications. This required applying five-fold cross-validation in conjunction with grid search techniques. Numerous models, such as LightGBM [41–43], XGBoost Classifier [44–46], SnapDecisionTreeClassifier, and SnapLogisticRegression [39, 40, 47], were subjected to this procedure. During the training phase, our main goal was to optimize each model's hyperparameters by using grid search to find the best combinations that would maximize the F1 score [50]. Table 1 displays the specific hyperparameter optimization settings for every model. The grid search technique made it easier to explore a predetermined range of hyperparameter values in a methodical manner. We were able to greatly increase the models' accuracy and predictive efficiency in identifying labor pain using ECG data by repeatedly evaluating different combinations. The most efficient hyperparameter combinations

Table 1 The hyperparameters of models for machine learning

Model	Hyperparameters	Values
LightGBM	n_estimators	368
	learning_rate	0.036
XGBoost Classifier	n_estimators	381
	learning_rate	0.02
SnapDecisionTreeClassifier	random_state	33
	max_depth	3
SnapLogisticRegression	random_state	33

The settings known as hyperparameters affect how machine learning models behave. The values mentioned above were applied to the models' training and assessment processes for every model were found through this iterative investigation, which improved overall performance and strengthened predictive abilities.

Model evaluation

We used a variety of performance metrics, such as Area Under the Curve (AUC), F1 score, accuracy, precision, recall, average precision, and log loss, in our thorough assessment of different machine learning models. We were able to thoroughly evaluate each model's predictive power for ECG-Based Monitoring of Labor Pain outcomes thanks to its multifaceted approach. We were able to fully comprehend the predictive strengths and limitations of each model by examining these metrics.

We integrated SHapley Additive exPlanations (SHAP) into our analysis to further explore the underlying mechanisms of these predictions. Clarifying the variables influencing the models' predictions was made possible through the use of SHAP analysis. We were able to determine the most important components of our questionnaire and how they affected ECG-Based Monitoring of Labor Pain by using this technique. We were able to use SHAP to not only identify the most important questionnaire items, but also to comprehend how these items combined affected our models' predictive accuracy. This degree of understanding is crucial for improving our machine learning models' interpretability and our method for tracking labor pain.

Software and package applicating for modeling

We used Python, more especially the Python Software Foundation version 3.9, as the main platform for our machine learning studies in this work. We made substantial use of the open-source Scikit-learn toolkit, which is well-known for having a wide variety of tools and techniques. The following were the main elements we used in our investigation: (1) Data Splitting: We used the sklearn.model_selection.train_test_split module to split our dataset into training and testing sections. This random partition was essential for assessing how well the models performed on new, untested data. (2) LGBM Model: An effective Light Gradient Boosting Machine (LGBM) model was built using the lightgbm.LGBMClassifier package. LGBM is especially well-suited for large-scale data applications due to its great performance and efficiency. (3) XGBoost Model: To create a reliable XGBoost model, we used the XGBoost Python module. This model has a solid reputation for being effective and having strong predictive capabilities. (4) SnapDecisionTreeClassifier: The SnapDecisionTreeClassifier algorithm, part of the IBM Snap ML library, was implemented to create a decision tree classifier. (5) Logistic Regression: For binary classification tasks, we used the sklearn.linear_model.LogisticRegression module. Logistic regression, a widely adopted algorithm, played a significant role in our analysis. To ensure the reliability of our results and to prevent overfitting, we adopted the sklearn.model_selection.StratifiedKFold module for stratified k-fold cross-validation. Our threshold for statistical significance was set at a p-value of 0.05.

Role of the funding source

We would like to explicitly acknowledge the specific organization that provided financial support for our study. It is crucial to clarify, nevertheless, that these donors were not involved in any part of the research process. This involves, but is not restricted to, the

design of the study, gathering and analyzing data, interpreting it, writing the article, and choosing whether to submit the work for publication. The rigorous division was meticulously upheld to guarantee the complete autonomy of the study, thereby excluding any possible partiality or impact from the sponsoring organization. Keeping the transparency principle in place, all authors involved in this work had unrestricted access to the entire dataset. This access played a crucial role in protecting the research's integrity and avoiding any improper impact on the study's conclusions. The corresponding authors were ultimately responsible for submitting the paper. They were tasked with making sure the study adhered to the strictest ethical and scientific requirements. This duty included ensuring that all the work included in the paper was accurate and honest. The authors' dedication to ensuring that the study complied with all applicable ethical guidelines and research protocols has strengthened the reliability and validity of our research findings.

Results

Description of patient population

In the context of this study, a frequency bin refers to a specific range of frequencies within the overall frequency spectrum of the ECG signals. These bins are formed by applying a Fourier Transform to the ECG data, converting it from the time domain to the frequency domain. The criteria for forming these bins include the sampling rate of the original ECG signal and the desired frequency resolution for analysis. Each bin captures the signal's power within a particular frequency range, enabling detailed examination of the ECG's frequency components. This approach allows us to systematically analyze the frequency domain characteristics of the ECG signals, which are crucial for monitoring labor pain. We thoroughly analyzed ECG frequency domain data in our work, focusing on a variety of frequency bins (0 to 59). This analysis covered features in the Training Set ($n=4{,}808$) as well as the Testing Set ($n=1{,}202$). Table 2 presents comprehensive patient demographic information. For every frequency bin, we gave average values and the standard deviations that went along with them, providing information about the distribution and variability of the data. For instance, we found that the Training Set's average $\pm$ standard deviation (SD) in Frequency Bin 0 was 59.4 ± 80.6, while the Testing Set's SD was 63.1 ± 77.7. The distribution and variability trend persisted in the other frequency bins. In addition, the NoM was evaluated, exhibiting a mean $\pm$ SD of 31.9 ± 23.6 in the Training Set and 30.2 ± 35.8 in the Testing Set. With regard to labor pain monitoring, these results offer a thorough understanding of the features in each frequency bin and their implications. They also draw attention to the variability and distribution patterns within the ECG data.

Model prediction ability

We used a number of important measures to analyze our prediction models' performance in order to fully determine their efficacy. The area under the curve (AUC) values of the models were used as a primary metric for evaluating their discriminative skills. The LightGBM model exhibited remarkable performance, as evidenced by its highest AUC score of 0.96 (see Fig. 2A), indicating its potent ability to discriminate between various classes. The XGBoost Classifier, which had an AUC of 0.95, came in second (Fig. 2A). Not to mention, the SnapLogisticRegression and SnapDecisionTree Classifier

Table 2 Nociception index and ECG frequency domain data descriptive analysis

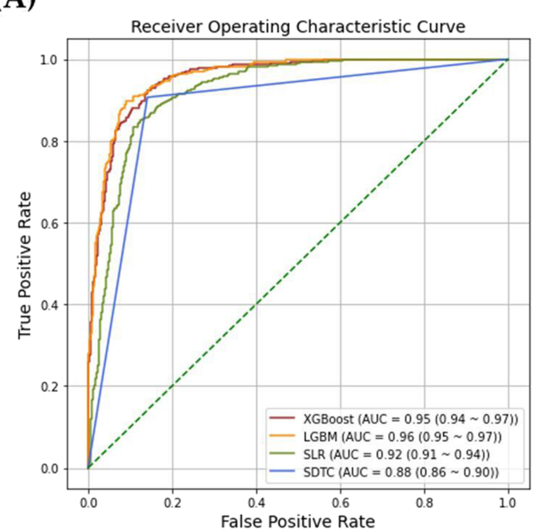
Characteristics	Training Set ($n = 4,808$)	Testing Set ($n = 1,202$)
Frequency Domain Data (ECG)		
Bin Frequency 0	59.4 ± 80.6	63.1 ± 77.7
Bin Frequency 1	58.4 ± 81.5	64.7 ± 76.5
Bin Frequency 2	59.0 ± 81.0	65.3 ± 76.2
Bin Frequency 3	58.5 ± 81.5	62.6 ± 78
Bin Frequency 4	57.9 ± 81.9	62.2 ± 78.9
Bin Frequency 5	57.3 ± 82.4	62.5 ± 78.3
Bin Frequency 6	58.1 ± 82.0	64.9 ± 76.7
Bin Frequency 7	58.5 ± 81.3	64.3 ± 76.5
Bin Frequency 8	59.3 ± 80.4	65.2 ± 76.2
Bin Frequency 9	58.8 ± 81	64.6 ± 76.6
Bin Frequency 10	57.8 ± 81.9	65.7 ± 75.9
Bin Frequency 11	59.2 ± 80.8	64.3 ± 76.1
Bin Frequency 12	59.1 ± 80.8	64.9 ± 76.4
Bin Frequency 13	57.9 ± 82	64.7 ± 76.3
Bin Frequency 14	58.8 ± 81.2	63.8 ± 77.3
Bin Frequency 15	59.5 ± 80.7	63.3 ± 77.6
Bin Frequency 16	59.9 ± 80	63.4 ± 77.8
Bin Frequency 17	59.7 ± 80.3	63 ± 77.8
Bin Frequency 18	59.7 ± 80.3	63.2 ± 77.8
Bin Frequency 19	57.9 ± 81.6	63.5 ± 77.3
Bin Frequency 20	59.9 ± 80.2	66.1 ± 75.6
Bin Frequency 21	59.9 ± 80.3	66.4 ± 75.2
Bin Frequency 22	60 ± 80.4	65.9 ± 75.8
Bin Frequency 23	58 ± 81.9	63.9 ± 76.8
Bin Frequency 24	58.7 ± 81.5	62.2 ± 78.6
Bin Frequency 25	58.3 ± 81.7	62.1 ± 78.7
Bin Frequency 26	59.6 ± 80.6	60.8 ± 79.5
Bin Frequency 27	59.9 ± 80.2	60.3 ± 79.9
Bin Frequency 28	59.5 ± 80.4	61.3 ± 79.4
Bin Frequency 29	58.5 ± 81.4	59.4 ± 80.8
Bin Frequency 30	58.8 ± 81.3	61 ± 79.6
Bin Frequency 31	58.4 ± 81.4	60.9 ± 79.6
Bin Frequency 32	58.2 ± 81.4	60.4 ± 80.3
Bin Frequency 33	59.1 ± 81	60.7 ± 79.8
Bin Frequency 34	59.4 ± 81	61.2 ± 79.4
Bin Frequency 35	59.6 ± 80.7	60 ± 80.1
Bin Frequency 36	59.4 ± 80.7	62.6 ± 78.6
Bin Frequency 37	59.9 ± 80.6	62.4 ± 79.3
Bin Frequency 38	60.8 ± 79.8	59.7 ± 81.2
Bin Frequency 39	59.6 ± 80.9	59.1 ± 81.3
Bin Frequency 40	57.5 ± 82.4	62 ± 79.1
Bin Frequency 41	57.8 ± 82.5	62.4 ± 78.3
Bin Frequency 42	59.2 ± 81.4	64.9 ± 75.8
Bin Frequency 43	58.3 ± 81.9	65.1 ± 75.9
Bin Frequency 44	57.9 ± 82.5	64.9 ± 76.1
Bin Frequency 45	58.5 ± 82.1	63.3 ± 77.6
Bin Frequency 46	59.3 ± 81.4	61.6 ± 78.7

Table 2 (continued)

Characteristics	Training Set (*n* = 4,808)	Testing Set (*n* = 1,202)
Bin Frequency 47	58.9 ± 81.5	60 ± 79.7
Bin Frequency 48	59.7 ± 80.7	60.5 ± 79.1
Bin Frequency 49	60 ± 80.7	60.6 ± 79.8
Bin Frequency 50	59.2 ± 81.2	62.5 ± 77.9
Bin Frequency 51	59.1 ± 81.3	62.1 ± 78.2
Bin Frequency 52	59.1 ± 81	61 ± 79.1
Bin Frequency 53	58 ± 81.9	63 ± 77.5
Bin Frequency 54	58.8 ± 81.1	65.3 ± 75.5
Bin Frequency 55	59.9 ± 80.4	63.9 ± 76.5
Bin Frequency 56	59 ± 80.9	63.9 ± 76.9
Bin Frequency 57	59.4 ± 80.7	65.4 ± 75.3
Bin Frequency 58	59.1 ± 80.9	64.1 ± 76.4
Bin Frequency 59	58.3 ± 81.6	64 ± 76.6
Index of Nociception		
NoP	31.9 ± 23.6	30.2 ± 35.8

The ECG results are displayed as mean ± standard deviation when expressed in frequency domain data. The Xth frequency bin, or frequency bin X, is the result of analyzing ECG waveforms using the Fast Fourier Transform (FFT). NoP: Index of Nociception

(A)



(B)

Models	Accuracy	Specificity	Sensitivity	Precision	F1 score	AUC
LightGBM	0.90	0.91	0.90	0.87	0.88	0.96*
XGBoost Classifier	0.88	0.87	0.87	0.86	0.87	0.95
SnapDecisionTreeClassifier	0.86	0.86	0.90	0.83	0.87	0.88
SnapLogisticRegression	0.85	0.88	0.84	0.84	0.84	0.92

Fig. 2 **A** Characteristic curves for receiver operations. and (**B**) Assessing Machine Learning Models' Performance. For every machine learning model, performance metrics such as AUC (Area Under the Curve), F1 Score, Accura-cy, Specificity, Sensitivity, and Precision were evaluated. An asterisk (*) denotes the LightGBM model's AUC value

models performed admirably, with AUC values of 0.92 and 0.88, respectively (Fig. 2A). Our evaluation also took into account the models' overall accuracy, which was quite important. With an accuracy score of 0.9, LightGBM fared better than the others in this regard (Fig. 2B). With accuracy ratings of 0.88, 0.86, and 0.85, respectively, the XGBoost Classifier, SnapDecisionTree Classifier, and SnapLogisticRegression came next (Fig. 2B). The models' ability to accurately detect positive cases is measured by sensitivity, and LightGBM and the SnapDecisionTree Classifier both achieved the highest rate of 0.9 (Fig. 2B). Sensitivity ratings of 0.87 and 0.84 were obtained by the XGBoost Classifier and SnapLogisticRegression, respectively (Fig. 2B). Both the LightGBM and XGBoost Classifiers achieved the maximum precision, which is a measure of the accuracy of positive predictions, with a precision of 0.87 (Fig. 2B). With precision scores of 0.84 and 0.83, respectively, SnapLogisticRegression and SnapDecisionTree Classifier came next (Fig. 2B). Both LightGBM and XGBoost Classifier scored 0.88 (Fig. 1B), indicating consistent performance according to the F1 score, a parameter that strikes a compromise between precision and sensitivity. SnapLogisticRegression scored 0.84 and SnapDecisionTree Classifier 0.87 on the F1 score (Fig. 2B). We decided to designate the LightGBM model as the "champion" model based on these thorough assessments. It was most suited for our ECG-Based Monitoring of Labor Pain study since it showed excellent discriminative skills and competitive scores on a range of performance criteria.

Feature Importance Ranks and SHAP values in the LGBM model

In the study, the Light Gradient Boosting Machine (LGBM) model's feature importance was assessed using SHapley Additive exPlanations (SHAP) values. This analysis revealed the most influential traits for the model's predictions, with the NoM and various frequency bins being the top features (Fig. 3A). The SHAP summary plot provides

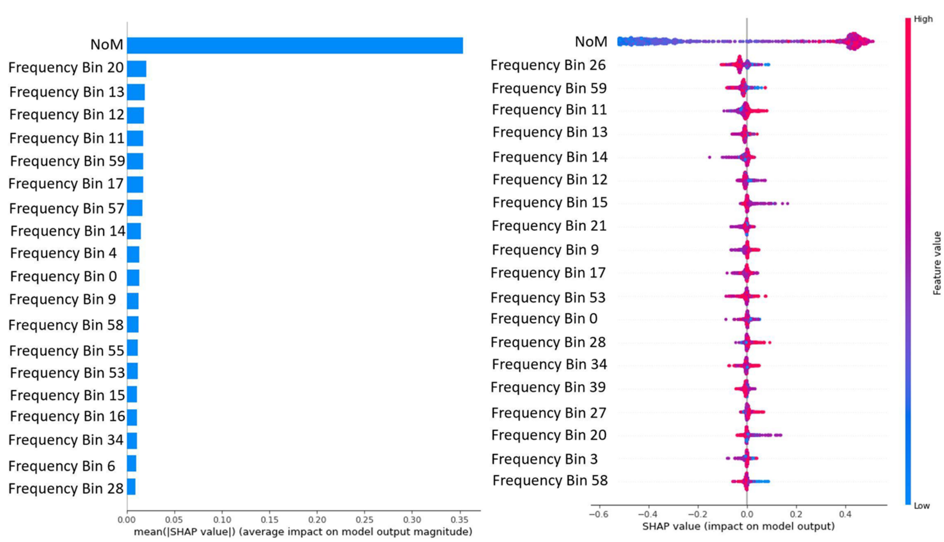


Fig. 3 Crucial Clinical Characteristics for Labor Pain Monitoring Based on ECG. **A** Features' Significance Plot of several clinical variables utilizing the Nociception Monitoring Index (NoM) and Machine Learning for ECG-Based Monitoring of Labor Pain. **B** The SHAP Summary Plot offers a concise synopsis of the key clinical characteristics that influence the Nociception Monitoring Index (NoM) and ECG-Based Monitoring of Labor Pain

a clear visual representation, illustrating how these features impact the model's predictions, thereby enhancing the interpretability of the LGBM model in assessing labor pain (Fig. 3B).

Explanation of the ML model at the individual level

The study employs LIME and SHAP plots to elucidate individual-level predictions of the machine learning model, focusing on the NoM for ECG-based labor pain monitoring. Two representative patient cases are analyzed in Fig. 4 using a LIME plot, which demonstrates the probability of experiencing labor pain and the influence of each variable on this likelihood. Case 1 shows a low labor pain probability (12%), while Case 2 indicates a high probability (98%). Variables negatively and positively correlated with labor pain are color-coded for clarity, with specific frequency bins and NoM ranges crucial in determining the predicted labor pain probability.

Discussion

Our research set out to revolutionize the monitoring and prediction of labor pain by utilizing a special blend of advanced machine learning techniques and comprehensive medical data. As shown in Supplemental Table 1, the first phase of our clinical research comprised collecting ECG and tocometry data from four laboring women. These datasets were painstakingly collected by us, who converted the 512 Hz ECG signals into frequency domain data. Our study's exact documentation of pain episodes during childbirth was a critical component. Using a visual analog scale (VAS), a nurse meticulously recorded the timing of the uterine muscle contractions and the corresponding Nociception levels. This first stage set the stage for more modeling and analysis. The intricate relationship between uterine contractions and Nociception was thoroughly investigated in our study, and distinct flat (TFlat (i)) and peak (TPeak (i)) phases were identified. In order to determine the ECGPeak (i) and ECG_Flat (i) during the peak and flat phases of contractions, we examined 10,000 ECG signals, each lasting 20 s. In order to improve our understanding of labor pain, we set out to uncover patterns that illustrate the connection between uterine contractions and Nociception. In both the Training and Testing Sets, we concentrated on the thorough analysis of ECG frequency domain data spanning Frequency Bins (0 to 59). The distribution and variability inside each frequency bin were better understood thanks to this analysis, which also offered crucial information for the next phases of our investigation. Our study's evaluation of our predictive models' performance was a crucial component. We evaluated these models according to important indicators to learn more about their efficacy. With an outstanding AUC score of 0.96*, the LightGBM model stood out and demonstrated its superior discriminating power. The XGBoost Classifier, SnapDecision-Tree Classifier, and SnapLogisticRegression followed soon behind, all of which showed impressive AUC values that confirmed the efficacy of our modeling strategy.

Our study examined the finer points of labor pain monitoring and prediction, emphasizing important performance indicators such as F1 score, accuracy, sensitivity, and precision. These metrics provided insight into the distinct advantages and disadvantages of every predictive model in addition to serving as indicators of the overall success of the model. Among the evaluated classifiers, the LightGBM model demonstrated the highest

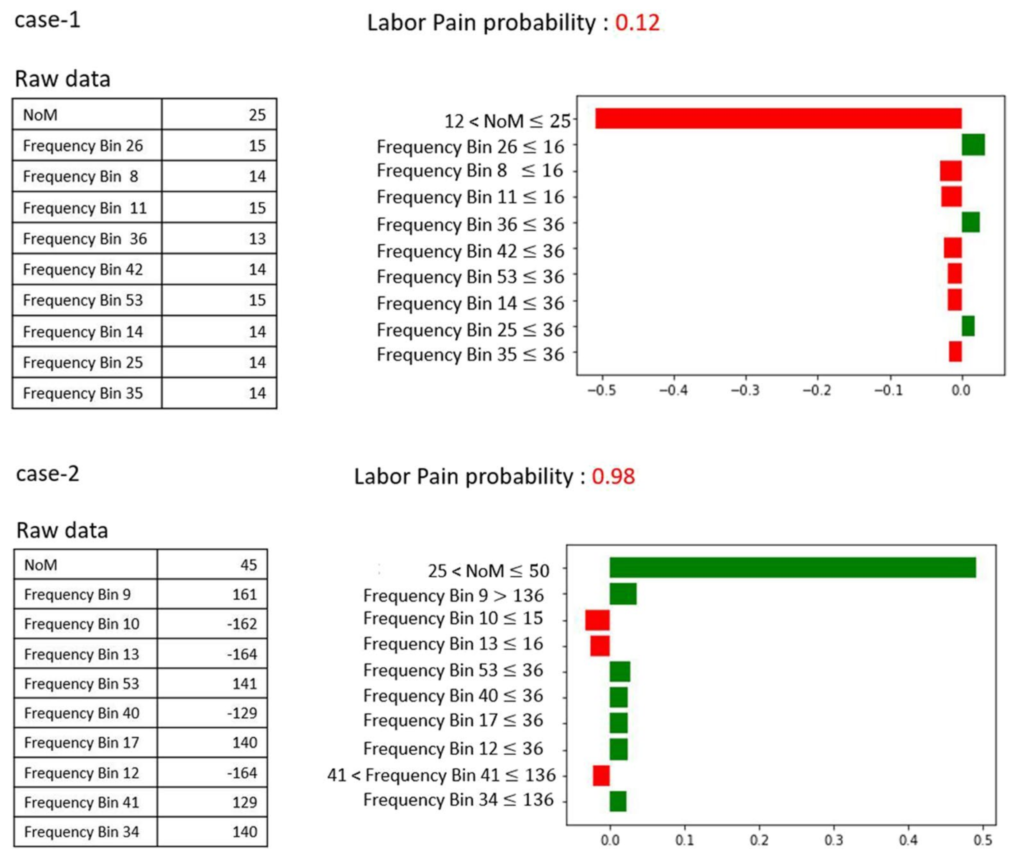


Fig. 4 Effects of Key Elements on ECG-Based Labor Pain Monitoring. This figure displays LIME (Local Interpretable Model-agnostic Explanations) force graphs to illustrate the impact of important aspects on the ECG-Based Monitoring of Labor Pain. Specifically, the Nociception Monitoring Index (NoM) and various frequency bins are shown to influence the probability of labor pain. These plots provide individual-level explanations by visually representing how each variable contributes to the likelihood of labor pain, with red bars indicating a decrease and green bars indicating an increase in the probability

accuracy and AUC score, establishing itself as the optimal model for ECG-based labor pain monitoring. With an accuracy of 90% and an AUC of 0.96, the LightGBM classifier outperformed other models, such as XGBoost, SnapLogisticRegression, and SnapDecisionTree, making it particularly suitable for precise and reliable pain assessment in clinical settings. This performance is on par with existing approaches like the Analgesia Nociception Index (ANI) and PMD-200, reinforcing the potential clinical utility of our method. The importance of the NoM as a critical component in ECG-based labor pain monitoring was a significant finding in our study. The consideration of SHAP (SHapley Additive exPlanations) values provided more support for this conclusion. SHAP values illustrated the significant significance that NoM played in this situation by providing a visual depiction of how various factors affected the predictive models. We went beyond a broad model analysis and conducted analysis at the individual level. We were able to comprehend the intricate relationship between the NoM and labor pain estimates based on electrocardiograms (ECGs) thanks to this method. Advanced analytical tools such as SHAP plots and LIME (Local Interpretable Model-agnostic Explanations) were utilized to provide comprehensive insights into the variables influencing the likelihood of labor pain in individual patients. These graphic aids clarified the fundamental dynamics of labor pain forecasts, highlighting the significance of NoM in addition to other pertinent variables. Our method goes beyond mere forecasting. Our goal was to change the way that mothers are cared for by developing an all-inclusive, user-friendly pain monitoring system. Our objective was to improve the quality of maternal healthcare by raising the bar for pain monitoring and prediction by identifying crucial pain indicators and offering a comprehensive solution.

The paper "Artificial Intelligence-Enhanced Electrocardiography in Cardiovascular Disease Management" offers a thorough analysis of how AI will improve ECG technology in the future to help diagnose cardiovascular disorders in high-risk populations [51]. The impact on clinical decision-making for patients with cardiovascular diseases is explored by the writers. Even though AI-ECG integration is still in its infancy, further clinical research will soon determine its actual worth. Before being a fundamental component of medical practice, AI-ECG integration requires extensive validation and verification, much as other medical technologies. The scientists are nevertheless upbeat about AI-ECG's revolutionary potential to change clinical treatment. Notably, there are very few studies that use a single, straightforward ECG parameter to detect or correlate with other vital indicators, such "pain sensation" in our work, and that incorporate machine learning and deep learning models. Many AI-driven research projects have recently focused on pain treatment, such as predicting the dosage of opioids and identifying patients who would benefit from preoperative consultation. This highlights how special and important our study is to adding to the corpus of knowledge in this field [52–56].

In a pioneering work, brain responses to painful and nonpainful heat stimuli were analyzed using functional magnetic resonance imaging (fMRI) and machine learning approaches [57]. This work represents a major breakthrough in the field because it demonstrated that a thorough machine learning analysis of whole-brain scans can detect pain more accurately than more conventional approaches that concentrate on certain brain regions linked to nociception. This result emphasizes how machine learning can improve pain detection over traditional imaging methods. Furthermore, the study of pain evaluation encompasses more than only imaging technology. One noteworthy example is the creation of the Nociception Level (NoL) index by Ben-Israel et al. [52], who used machine learning to examine data from skin conductance waveforms and photoplethysmograms obtained from 25 patients undergoing elective surgery. Within the study itself, a novel and well validated methodology was used to create this NoL index. An additional degree of complexity to the assessment of pain was introduced by the technique, which combined indices of stimulation and analgesia and included an arbitrary rating of intraoperative noxious stimuli [58]. Together, this research demonstrate how versatile and effective machine learning is in improving our knowledge of and ability to control pain. The capacity of machine learning to analyze intricate datasets from several sources creates new avenues for pain perception research and provides more precise and subtle techniques for pain treatment.

In order to anticipate patient reactions to postoperative opioid therapy for acute pain, machine learning has been used to evaluate electroencephalography (EEG) signals; however, this approach has only been able to predict with an accuracy of 65% [56]. In an additional attempt to predict opioid dose, Olesen et al. [55] examined single-nucleotide polymorphisms (SNPs) in 1,237 cancer patients; however, no meaningful relationships were discovered. This research highlight the intricacies and difficulties associated with assessing and managing pain, especially when it comes to creating an ideal model in the face of irregular pain onset and the challenge of obtaining sufficient data for efficient AI learning. Numerous methods, including uterine ergometers, intrauterine pressure catheters (IUPC), and electromyography (EMG), commonly referred to as electrohysterography (EHG), have been used in the field of uterine activity monitoring. EHG is used by a US-patented obstetric analgesia system to identify the beginning of contractions [59]. This method is essential for directing the administration of analgesics and comprehending the connection between medication analgesia and pain generated by contractions. Expanding upon this, our model draws inspiration from the obstetric analgesia system and aims to forecast the onset and severity of pain caused by contractions. Our approach computes the rhythm of pain feeling using AI-driven analysis in an effort to precisely forecast when pain will occur. Real-time pain scoring and proactive pain management are made possible by this method, which has the potential to revolutionize pain management techniques [60]. Our model is superior to earlier devices because it can provide immediate information and forecast the start of pain, allowing for prompt pain-preventive measures. earlier devices depended on heart rate variability (HRV) analysis, which had limited clinical applicability [61]. For instance, respiratory sinus arrhythmia is used by the Analgesia Nociception Index (ANI) to analyze the parasympathetic component of autonomic nervous system activity [30]. On the other hand, our strategy provides a more direct and possibly more efficient way to diagnose and treat pain.

Innovations in pain monitoring technology have produced devices such as PMD-200™, ANI I, and ANI II. All these gadgets have significant drawbacks but also special features and benefits. Their predictive skills have been acknowledged in worldwide studies, underscoring their usefulness in therapeutic settings [62]. The PMD-200™ stands out from the others because to its intuitive interface and incorporation of the proprietary NoL® technology. This method gathers a range of physiological signals using a noninvasive finger probe equipped with sensors. AI algorithms are employed to process and analyze several physiological characteristics connected to pain, such as heart rate (HR), heart rate variability (HRV), skin conductance level (SCL), pulse wave amplitude from photoplethysmography, skin conductance variations, and skin temperature [63]. Like this, our model measures parasympathetic tone by utilizing the transient and fast variations in HRV brought about by each respiratory cycle, whether it be artificial or spontaneous. Even while our study offers fresh and insightful perspectives, it's important to recognize some limitations. First off, while our investigation using machine learning methods to correlate ECG waveforms and uterine contractions reveals an association, it does not ensure high prediction accuracy for the onset of uterine contractions. Larger datasets and more algorithms could be useful in future study to increase prediction accuracy. Second, the accuracy of contraction pain as a predictor of uterine contractions is not thoroughly examined in our study. The effect of strong, maybe non-pain-related muscle uterine contractions on the ECG waveform is a serious concern. This phenomenon was initially observed in 1979 and implies that exercise-related factors can influence different ECG waveform characteristics in addition to heart rate [64]. When interpreting ECG data in relation to uterine contractions and pain evaluation, this intricacy needs to be taken into an account.

The authors of the study concluded that although the observed waveform changes may be related to pain, it is unclear if these changes are caused by pain or by major physiological changes in the cardio-vascular system following uterine contractions. We suggest a parallel study that uses Principal Component Analysis (PCA) to compare data before, during, and after uterine contractions and contraction-induced pain in order to address this uncertainty. The study will investigate ECG waveforms from the same NSD patients. A crucial question is whether discomfort from contractions accurately depicts other types of pain. A similar study that verifies our machine learning approach in patients recovering from postoperative surgical procedures can address this problem. We want to conduct two more experiments in other study populations undergoing procedures involving anesthesia or analgesic medicines to further validate our novel technique of using regular, cyclic uterine contraction pain for pain algorithm discovery. It's important to remember that determining the difference between acute and chronic pain can be difficult when taking the affective component of pain into account. Moreover, factors such as patient anatomy and sensor location may affect tocometry results. Furthermore, this element is made more problematic by the subjective nature of pain perception in parturient women.

Although the feeling of pain is subjective by nature, this study seeks to find a biomarker that establishes a relationship between an objective indicator and the subjective perception of pain, as do many others in the area. Women can perceive pain differently, for example, some may find labor to be less difficult than others. In this work, we go beyond the simple evaluation of nociception and toward a more objective assessment of conscious pain. The Visual Analog Scale (VAS) pain score was used to connect tocometry data on uterine contractions with patients' self-reported pain levels to improve the study design. The investigating nurses were carefully informed of this correlation, and it was carefully recorded. Regarding the application of this: (1).Improving the Accuracy of Pain Assessment: These results highlight the necessity for more accurate pain assessment techniques that capture a thorough comprehension of pain. We can increase the validity of our suggested pain algorithm and its suitability for a range of clinical situations by carrying out more research in different demographics. (2).Progressing Pain Management: The methodical approach taken by this research to objectively measure pain has the potential to completely transform pain management techniques. The relationship between tocometry and VAS pain scores helps us better target pain therapies, which in turn improves patient outcomes.

It is important to recognize the limitations of this study in order to fully comprehend its scope and its consequences. First off, while the results of our analysis, which concentrated on the relationship between machine learning algorithms, are encouraging, more research with bigger datasets and more algorithms is necessary to improve the precision and resilience of uterine contraction prediction. Second, it's still difficult to distinguish between ECG waveform alterations brought on by pain and those brought on by physiological changes brought on by uterine contractions. Further investigation using PCA and comparison of ECG data prior to, during, and following contractions may provide light on this matter.

Conclusion

The study successfully leveraged machine learning algorithms to enhance the monitoring of labor discomfort associated with uterine contractions through the analysis of ECG waveforms. This innovative technique, which extends beyond labor pain, provides a precise and user-friendly approach for real-time pain monitoring across various clinical settings. The model's 90% accuracy in assessing pain is on par with other approaches currently in use, such as ANI or PMD-200. Subsequent investigations ought to examine its applicability to other demographics and categories of pain. By combining factual physiological data with subjective pain experiences, this approach represents a breakthrough in pain monitoring and has the potential to transform clinical procedures and improve patient outcomes.

Supplementary Information

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Supplementary Material 1.

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Authors' contributions

Conceptualization—Saint Shiou-Sheng Chen; Jui-Sheng SUN; Li-Kuei Chen. Data curation—Yuan-Chia Chu; Tzu-Kuei Shen; Li-Kuei Chen. Formal analysis—Yuan-Chia Chu; Tzu-Kuei Shen; Li-Kuei Chen. Funding acquisition—Yuan-Chia Chu; Saint Shiou-Sheng Chen; Li-Kuei Chen. Investigation—Saint Shiou-Sheng Chen; Jui-Sheng SUN; Li-Kuei Chen. Methodology—Yuan-Chia Chu; Tzu-Kuei Shen; Li-Kuei Chen. Project administration—Kuen-Bao Chen; Jui-Sheng SUN. Resources—Kuen-Bao Chen; Jui-Sheng SUN; Li-Kuei Chen. Software—Yuan-Chia Chu; Tzu-Kuei Shen. Supervision—Saint Shiou-Sheng Chen; Kuen-Bao Chen; Li-Kuei Chen. Validation—Yuan-Chia Chu; Tzu-Kuei Shen; Li-Kuei Chen. Visualization—Saint Shiou-Sheng Chen; Jui-Sheng SUN; Li-Kuei Chen. Roles/Writing—original draft—Yuan-Chia Chu; Saint Shiou-Sheng Chen; Li-Kuei Chen. Writing—review & editing—Saint Shiou-Sheng Chen; Kuen-Bao Chen; Li-Kuei Chen.

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Availability of data and materials
Upon reasonable request, the datasets created and/or analyzed for this study are made available. To obtain access, please contact Li-Kuei Chen via email at clk0619@ntu.edu.tw.

No datasets were generated or analysed during the current study.

Declarations

Competing interests
The authors declare no competing interests.

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