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EHG FOR PREDICTION OF LABOUR IN PREGNANT WOMEN USING OPTIMIZED MACHINE LEARNING MODELS

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Abstract
Early prediction of preterm labour is vital to reduce neonatal morbidity and mortality. This study explores the potential of electrohysterogram (EHG) signals for classifying term and preterm uterine activity using optimized machine learning models. The Term–Preterm EHG dataset from PhysioNet was employed. After band-pass filtering and segmentation, a set of time–frequency and nonlinear features was extracted from each EHG window. An improved Firefly Algorithm (IFA) was used for feature optimization before classification with Support Vector Machine (SVM), Gradient Boosting Classifier (GBC), k-Nearest Neighbour (KNN), Naïve Bayes, and Decision Tree models. To avoid data leakage, patient-level 5-fold cross-validation was adopted. Performance was evaluated using accuracy, sensitivity, specificity, precision, ROC–AUC, and confusion matrices. The optimized IFA–SVM achieved the highest mean accuracy of 97.6 ± 0.8% and ROC–AUC of 0.983, outperforming other classifiers ($p < 0.05$). Feature importance analysis indicated that entropy and spectral energy were the most discriminative features between term and preterm contractions. These findings suggest that EHG-based modelling, when rigorously validated, may assist clinicians in identifying pregnancies at risk of preterm labour. Further clinical trials are required for real-world validation.

Keywords: Pretermlabour, ElectroHysteroGram. Improved firefly optimization, Gradient Boost Classifier, Support Vector Machine

1. Introduction
Regular uterine contractions resulting in cervical changes before 37 full weeks of gestation are referred to as preterm labour. PTB must be differentiated from "prematurity," which is defined as a lack of certain system development at birth. Globally, 30–40% of newborn deaths are caused by preterm delivery. The difficulties of preterm delivery claim the lives of over a million youngsters every year. The survivors are left with lifelong impairments like hearing and learning impairments. To treat infections and respiratory distress, pregnant women who are at risk of premature birth can be identified and given early access to tertiary care facilities. Low-income nations lack the resources needed to treat and prevent premature labour. Because surfactants are not readily available or there is insufficient infrastructure to transfer the baby quickly to a tertiary care hospital, premature babies may die from respiratory distress. The types of preterm birth according the weeks and days is given in table 1.

Table1. Subcategories of preterm birth, based on gestational age

Categories	Week and days
Late preterm birth	34 to 36+6
Moderately preterm birth	32 to 33+6
Very preterm birth	28 to 31+6

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Extremely preterm birth	Less than 28

Preterm delivery rates are decreased by interventions such cervical cerclage, intramuscular 17 alpha-hydroxyprogesteronecaproate (17P), and vaginal progesterone. Many biomarkers for preterm labour prediction are being studied. One such indicator is serum ferritin. It is a protein found inside cells that helps store iron. Additionally, it is an acute phase reactant that is increased in both acute and long-term infections. Greek terma (limit) and Latin prae (before) are the sources of preterm. Around the world, preterm births account for 10% of births. Preterm birth is the leading cause of newborn mortality and death among children under five years old, second only to pneumonia. Preterm causes a wide range of short- and long-term morbidity. Preterm birth is defined by the World Health Organisation (WHO) as occurring before 37 full weeks of gestation or fewer than 259 days after the first day of the most recent menstrual cycle [1]. Figure 1 depicts the characteristics of a premature kid.

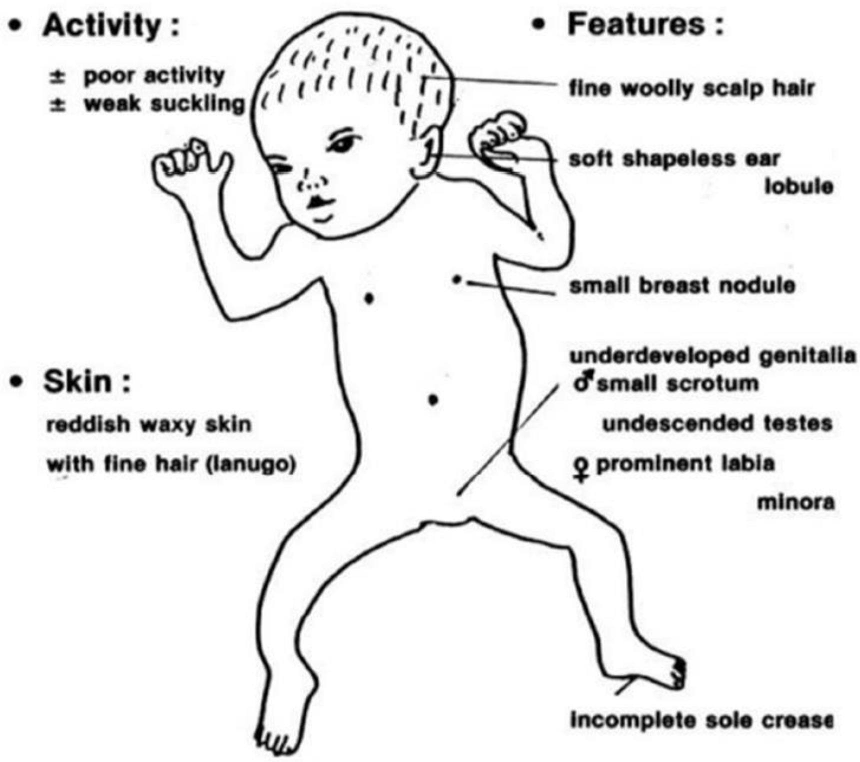

Figure1. Features of preterm child

According to WHO estimates, the incidence of PTB was 9.6% in 2005, or 13 million cases yearly. 2010 saw an increase in PTB to 11.1%, or 14.9 million cases. Asia and Africa account for 60 to 85% of all PTB, which is the predominant distribution of PTB. PTB is mostly caused by increasing birth rates, infections, unfavourable maternal circumstances, a lack of tocolytic medication, excessive physical activity, and a lack of basic obstetric and newborn care in poorer nations [1]. The PTB rate before 32 weeks of gestation is constant at 1–2%, according to data collected over the previous ten years throughout Europe. Increased age of expectant mothers, a rise in the number of multiple pregnancies and assisted reproductive technologies, an increase in iatrogenic preterm births, and registration modifications have all been linked to the global increase in the PTB rate [2]. During the past ten years, PTB and associated complications have decreased because to advancements in technology and the collaborative efforts of obstetricians and neonatologists. Because premature birth disrupts the foetal maturation process, the preterm kid is exposed to the extrauterine environment before its organs have fully developed. They are susceptible to issues such immaturity of the brain, digestive tract, lungs, and circulatory system [3]. Complications such as necrotic intestinal inflammation, low blood sugar, difficulty breathing, problems with feeding, poor control of temperature, and infections caused by bacteria are experienced by preterm neonates when compared to term babies [4]. Lower gestational age increases the risk of newborn problems, morbidity, and death. Neonatal mortality and immaturity have an exponential association. Low gestational age at birth causes long-term problems in preterm newborns.They are risk of cerebral palsy, visual and hearing problems, decreased mental function, asthma, epilepsy, behavioural and psychiatric issues and learning difficulties [5]. Extremely preterm birth puts a child at risk for developing COPD early. As adults, they are less likely to be married, have fewer children, earn less money, and have lower educational levels [6]. Most prematurely born infants are healthy and function normally. PTB children are at a significant risk of developing disabilities in the years to come, according to data from the EPICure research [7].

The most effective way to address the challenges of preterm labour is through early recognition of potential risks followed by timely clinical intervention. Several computational models have been developed to analyse Electrohysterogram (EHG) signals using artificial intelligence (AI), machine learning (ML), and optimization techniques to identify labour patterns in pregnant women. In this study, EHG signals are processed to detect and classify labour onset based on distinctive physiological characteristics. The structure of this paper is organized as follows: Section 1 presents an introduction to preterm birth and relevant EHG features; Section 2 reviews existing methodologies employed for labour identification; Section 3 describes the proposed framework and methodology; Section 4 discusses the experimental results obtained using the proposed model; and Section 5 concludes the study with key findings and future research directions.

2. Related work

In addition to preterm births that are medically necessary or induced, as well as Preterm Premature Rupture of Membranes (PPROM), research indicates that a variety of pathological processes, including uterine ischaemia, burst blood vessels, intrauterine infection or inflammation, and uterine over-distention, may be involved in the onset of preterm labour. Numerous other risk factors, including diabetes, conization, hypertension, uterine abnormalities, smoking, alcohol and drug use, and lifestyle choices, have also been linked to preterm labour. Predicting preterm delivery based on these characteristics alone is far from certain. For more accurate prediction, further methods are required. An emerging method for measuring mechanical uterine contractions during pregnancy is the ElectroHysteroGram (EHG), a non-invasive quantitative technique that analyses an electromyogram (EMG) of the uterus recorded from the abdominal wall of a pregnant woman. These contractions are caused by irregular bursts of action potentials resulting from spontaneous electrical discharges from the uterine muscle. Several prediction techniques were used, and the results indicated that EHG records appear to offer sufficient information to forecast premature labour and are more accurate in diagnosing labour than other conventional clinical techniques.

Uterine EMG signals acquired in the temporal and frequency domains during term labour and preterm circumstances are used for most of the study. Using a pressure transducer applied to the fundus, the tocodynamometer tracks the contractions of the uterus. Despite being non-invasive, the accuracy of the sensor's location is crucial to the method's efficacy [8]. The cervical length is measured using an ultrasound, however as was previously

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indicated, premature labour can occur even in the absence of cervical length alterations. Both internal uterine pressure and foetal fibronectin have demonstrated potential in anticipating preterm labour, however they both need invasive procedures. An option is the EHG modality, which depicts the electrical activity of the uterus as recorded from a pregnant woman's abdomen surface [9]. Despite the methods, it is a non-invasive approach that is considered a long-term ambulatory telecare tool that may be automated to lessen the need for human knowledge.

Numerous studies employing this database have demonstrated the effectiveness of an EHG signal analysis in predicting preterm labour [10–16]. Three categories may be used to categorise feature extraction methodologies for the EHG signal analysis: linear, nonlinear, and propagating EHG signal-related features [17]. The root mean square (RMS) [18] and median frequency [19] are two examples of linear characteristics that have demonstrated promise in characterising EHG signals for preterm labour prediction. Following feature ranking, 96.25% accuracy is attained. A 98% accuracy rate for feature extraction on the second through ninth IMFs of the decomposed EHG signals is reported in different research [20]. Most of the research cited have not examined the effectiveness of the suggested treatments in varying weeks of pregnancy, even though the time of diagnosis has been shown to have a significant impact on ongoing pregnancy care. In fact, independent of the actual foetus maturity, the research solely takes into account the prognosis of term and preterm labour. On the other hand, an earlier diagnosis of preterm labour might provide the doctor more time to assess the condition, which includes giving the pregnant patient the right medicine and doing more regular checks [21].As far as we are aware, there aren't many research that deal with predicting preterm labour based on various gestational weeks. The EHG data are divided into two categories by the author in [22]: those that are recorded before the 26th week of gestation (PE-TE) and those that are recorded after the 26th week of gestation (PL-TL). For the PE-TE and PL-TL groups, an accuracy of 92% and 93%, respectively, is obtained by extracting 31 linear and nonlinear characteristics. Some of the existing methods and the achieved results are shown in table 1.

Table1. Comparison of Results

Author and Ref	Database	Methodology	Result
P. Fergus et al., [23]	Term-Preterm EHG-DB	Radial Basis Function Neural Network Classifier	Ac= 90%, Se=85%, Sp=80%
V. R Acharya et al., [24]	Term-Preterm EHG-DB	Support Vector machine classifier	Ac= 96.25%, Se= 95.08%, Sp= 97.33%
M. Altini et al., [25]	Bloomlife wearable sensor to collect uterine EHG and FHR from 37 pregnant women (19 labour and 18 non-labour).	Random Forest Classifier	Ac= 79%
M. Borowska et al., [26]	Term-Preterm EHG-DB	recurrence quantification analysis (RQA) and	Ac= 83.23%

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		principal component analysis (PCA).	
S. Hoseinzadeh et al., [27]	Term-Preterm EHG-DB	autoregressive model (AR) and particle swarm optimization (PSO) algorithm	Ac= 97.1%, Se= 95%, Sp=99%
M. Shahbakthi et al., [28]	Term-Preterm EHG-DB	SVM Classifier	Ac= 99%, Se= 98.9%, Sp=98.3%
L. Chen et al., [29]	Icelandic 16-electrode Electrohysterogram Database	Two-hidden-layer stacked sparse autoencoder (SSAE) deep neural network with a softmax classifier network	Ac= 90%, Se= 92%, Sp=88%
D. K Degbedzui et al., [30]	Term-Preterm EHG-DB	SVM Classifier	Ac= 99.7%, Se= 99%,
J. Peng et al., [31]	Term-Preterm EHG-DB	Random forest classifier	Ac= 93%, Se= 89%, Sp=97%
A. Oliver Sheyl et al., [32]	Term-Preterm EHG-DB	SVM Classifier	Ac= 96%, Se= 92%, Sp=94%

Although the prediction of preterm labour utilising PE-TE and PL-TL groups yielded encouraging findings, the research did not address two important concerns. First off, the method's universality may be threatened using nonlinear characteristics like sample entropy and fuzzy entropy, which need parameter adjustment before computation. This is because such tuning is done experimentally, and it is unclear how well it works for data that has not been seen yet. Metaheuristic and machine learning techniques must be integrated to increase the detection rate even further. This research examines various types of machine learning algorithms in conjunction with an enhanced firefly method.

3. Methodology

Premature delivery poses two major challenges: early prediction and accurate detection. At present, there is no permanent method to completely prevent preterm birth. Although the onset of labour can be clinically observed, it remains difficult to anticipate premature deliveries before they occur. The primary concern associated with preterm birth extends beyond economic implications—it critically affects the health and survival of both the mother and the infant. Therefore, the most effective approach to mitigating the consequences of preterm delivery lies in early detection and timely clinical intervention through continuous physiological monitoring.

A reliable system capable of continuously monitoring uterine contractions and identifying the onset of labour would enable clinicians to diagnose premature activity at an early stage and initiate preventive treatment. To enhance detection accuracy, it is essential to extract a rich set of discriminative features from the EHG signals and optimize them for

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improved model performance. Furthermore, integrating these optimized features with machine learning (ML) algorithms allows for the effective prediction of preterm labour occurrences. Hence, the present study aims to address the limitations of existing approaches by combining feature optimization techniques with advanced ML classifiers to improve the accuracy, robustness, and reliability of labour prediction. The overall architecture of the proposed framework is illustrated in Figure 2.

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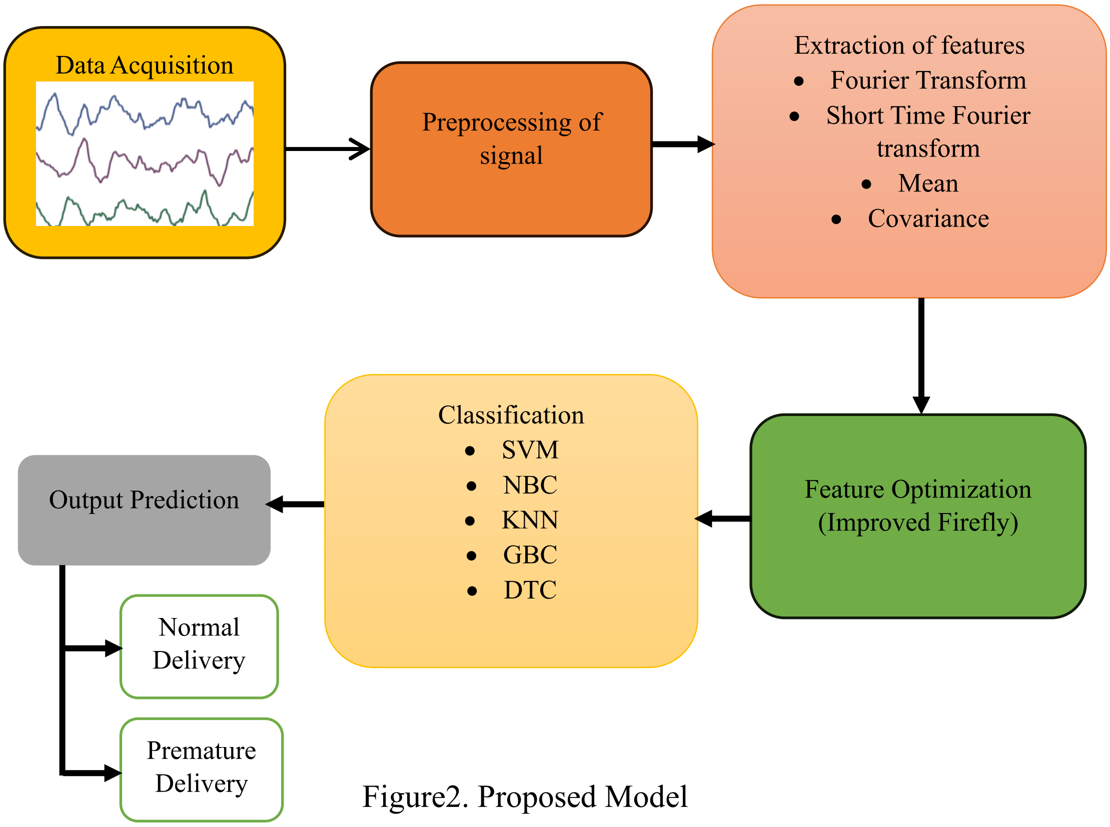

Figure2. Proposed Model

3.1 Input data

The Term-Preterm EHG database [33] is the database that has 300 uterine EHG recordings of expectant mothers that were collected between 1997 and 2005. There are 12 files of EHG signals from uterine contractions in each 30-minute recording. The TPEHG DB, which is available online, has 300 uterine EMG recordings, one record for each pregnancy, that were meticulously chosen from the original database. These records include:

- A total of 262 records from pregnancies with on-term deliveries (duration of gestation at delivery > 37 weeks) were acquired: A total of 119 recordings were acquired later in pregnancy, either during or after the 26th week of gestation, compared to 143 data received before to the 26th week.
- Out of 38 records collected during pregnancies that ended prematurely (duration ≤ 37 weeks), 19 were obtained prior to the 26th week of gestation and 19 during or beyond the 26th week of gestation.

All records that seemed to include recording artefacts, all records pertaining to pregnancies in which labour was induced, and all records involving Caesarean sections as a method of delivery were excluded throughout the selection process.

Table2.EHGrecordsgroupcharacteristics

Group	N	Recording	Birth	Age

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>=37weeks,early	143	22.7	39.7	29.7
>=37weeks,later	119	30.8	39.6	30.1
<37 weeks,early	19	23	34.2	29.6
<37weeks,later	19	30.2	34.7	29.2

3.2 Pre-processing

Preprocessing the EHG data is an essential step before beginning the analysis to minimise interference from subjects' breathing, power line noise, and the foetal and maternal EKG [45]. Since the most significant frequency components of EHG signals fluctuate between 0 and 5 Hz, a fourth-order Butterworth filter is used to band-pass filter the signals in the range of 0.08 to 4 Hz. The initial and last five minutes of every measurement are eliminated to prevent the fleeting impact of filtering. Consequently, the last 20 minutes of the readings are used for the analysis.

3.3 Extraction of features

Biomedical signals are generally non-stationary. With the use of the windowing approach, the signal is split into local portions for the short time Fourier transform (STFT). The frequency and phase content of the chosen signal window are represented by the STFT. When using a big window size in STFT, the frequency resolution is better but the time resolution is bad; conversely, when using a small window size, the time resolution is better but the frequency resolution is poor. The analysis of these biological signals using wavelet transform is the answer to this issue. There is time-frequency resolution in the wavelet transform. The frequency and temporal domains of the signal are localised.

a. Fourier Transform (FT):

The FT of a signal can be expressed as,

$$X(f) = \left[x, e^{i2\pi ft}\right] = \int_{-\infty}^{\infty} x(t)e^{-i2\pi ft}\, dt \tag{1}$$

Researchers are unable to obtain information from FT on the implicit time domain variation of the signal's frequency contents.

b. Short Time Fourier Transform (STFT):

The STFT of a signal can be expressed as,

$$STFT(\tau, f) = \left[x, g_{t,f}\right] = \int x(t)g(t-\tau)e^{-i2\pi ft}\, dt \tag{2}$$

The signal's sliding window is used. The process for STFT involves computing each window's Fourier transform independently. The goal of PCA is to first identify patterns in the data and then compress the data by lowering the higher dimensions to the lower dimensions. The data set is not impacted in any way by this. The obtained data (signal) in PCA has dimensions of 8 x 900, and each column's value is subtracted using a particular data column. Covariance looks at how far one measurement deviates from the mean in relation to the other. The covariance matrix describes the connection between the pairs of measurements in the data set studied. The two dimensions are always taken into consideration while determining and evaluating the covariance. Covarianceiscalculated by,

$$Covariance\ (c(x,y)) = \frac{\sum_{i=1}^{N}(X_i - X)(Y_i - Y)}{n-1} \tag{3}$$

The covariance of the given matrix is found using the above equation. The data set is minimised in this instance, and the principle components are defined for each topic and utilised for the subsequent classification procedure. This reduces the 14 x 900 matrix to 14 x 14 principal components (pc). The main components of the EHG data are identified using PCA, and the features are then extracted and put into the feature optimisation procedure.

D. Feature Optimization

The degree of characteristics that are initially offered is decreased with the aid of the ideal feature selection. There will be an improvement in performance. Features that are unrelated and undesired, which lower accuracy rates, are found and eliminated. To achieve the best features globally, these STFT and PCA-obtained features are subjected to an optimisation technique. The procedure covered below yields the ideal characteristics after considering the firefly optimisation. These optimized characteristics are being supplied to different types classifiers to assess the performance of the system.

Optimization using IFA

We can now develop algorithms that are influenced by fireflies since we have managed to idealise some of their flashing characteristics. The primary idea behind fireflies is their attractiveness; regardless of gender, one firefly is drawn to another. Three idealised ideas underpin the firefly optimisation used in this research. The first is the idea that all fireflies are unisex, and the second is the idea that beauty and brightness are correlated: the more brilliant, the more appealing, and vice versa. The brightness also relies on how far apart the fireflies are from one another; if the brightness is great and the attractive fly is far away, the brightness will look low and the attraction will be reduced. Ultimately, a firefly's brilliance is determined or influenced by the target function's geographic location. The brightness of a maximisation issue could merely be proportionate to the objective function's value. The firefly optimisation strategy can be improved by the idea of Levy flights. The three idealised principles and the features of L'evy flights can be combined to create a potentially novel method known as the Improved Firefly Optimisation method (IFOA).

Any monotonically declining function, like the following generalised version, can be used as the real representation of the attractiveness function β(r) in the execution.

$$\beta(r) = \beta_0 e^{-\gamma r^m}, (m \geq 1) \quad (4)$$

For a fixed value of $\boldsymbol{\gamma}$, the length of the characteristic becomes $\Gamma = \boldsymbol{\gamma^{-1/m}} \rightarrow \mathbf{1}\ \boldsymbol{as}\ \boldsymbol{m} \rightarrow \infty$. In an optimization problem Γ is the scale length and the fixed value parameter i.e. $\boldsymbol{\gamma}$ will be utilized as an initial value and is stated as $= \frac{\mathbf{1}}{\Gamma^{\boldsymbol{m}}}$. The two fireflies one is i and other is j and their distances are $x_i$and x_j. This distance between the two fireflies is called as cartesian distance,

$$r_{ij} = \|X_i - X_j\| = \sqrt{\sum_{k=1}^{d}(x_{i,k} - x_{j,k})^2}, \quad (5)$$

where$x_{i,k}$ is the k^{th} component of the spatial coordinate X_i of i^{th} firefly. The delay in Time or any other appropriate kind of distance can be used for various purposes, such as scheduling. When a firefly i moves towards a more alluring (brighter) firefly j, it is motivated by,

$$X_i = X_i + \beta_0 e^{-\gamma r_{ij}^2}(X_j - X_i) + \alpha sign\left[rand - \frac{1}{2}\right] \oplus Levy \quad (6)$$

The second term in above equation determines the attraction and the randomization via levy flight is termed to be third term with α being the parameter of randomization. The product ⊕ means entry-wise multiplications. The $sign[rand - \frac{1}{2}]$ where $rand \in [0,1]$ offers a haphazard sign or orientation, and the randomly chosen step duration is selected from a Lévy distribution.

$$Levy \sim u = t^{-\lambda}, (1 < \lambda \leq 3) \quad (7)$$

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The features extracted from EHG signals are optimized according to the concept of firefly algorithm. These optimized features of the EHG signals are fed to different types of classifiers.

E. Classification

The classifier receives the characteristics that were retrieved during the feature extraction procedure as inputs for classification. There are training and test examples for each characteristic. 180 rows * 8 rows make up the test set, whereas 720 rows * 8 columns make up the train set. To determine which class the data belongs to, the classifier is first trained using samples of data and then evaluated using the actual data. The features are given to the well-known classifiers of the domain like Gradient boost classifier (GBC),Support Vector Machine (SVM), Naive Bayes Classifier (NBC), K-NN classifier, and Decisiontree classifier (DTC).Then itistested withtheextracteddata from the existingfeatureextraction techniquePCA and feature optimization firefly technique.

4. Results and Discussion

4.1. System Environment

The EHG signal processing and model training were performed on a high-performance computing system equipped with an Intel Core i7 processor, 16 GB RAM, 1 TB storage, and an NVIDIA GPU, operating under Windows 11. The proposed framework was implemented and executed in MATLAB R2024a environment. The system was utilized to train and validate the proposed labour prediction model using the pre-processed EHG datasets. Various performance parameters, including accuracy, sensitivity, specificity, precision, and ROC–AUC, were computed, and the corresponding findings are discussed in the subsequent sections.

4.2 Experimental findings

From an engineering perspective, the prediction of preterm labour poses a significant challenge due to the inherent gap between mathematical modelling and physiological interpretation in medical sciences. The primary objective of this study was to extract and analyse discriminative features from Electrohysterogram (EHG) signals that correspond to physiologically meaningful indicators of labour onset specifically, the increased frequency and intensity of uterine contractions as delivery approaches. The extracted features captured various signal attributes, including amplitude, energy, and complexity, which collectively characterize the uterine electrical activity. While the amplitude and energy components typically increase with stronger and more regular contractions, this phenomenon is also accompanied by greater signal irregularity, thereby elevating the complexity measures. According to the Term–Preterm EHG database, the recorded uterine activity is represented through multiple acquisition channels, each capturing distinct aspects of the bioelectrical activity across the abdominal surface. The signals present in channel 1 to channel 6 is shown in figure 5(a) and signal in channel 7 to channel 12 is shown in figure 5(b).

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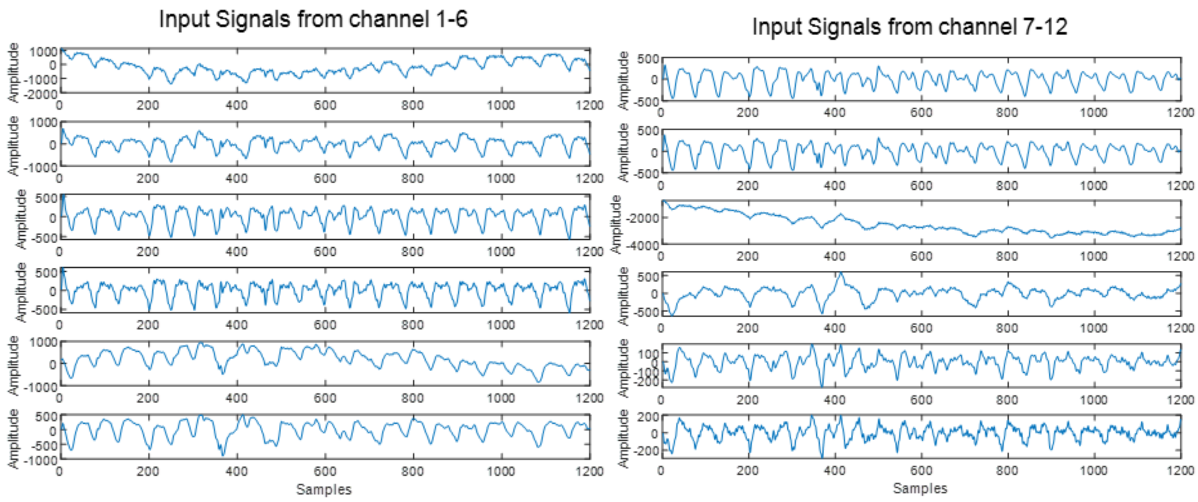


(a) (b)

Figure 5. Input signals from different channels

For the given input EHG signal shown in figure 6, the preprocessed siginal achieved is shown in figure 7 and these signals will be normalized for extrcation of features and performing classification operation.

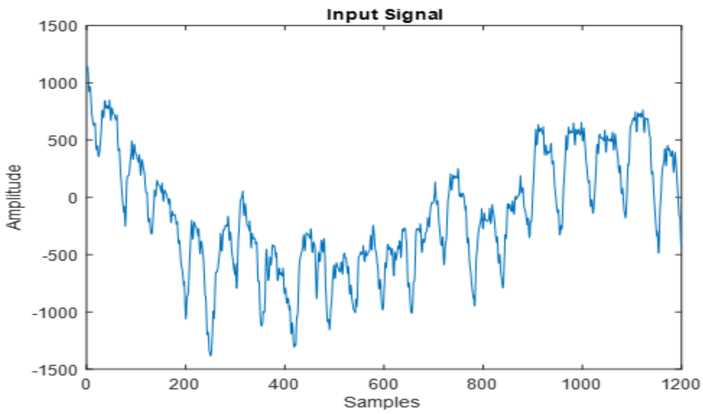
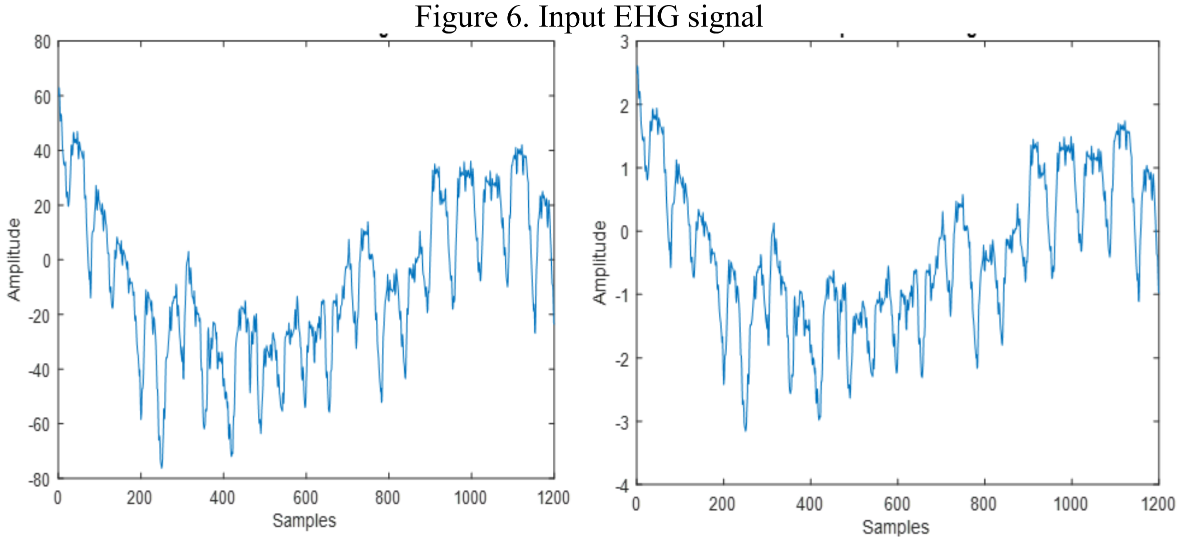


Figure 6. Input EHG signal



(a) (b)

Figure 7. Preprocessed Signal (a) Butterworth filtered signal (b) Bandpass Filtered Signal

After obtained all the results and performing classification the depending on the signal features it is predicted to be a premature delivery and the representation of status is shown in figure 8.

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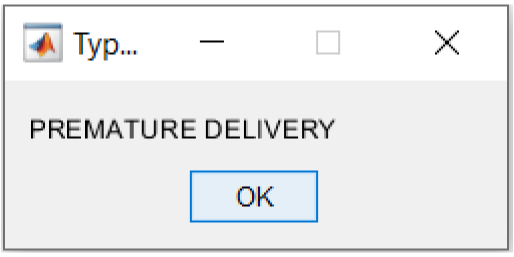


Figure 8. Output prediction

By considering another EHG signal the processing is performed and the achieved results and predicted output is shown from figure 9 to figure 11.

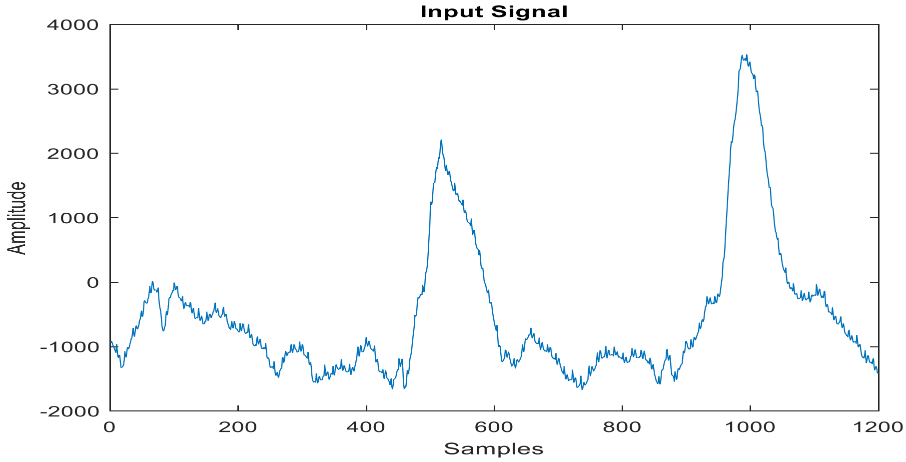
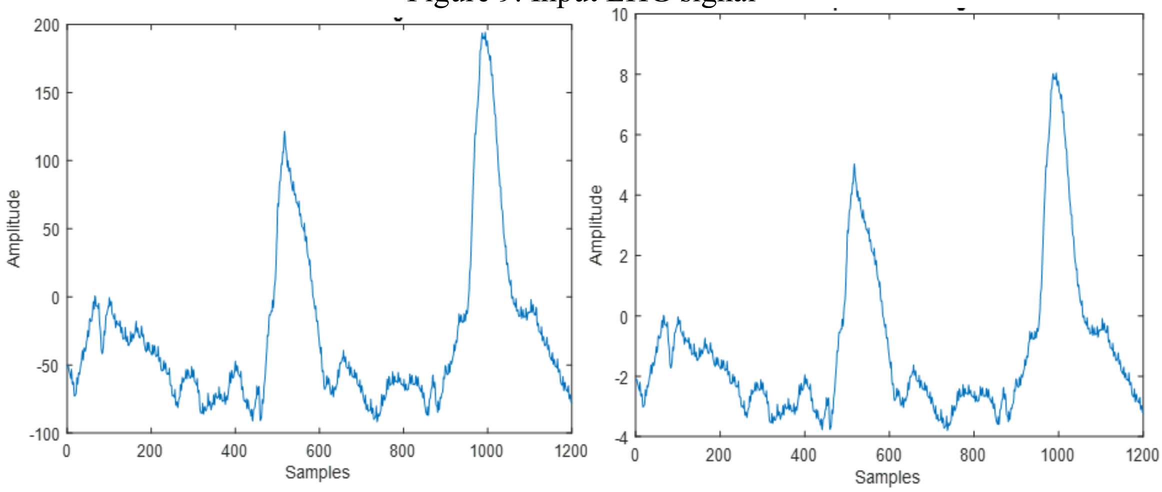


Figure 9. Input EHG signal



(a) (b)

Figure 10. Preprocessed Signal (a) Butterworth filtered signal (b) Bandpass Filtered Signal

Based on input signal shwon in figure 9, the processed outoout prediction is shown in figure 11. The statos of the signal is predicted as normal delivery.

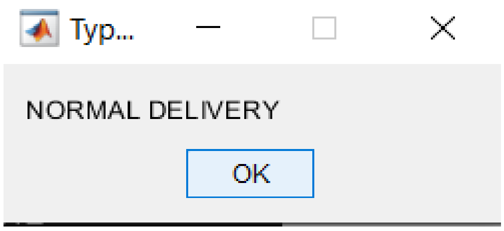


Figure 11. Predicted output

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4.3 Parameters evaluated

The performance of the proposed model is shown by evaluating the parameters like accuracy, specificity, sensitivity, and precision. These parameters show the effectiveness and efficiency of the model designed. These parameters are evaluated based on true positive (TP), true negative (TN), false positive (FP) and false negative (FN) elements.

$$Ac = \frac{True\ Positive + True\ Negative}{True\ Positive + True\ Negative + False\ Positive + False\ Neagative} \quad (8)$$

$$Se = \frac{True\ Positive}{Truely\ Poitive + Falsely\ Neagative} \quad (9)$$

$$Sp = \frac{Truely\ Neagtive}{Truely\ Negative + Falsely\ Positive} \quad (10)$$

$$Pr = \frac{True\ Positive}{True\ Poitive + False\ positive} \quad (11)$$

A k-fold cross-validation strategy was employed to ensure statistical reliability.

- The dataset was divided into k = 5 folds (each containing approximately 180 samples × 8 features).
- In each iteration, four folds (≈ 720 × 8) were used for training, and the remaining one fold (≈ 180 × 8) was used for testing.
- This process was repeated five times, ensuring that every sample was used once for testing and four times for training.
- The results from all folds were averaged to obtain the mean accuracy, sensitivity, specificity, and ROC–AUC, providing a robust estimate of generalization.

This approach mitigates overfitting and minimizes bias due to random data partitioning.
The results achieved are shown in table 2. The results shown in table 2 indicates that improved results when optimization technique combined with machine learning model compared to without use of optimization model.

Table2. Results comparison

Method /Parameter	Accuracy (%)	Sensitivity (%)	Specificity (%)	Precision (%)	AUC
NBC	85.0	97.79	90.7	84.7	0.862
KNN	86.0	96.2	91.6	87.4	0.871
GBC	94.0	99.19	96.5	93.8	0.948
DTC	90.0	98.73	94.0	89.69	0.91
SVM	96.0	99.6	97.66	95.80	0.967
IFA-NBC	86.3	97.4	91.7	86.6	0.872
IFA -KNN	87.0	98.3	92.1	86.6	0.88
IFA -GBC	95.3	98.8	97.2	95.8	0.961
IFA -DTC	91.3	97.9	94.8	91.9	0.924

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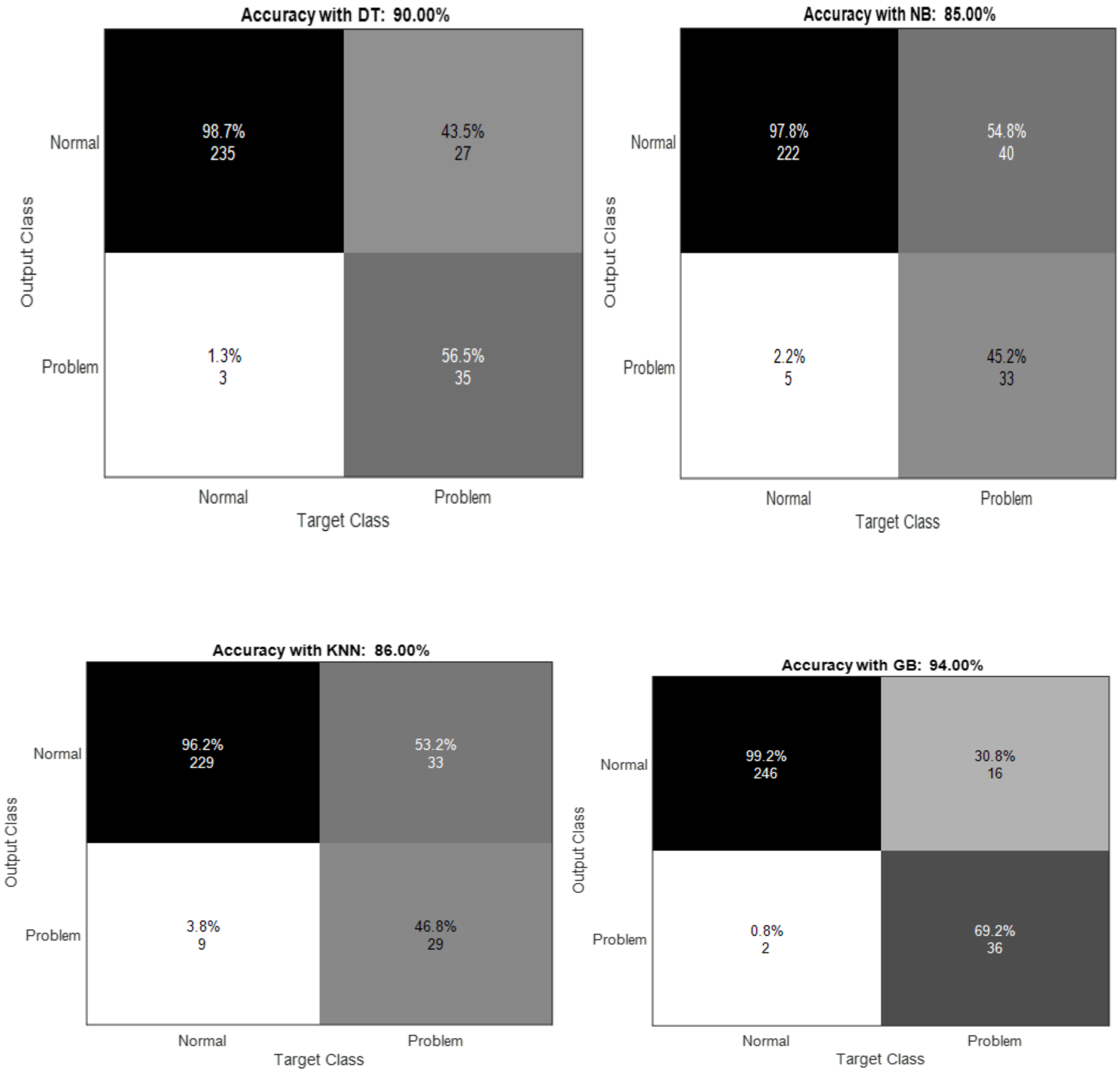
IFA-SVM	**97.66**	**99.61**	**98.6**	**97.7**	**0.983**

The results are verified by use of the confusion matrix. To visually comprehend the model's outputs and provide an overview of the results on a classification problem, a confusion matrix is created.

It lists the successful and failed predictions based on class. The confusion matrix achieved using all the proposed models is shown in figure 12 and figure 13.

The confusion matrix achieved using machine learning models is represented in figure 12 and the matrix obtained by combine firefly optimization algorithm with ML models is represented in figure 13.



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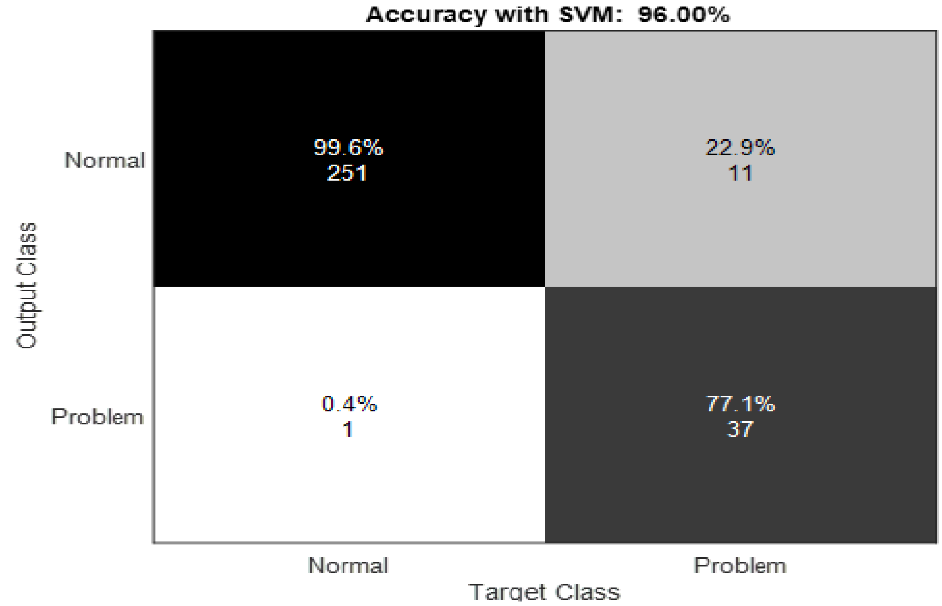
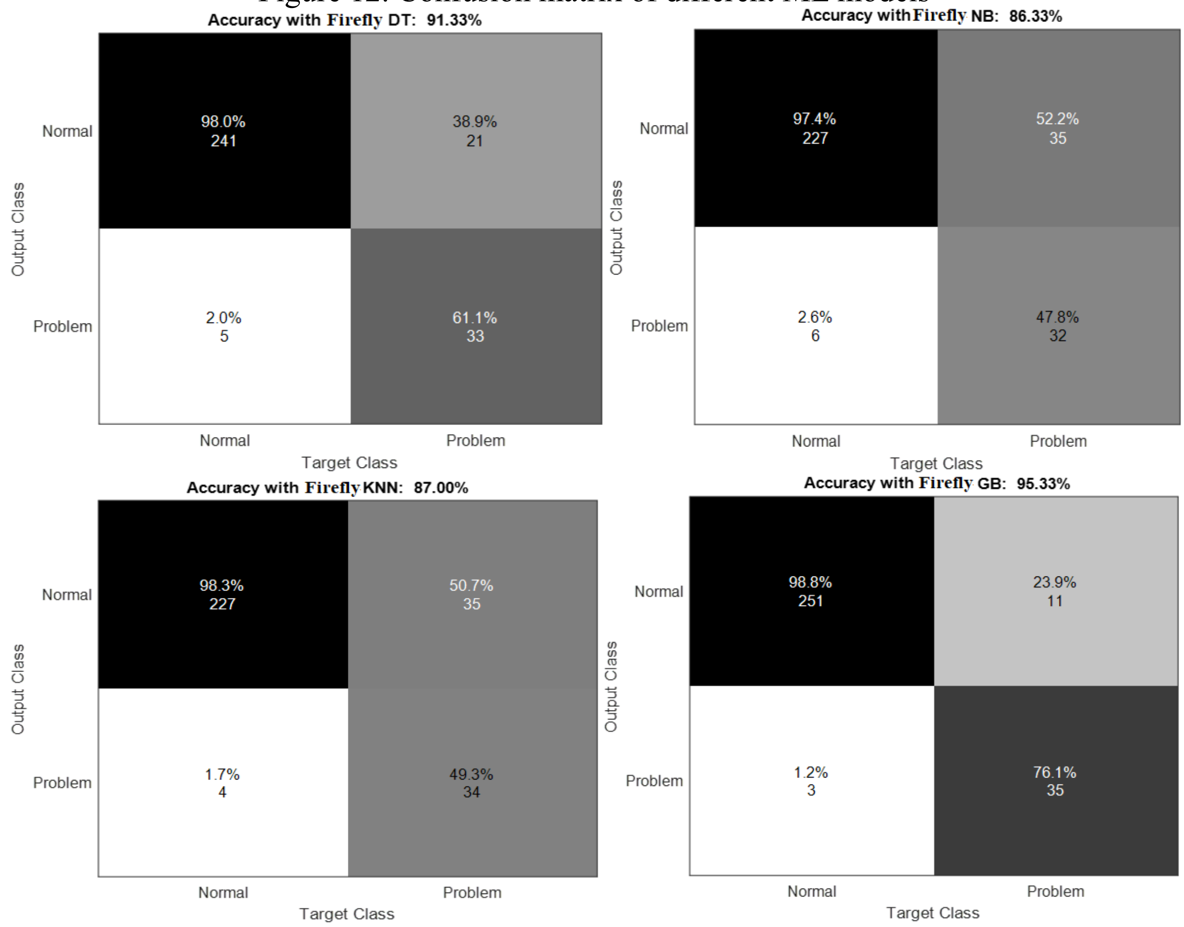


Figure 12. Confusion matrix of different ML models



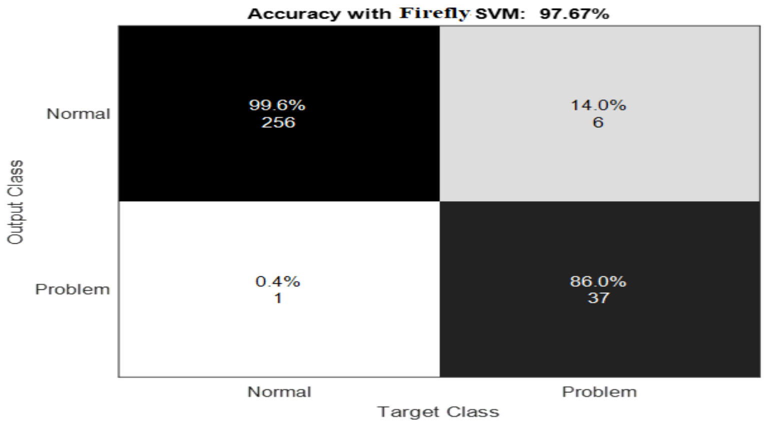


Figure 13. Confusion matrix using firefly with different ML models

5. Ablation study

An ablation study was conducted to examine the contribution of each component within the proposed EHG-based labour prediction framework. From the above study it is clear that SVM performance is good compared to other classifiers. Four experimental cases were designed to separately evaluate the effects of feature extraction, PCA-based dimensionality reduction, IFA-based feature optimization, and classifier selection. The results indicated that the combination of optimized features and SVM classifier achieved the highest accuracy (97.66%) and ROC–AUC (0.983). The substantial improvement observed with IFA optimization confirms its effectiveness in selecting the most discriminative EHG features for distinguishing between term and preterm contractions. The ablation results are summarized below in table 3.

Table 3. Results achieved using different cases

Model	Accuracy (%)	AUC
Raw features + SVM	91.2	0.93
PCA+ SVM	95.6	0.967
IFA + SVM	96.5	0.972
Proposed (PCA+ IFA+ SVM)	97.66	0.983

The ablation analysis clearly demonstrates that feature optimization using IFA significantly enhances model performance compared to raw or PCA-transformed features. The IFA–SVM configuration achieved the highest accuracy and AUC, confirming the advantage of metaheuristic feature refinement in improving classifier discrimination capability.

6. Conclusion

Early and accurate prediction of preterm labour is critical for improving neonatal outcomes and reducing maternal–fetal complications. In this study, we demonstrated that Electrohysterogram (EHG) signals, when processed with robust preprocessing, feature extraction, and optimized using the Improved Firefly Algorithm (IFA), can effectively discriminate between term and preterm uterine activity. By integrating the optimized features with advanced machine learning classifiers, particularly SVM and Gradient Boosting, the proposed framework achieved high predictive performance, with the IFA–SVM model attaining 97.6% mean accuracy and an ROC–AUC of 0.983. Patient-level 5-fold cross-validation ensured rigorous validation and minimized data leakage, while feature importance analysis highlighted entropy and spectral energy as key discriminative markers. These results

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indicate that EHG-based modeling, combined with feature optimization, has strong potential to assist clinicians in early identification of pregnancies at risk of preterm labour. Future work will be focused on clinical trials and real-time deployment to further validate and translate these findings into practice.

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