Research Article

Detection of Preterm Labor from Electrohysterogram (EHG) Data Using Empirical Wavelet Transform-Based Machine Learning Methods

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Abstract— **Accurate early prediction of preterm labor can significantly reduce birth complications for both mother and baby. This situation increases the need for an effective technique in early diagnosis. Therefore, machine learning methods and techniques used on Electrohysterogram data are increasing day by day. The aim of this study is to evaluate the effectiveness of the Empirical Wavelet Transform approach on Electrohysterogram data and to propose an algorithm for early prediction of preterm labor using single Electrohysterogram signal. The data used in the study were taken from Physionet's Term-Preterm Electrohysterogram Database and scored in one-minute windows. The feature matrix was obtained by calculating the sample entropy value from each of the discretized Electrohysterogram modes obtained as a result of this method, which was used for the first time on Electrohysterogram data, and the average energy value from the signal obtained by recombining the modes. The obtained features were applied to Random Forest, Support Vector Machine, Long Short-Term Memory algorithms to predict preterm birth. Among the classifier algorithms, the Random Forest algorithm achieved the best result with a success rate of 98.20%.**

Index Terms— **Classification, Electrohysterogram, Empirical Wavelet Transform, Preterm Birth.**

I. INTRODUCTION

THE AVERAGE gestation period in humans is between 37-42 weeks. Births occurring between these weeks are called term births. Births after 42 weeks are called late births. Births ending between 24-37 weeks are called Preterm births. Preterm birth is one of the leading causes of infant mortality and can have long-term negative consequences. Therefore, accurate and early diagnosis is very important [1-3]. Accurate diagnosis of preterm labor is one of the most important problems faced by obstetricians [4]. Many methods have been researched and tried to detect preterm birth. Commonly used methods; tocodynamometer device, Transvaginal Cervix Length measurement, Bishop Score and Electrohysterogram (EHG) signal. Tocodynamometer is the recording of uterine contractions and baby movements. It measures the contractions that occur on the uterine surface. Transvaginal Cervix length can be measured with the help of ultrasound. The shorter the length, the higher the risk of preterm delivery. The Bishop score is calculated from many values such as the amount of expansion of the pelvis, the rate of shortening of the uterus, its location and condition. The higher the Bishop Score, the higher the probability of normal delivery. All these methods have been used for preterm birth detection [5]. The other method is to examine the EHG signals recorded with the electrodes on the outer surface of the uterus. EHG signals for preterm birth detection give more applicable and reliable results compared to other methods applied. These signals are one of the most important sources of information for the prediction of preterm labor. Electrodes are placed at specific points on the uterine surface to record the signals. Electromyogram (EMG) signals are recorded from the uterus at different times of pregnancy or at the time of delivery [6]. EMG signals are not stationary signals, so the signals are difficult to distinguish visually. Due to such complex feature of EMG signals, it is possible to distinguish between preterm birth or term birth by determining various features with machine learning methods 7].

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Many studies in the literature have used EHG signals to distinguish between term and preterm birth. From studies using the Term-Preterm EHG Database, Shahrdad et al. [8] presented a new approach to estimating the risk of preterm labor by analyzing EHG signals and classifying term/preterm signal recordings. EHG signals are divided into windows and linear predictive coding technique is applied to extract features from each window. The data were analyzed in 5 different clusters, and term and preterm deliveries detected before the twenty-sixth gestational week were classified with the highest accuracy (100%). Fergus et al. [9] used radial basis function neural network and random neural network classifiers in their study. As a result of the filtered and single channel (0.34–1 Hz filter on Channel 3) study, they reached 91% sensitivity. In the study by Vinothini et al. [10], EHG signals recorded before the twenty-sixth week of pregnancy were analyzed using topology-based shape features to distinguish between term and preterm states during early pregnancy. The signals were passed through the discrete Fourier transform. As a result of classification using Naive Bayes (NB), Decision Tree (DT) and Random Forest (RF) algorithms, a success rate of 98.6% was achieved with the RF algorithm. Far SM et al. In the study by [11], a single channel EHG signal was divided into two modes using Empirical Mode Decomposition (EMD) and sample entropy, Root Mean Square (RMS) and mean teager–kaiser energy values were calculated. In total, six features were extracted from each channel. Data were scored in one minute windows and 0.08-4 Hz. passed through a band pass filter. Three classifier performances were evaluated; K-Nearest Neighbor (KNN), Support Vector Machine (SVM) and DT. As a result of the term and preterm classification, they reached a success rate of 99,7% with the SVM algorithm. In the study by Lou et al. [12], they used entropy features extracted from time-frequency expansion. These entropy properties were then rescaled for gestational age to characterize the rate at which the uterus evolves towards birth. By using the Gaussian Naive Bayes (GNB) classifier, Principal Components Analysis (PCA), the relevant frequency components were selected, trained with samples prepared under the division-synthesis high sampling scheme, and a success rate of 75% was achieved. Huseyin et al. [13] achieved 90% accuracy using the neural network immunity algorithm. They argued that the proposed Dynamic Self-organized Network Inspired by the Immune Algorithm (DSIA) model performs well and that supervised and unsupervised learning techniques can be associated with the DSIA model. In their study, Xu et al. [14] evaluated studies in the literature addressing barriers to EHG signal analysis and machine learning algorithms. They stated that RMS and power spectrum are candidates for measuring changes in EHG signal and are frequently used in related studies. They stated that the approximate entropy and sample entropy values did not show very satisfactory results due to the interference of different noisy sources in the recorded EHG signal. Similarly, Lyapunov exponent, linear/non-linear correlation etc. They also stated that attempts to introduce new sizes such as They noted that when EHG signals were recorded long before birth, the signal-to-noise ratio was lower. They argued that recent research has focused on the classification of contractions during pregnancy rather than directly predicting preterm labor. Nsugbe et al. [15] used Linear Series Decomposition Learner (LSDL) to predict preterm birth from EHG and tocodynamometer signals in his study. It used two different classifier algorithms. By using LSDL, they determined that less storage space is needed for data and achieved a success rate close to 100%. They noted that the EHG signal is attenuated before it reaches the surface and recording instrumentation, and the tocodynamometer signal provides better accuracy for classifiers. The study by Dine et al. [16] used data from 57 women at the University Hospital Landspitali and 79 women at the Center for Obstetrics and Gynecology. In this study, it was aimed to improve and compare the classification between labor and pregnancy contractions. They investigated the effect of graphic parameters in characterizing the evolution of the uterine connection from pregnancy to delivery and distinguishing between pregnancy and labor contractions. They examined the performance of different classification methods from the classifier algorithms (Artificial neural network (ANN), SVM, RF, Recurrent Neural Network (RNN), Long Short-Term Memory (LSTM)) and reached a success rate of 94.46% with the RF algorithm.

In our study, algorithm is proposed in which the effectiveness of the Empirical Wavelet Transform (EWT) approach is also evaluated to predict preterm labor from a single EHG channel. At the same time, machine learning method has been tried to be adopted to classify the data without the need for feature reduction algorithms. The second section of the manuscript includes methods and techniques, the third section includes the results, and the fourth section includes the discussion section where our study is compared with studies in the literature.

II. Materials and Methods

A. The Proposed Method

The block diagram of the proposed method is shown in Figure 1. After EHG data was recorded, the data were divided into one-minute windows. Each window data is separated into 5 modes with the EWT approach. The feature matrix was obtained by calculating the sample entropy value from each mode and the average energy value from the signal obtained by recombining the modes. The obtained feature matrix was given as input to the classifier algorithms and term/preterm classification was made.

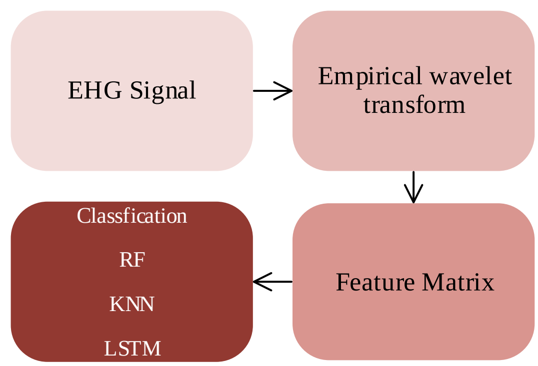

Fig.1. Flow chart of the proposed method

B. Dataset

EHG records in Physionet's Term-Preterm Electrohysterogram Database (TPEHGDB) were obtained from Ljubljana University Medical Center between 1997-2005. There are 300 EHG records, of which 262 are term and 38 are preterm deliveries. These records were divided into two groups according to the weeks of gestation as 143 term and 19 preterm records before the 26th gestational week, 119 term and 19 preterm records at and after the 26th gestational week. The recordings consist of three channels recorded from four electrodes placed on the abdominal surface of pregnant women as shown in Figure 2. Electrodes were placed symmetrically above and below the navel at a distance of 7 cm on the abdominal surface. Using the differences in the electrical potentials of the electrodes, three channels were used, namely Channel 1 (CH1)=E2-E1, CH2=E2-E3 and CH3=E4-E3. Unfiltered channel data, 0.08-4 Hz. filtered in the range of 0.3-3 Hz. filtered in the range and 0.3-4 Hz. 4 separate data are available for each channel, including the channel data filtered by the Butterworth band-pass filter in the range. Each recording takes 30 minutes. Sampled at 20 Hz with 16-bit resolution in the ±2.5 millivolt range. Due to filtering, the first and last 180 seconds of each record have been removed [17]. In this study, 0.3-4 Hz in channels. Filtered channel data is used in the range. Figure 3 shows the one minute EHG signal from three channels.

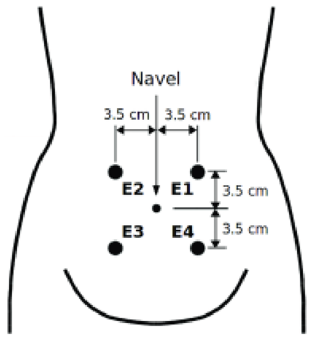

Fig.2. The placement of EHG electrodes [18]

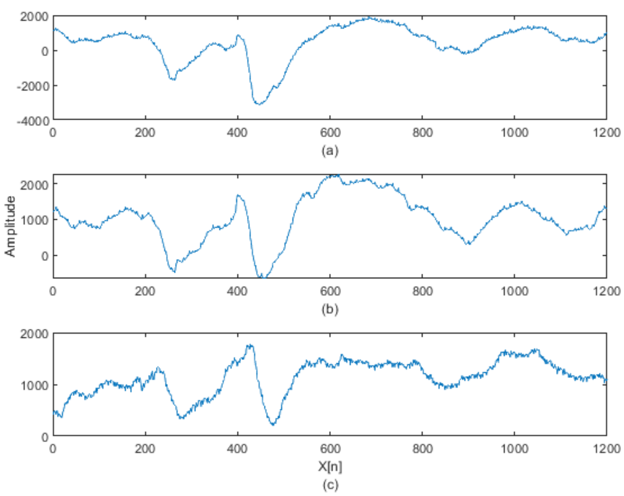

Fig.3. Example of a randomly selected one-minute full-term birth EHG signal (a) Channel 1 (b) Channel 2 (c) Channel 3

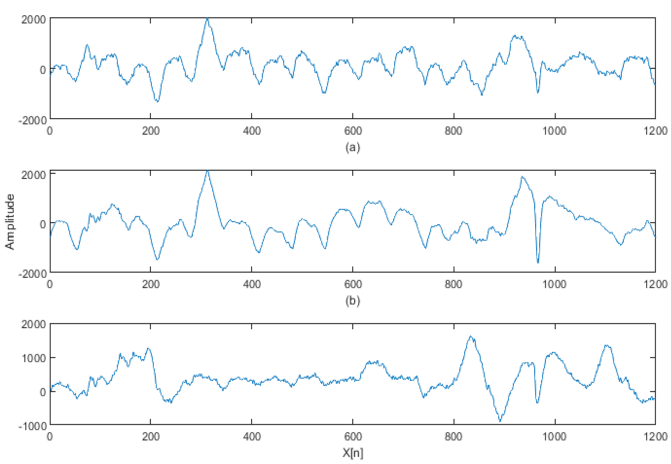

Fig.4. Randomly selected one-minute preterm birth EHG signal sample (a) Channel 1 (b) Channel 2 (c) Channel 3

Figure 4 shows 3 channel data of a randomly selected one-minute window of a person who has given birth prematurely. A randomly selected one-minute data sample from the CH1 channel is shown in the data set. Figure 5(a) shows a cross-section of the data sample that is term birth, while Figure 5(b) shows a cross-section of the data sample that is preterm.

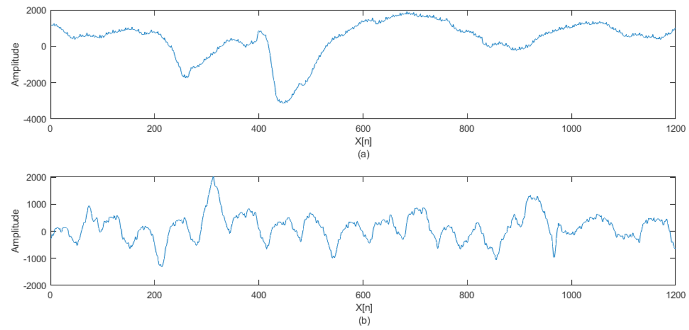

Fig.5. One-minute EHG channel data (a) term birth data (b) preterm birth data

C. Feature Extraction

The conversion of raw data into numerical features that can be processed without losing its originality is called feature extraction. It allows easier processing of data in large data sets. In this study, sample entropy and average energy values obtained from EWT and EWT modes are used as features.

2.3.1 Empirical wavelet transform

Adaptive methods used to analyze a signal are of great importance for the detection of information contained in the signal. The purpose of adaptive methods is to identify modes that represent the signal based on the information contained in the signal and to establish an appropriate basis. EWT is a proposed technique operating in the frequency space to detect different modes of the signal and generate empirical wavelets to represent the signal. Empirical wavelets mean generating a set of wavelets adapted to the processed signal. Modes are the main components of the signal that completely represent the signal. This method works in four steps. 1) Fast Fourier Transform algorithm is used to obtain the spectrum of the processed signal. 2) Calculate the local maximums of the spectrum. 3) Boundaries are detected and divided into windows. 4) Empirical wavelets are generated and the signal is decomposed into its different components [19-21]. Figure 6 shows an example of a normal birth EHG signal from a randomly selected 1-minute epoch and the EWT modes derived from this signal. Figure 7 shows the preterm EHG signal sample from an epoch and the EWT modes obtained from this signal. The feature matrix was obtained with the data obtained from these 5 modes in this study.

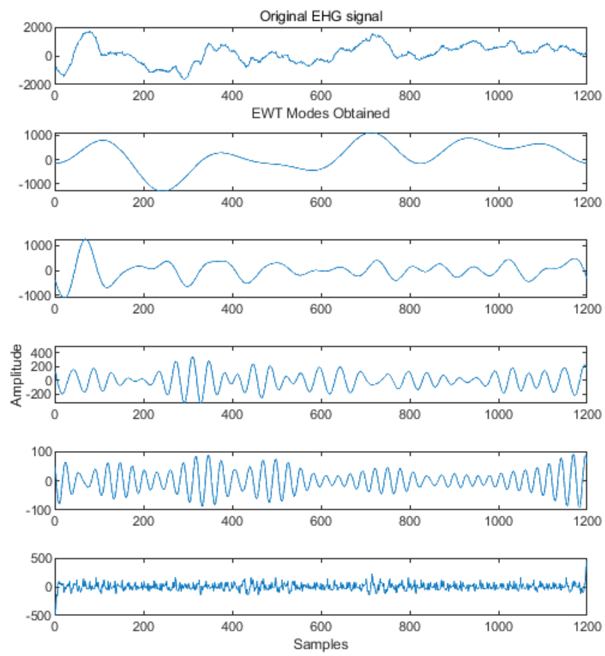

Fig.6. One-minute term EHG signal sample and EWT modes

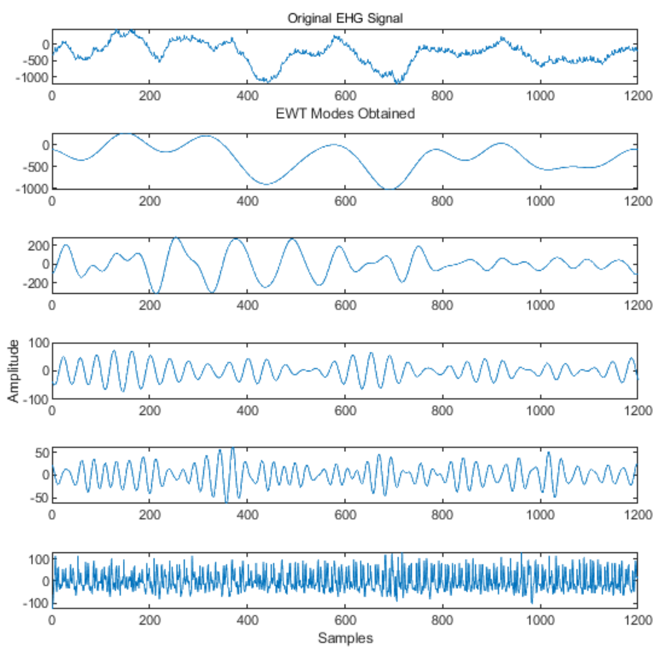

Fig.7. One minute preterm EHG signal example and EWT modes

2.3.2 Sample entropy

Sample Entropy has been proposed to measure the complexity of the array. It is basically a negative logarithm of the conditional probability of sequences of a data vector. If a vector of length N repeated for m points, it will repeat for m+1 points. Therefore, high sample entropy value means lower regularity and more complexity in the data [22, 23]. It is expressed mathematically as in Equation (1).

$$\text{SampEn}= -log\frac{A}{B} \tag{1}$$

where B is the total number of matches of length m and A is the total number of forward matches of length m+1.

2.3.3 Average energy

Indicates the amount of power in the signal. It represents the power of ripple. It is expressed mathematically as in Equation (2) [22, 24].

$$AvEn = \frac{1}{N}\sum_{n=1}^{N}(X_n)^2 \tag{2}$$

D. Classification

The concept of artificial intelligence, which is one of the common working areas in many different disciplines, which is frequently encountered in recent years, is called self-improving systems that try to imitate human intelligence. The main purpose of the studies is to enable machines to think like humans and to create an autonomous system that can decide on its own. The classification process, which is a part of these processes, is the process of classifying the values in a data set. This method, which aims to separate the data and assign it to the class it belongs to; It is used in many fields such as analysis of biomedical signals, computer aided diagnosis systems. There are many different classifier algorithms according to their calculation methods. When choosing algorithms, the method that will minimize the error in the classification phase is investigated and preferred [25-27]. In this study, using the feature vectors obtained as a result of the previous stages, classification process was performed with KNN, RF and LSTM algorithms, which are widely used in the literature.

2.4.1 Random forest

The RF algorithm was developed by Leo Breiman. It is an algorithm that consists of many independent decision trees and chooses the appropriate one. It is one of the preferred algorithms in many studies because it is a feasible method on classification and regression problems. It uses multiple randomly generated decision trees to classify the data. In the first step, the data that can distinguish the best among the randomly selected data is selected. The nodes are divided into branches and the tree structure is developed by randomly selected. Creates a decision tree for each instance. Estimated value results of each decision tree are obtained. It performs voting for each value formed as a result of the prediction. Finally, the result is reached by choosing the most voted value for the prediction. Two parameters must be defined by the user to start the RF algorithm [28, 29]. These parameters used to determine the best split are the maximum depth and the number of trees in the random forest [30]. In this study, the maximum depth was determined as 70 and the number of trees as 50, and the classification process was carried out with the help of the RF algorithm.

2.4.2 K-nearest neighbors

The KNN algorithm is based on separation from each other by calculating the distance between the data using distance functions. It determines the classification according to the majority of neighboring data. Each data point is associated with labels in its nearest neighbors. Therefore, this algorithm works on the assumption that similar data are close to each other. The KNN algorithm has two user-specified parameters that affect the classification results. One of them is the number of K neighbors and the other is the distance function. Two parameters are determined by the user [31, 32]. In this study, K=3 neighborhood and Euclidean distance function are based. The Euclidean Distance calculation used to calculate the given distance between two data is given in Equation (3) [33].

$$\text{Distance} = \sqrt{\sum_{i=1}^{n}(p_i - q_i)^2} \tag{3}$$

Here $p_i - q_i$ represent two data..

2.4.3 Long short-term memory

The long-short-term memory model is known as a recurrent RNN neural network. The problems experienced in the training of traditional RNN neural networks have been completely eliminated in LSTM. LSTM architecture basically consists of input, output, forget gates and memory cells. The cell remembers values at random intervals. All three doors regulate the entry and exit of information entering the cell. It is frequently used in time series signals such as biomedical signals because it can learn long-term dependencies. Because of its ability to learn long-term correlations in the series, LSTM networks have the ability to accurately model complex multivariate sequences. [34, 35]. The topology of the designed LSTM consists of an input layer, an LSTM layer, a dropout layer, and an output layer, as shown in Figure 8. There are 4 layers in the designed architecture. The developed model has an LSTM network layer with tanh activation and dropout to prevent over-learning. The model was implemented in Matlab environment. The number of cells in the LSTM layer was determined as nine, the learning coefficient (β) was chosen as 0.001 and Adam optimization was used in the model.

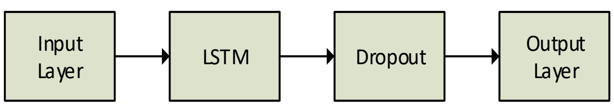

Fig.8. The LSTM neural network model used in the study

2.5 Evaluation Metrics

Confusion matrix is generally used to evaluate the performance of classification algorithms used in machine learning and similar fields. The confusion matrix is also called the classification accuracy table. The data in this table are obtained by comparing the classified value with the reference values [36]. Many metrics can be calculated from this matrix to evaluate the performance of the classifier models. In this study, Precision (Pre), Recall (Re) and Accuracy (Acc) metrics were calculated to evaluate the performance of the classifiers. These metrics are calculated as shown in Equations (4), (5) and (6) [37].

$$Pre = \frac{TP}{TP+FP}x100 \tag{4}$$

$$Re = \frac{TP}{TP+FN}x100 \tag{5}$$

$$Acc = \frac{TP+TN}{TP+TN+FP+FN}x100 \tag{6}$$

where TP and FN represent the number of correctly and incorrectly classified cases, and TN and FP represent the number of correctly and incorrectly classified cases. The Precision metric shows how many of the values classified as positive are actually positive. Recall is a metric that shows how much of the values that should be classified as positive are classified as positive. To validate the performance of the classifiers, 80% of randomly selected data from the entire dataset was used for training and the remainder was used for testing.

III. RESULTS

Premature birth is one of the health problems that negatively affect human life. The mother at risk of preterm birth should stay in the hospital after the birth and the treatment should be applied carefully to both the baby and the mother. In addition, preterm babies may have more health problems in their later years than babies born at normal time. Since human life is at stake, being able to predict this problem will be a solution to many permanent or non-permanent problems in the future or immediately after birth [38, 39]. The first step in the study is to classify preterm and full-term birth signals from EHG signals recorded in the physionet database with machine learning techniques. For this, the data is divided into one-minute windows and a label is assigned for each window. Using EWT, each window data was analyzed in five modes and features were extracted from each of the discretized EHG modes. Obtained features were given as input to three different classifier algorithms and the results were evaluated. The other step in the study is to classify the data recorded before and after the twenty-sixth week from the EHG signals recorded in the same database as preterm or term birth among themselves. For this, the data is divided into windows as in the first step and labels are assigned to each window. Using EWT, each window data was analyzed in five modes and features were extracted from each of the discretized EHG modes. The obtained features were given as input to the classifier algorithms and the results were evaluated. Except for the LSTM algorithm, the classification success of other algorithms was found to be higher in CH3 data. As a result of the classification made with CH3 data, the success rate of the RF algorithm was 98.19%. This rate was followed by the classification result made with the KNN-3 algorithm. The lowest classification success rate was obtained as 87.83% as a result of the classification made with the LSTM algorithm.

The time for classifier algorithms to classify test data is determined as 0.28 seconds for the RF algorithm, this time for LSTM. 2.02 seconds was determined as 1.34 seconds for the KNN algorithm. The hardware features of the computer on which the study is performed are “Intel(R) Core(TM) i3-6006U CPU @ 2.00GHz” and 4 GB Ram. The RF algorithm performed very fast compared to both KNN algorithm and LSTM, which is a deep learning architecture. Table 2 shows the success rates obtained as a result of the classification of the EHG signals obtained before the 26th week and labeled as preterm or term delivery. Similar to the results in Table 1, a high success rate was achieved by using the RF algorithm with the data received from the CH3 channels. This rate was followed by LSTM and KNN-3 algorithm results, respectively. When Table 2 is examined in terms of the classification times of the test data, the RF algorithm was found to be the fastest algorithm with 0.06 seconds.

TABLE 1
CLASSIFIER PERFORMANCE RESULTS OF DIFFERENT CHANNEL CONFIGURATIONS CREATED FOR PRE-TERM AND TERM CLASSIFICATION

Classifier	Channel name	Precision (%)	Recall (%)	Acc. (%)	Elapsed time for test data (second)
KNN-3	CH1	79.70	84.50	84.51	1.2
	CH2	81.10	84.90	84.90	1.2
	CH3	95.10	95.20	95.15	1.34
LSTM	CH1	76.10	87.10	87.05	1.18
	CH2	87.10	87.80	87.83	1.62
	CH3	87.10	87.80	87.83	2.02
RF	CH1	81.70	87.70	87.61	0.17
	CH2	90.10	90.40	90.42	0.13
	CH3	98.20	98.20	98.19	0.28

TABLE 2
PERFORMANCE METRICS AND DURATIONS OBTAINED AS A RESULT OF THE CLASSIFICATION OF SIGNALS TAKEN BEFORE THE TWENTY-SIXTH WEEK OF PREGNANCY AND LABELED AS PRETERM/TERM BIRTH

Classifier	Channel name	Precision (%)	Recall (%)	Acc. (%)	Elapsed time for test data (second)
KNN-3	CH1	79.60	84.70	84.65	0.44
	CH2	80.60	84.80	84.75	0.36
	CH3	82.60	86.20	86.22	0.88
LSTM	CH1	76.10	87.01	87.05	1.2
	CH2	86.70	87.30	87.26	1.3
	CH3	76.10	87.01	87.05	1.2
RF	CH1	89.20	87.70	87.68	0.06
	CH2	77.70	86.60	86.63	0.06
	CH3	89.20	89.00	89.03	0.06

Table 3 shows the success rates obtained as a result of the classification of signals obtained after the twenty-sixth week and labeled as preterm or term birth. Similar to the results in Tables 1 and 2, the highest success rate was achieved with the RF algorithm. Considering the classification times of the test data, the times close to the times in Table 2 were obtained, as expected.

TABLE 3
PERFORMANCE METRICS AND DURATIONS OBTAINED AS A RESULT OF THE CLASSIFICATION OF SIGNALS OBTAINED AFTER THE TWENTY-SIXTH WEEK OF PREGNANCY AND LABELED AS PRETERM/TERM BIRTH

Classifier	Channel name	Precision (%)	Recall (%)	Acc. (%)	Elapsed time for test data (second)
LSTM	CH1	74.9	86.40	85.82	1.08
	CH2	74.9	86.40	85.65	1.36
	CH3	86.70	87.60	87.63	0.05
RF	CH1	82.80	86.70	86.65	0.06
	CH2	83.60	86.90	86.90	0.06
	CH3	74.9	86.40	86.41	1.33
KNN-3	CH1	77.80	82.60	82.61	0.27
	CH2	82.70	84.80	84.82	0.27
	CH3	81.70	85.10	85.06	0.5

When the results obtained are examined in terms of success rates and processing load, it has been observed that the LSTM model, which is a deep learning architecture, has quite a long time to classify test data compared to RF and KNN models. The RF algorithm, known as fast, performed better than other algorithms in terms of processing load in the classification of EHG datasets. As expected, LSTM algorithm did not perform better than other algorithms in terms of processing load compared to RF and KNN algorithms. RF outperformed other algorithms in terms of both success rate and processing load.
The success of the classifier algorithms is directly related to the obtained features. Therefore, the EWT method used on EHG signals and the obtained features contribute to the success rates. The efficiency of both the classifier algorithms and the EWT method has been demonstrated by the classification study performed separately for each channel. EWT has been evaluated in signal processing methods in many different areas, but its effectiveness on EHG signals has not been evaluated in any study. Compared to the new methods, it is shown that the features used and the created model distinguish term and preterm data well. Thanks to signal analysis and machine learning algorithms on EHG signals, this and similar studies are promising in terms of preterm birth diagnosis with 100% classification accuracy.

IV. DISCUSSION

In this study, an algorithm that can classify from a single channel using EHG signals to recognize preterm birth is presented. The classification of preterm and term delivery was considered important rather than early or late recording of EHG records. The study is based on the EWT-based feature extraction approach. High accuracy rates have been achieved with the RF classifier, which is a successful model with less processing load, by calculating the processing load. Results from other studies using the TPEHGDB database are compared with this study in Table 4.

TABLE 4
COMPARISON OF STUDIES CONDUCTED WITH THE SAME DATA SET

Author	Database	Channel name	Best classifier	Train/Test Method	Acc.	Term /Preterm

Fergus et al. [8_9]	TPEHGDB	0.34–1 Hz. filter on Channel 3	LMNC, RBNC, RNNC combined	80% train, 20% test	90%	262/38
Huseyin et al. [12_13]	TPEHGDB	0.3–3 Hz. filter on Channel 3	DSIA	60% train, 25% validation, 15% test	90%	262/38
Vinothini et al. [9_10]	TPEHGDB	0.3–3 Hz. filter on Channel 3	RF	5-fold cross validation	98.6%	143/19
Far et al. [10_11]	TPEHGDB	0.08- 4 Hz. filter on Channel 1	SVM	10-fold cross validation	99.7%	262/38
Lou et al. [11_12]	TPEHGDB and ICLEHG	0.3–4 Hz. filter on Channel 3	GNB	80% train, 20% test	75%	262/38
This	TPEHGDB	0.3–4 Hz. filter on Channel 3	RF	80% train, 20% test	98.19%	262/38
				10-fold cross validation	98.10%	

When the studies in Table 4 are examined, it can be seen that the highest classifier performance was obtained in the study conducted by Far SM et al. [11]. I believe that the preferred channel data, filter range and classifier algorithm have an impact on achieving this success rate. I believe that the small number of data in the data set used in the study conducted by Vinothini S et al. [10] affects the performance. In the study conducted by Vinothini S et al. [10], the RF algorithm gave successful results, similar to the manuscript. Higher performance was achieved in this manuscript compared to other studies in Table 4. Unlike the studies in the literature, a different feature extraction method was applied to EHG data by using the EWT approach. However, the results obtained show that the applied method and technique are successful. In addition, it has been revealed that the performances of classifier algorithms can be analyzed one by one in terms of processing load and can be integrated into embedded systems. Many of the studies in the literature are analyzed in terms of method technique, but not in terms of processing load. In this respect, I believe that it has made a significant contribution to the literature. I could not find any study in the literature that used EHG data sets and was based on the EWT approach. Therefore, the evaluation of the effectiveness of the EWT approach on EHG data has been introduced to the literature with this manuscript.

V. CONCLUSION

In recent years, the development of artificial intelligence techniques has played an important role in the biomedical field. Thanks to this situation, it has become easier and faster to remove biological patterns in biomedical signals. In addition, feature extraction from data, evaluation of various methods and techniques on biomedical signals are widely used for solving problems. This article presents an EWT-based algorithm for accurate classification of term and preterm births using a single EHG channel. At the same time, EHG records before and after the twenty-sixth week were scored separately and the results were evaluated. Different classifiers were used based on the EWT approach to classify term and preterm records. The results show that the optimal classifier is RF with 98.20% precision, 98.20% recall and 98.19% accuracy, both in terms of performance and overhead. These results are encouraging for machine learning and show that the proposed approach is worth pursuing. The adequacy of the extracted features and the method according to the classification results made with the data obtained from different channels has been verified.

The limitation of the study is the small number of preterm samples. To eliminate this situation, synthetic data can be used or real hospital data can be added to the study. Adding synthetic data can reveal an over-learning situation in terms of machine learning. Therefore, it may be a more accurate way to balance the data set by adding hospital records obtained from pregnant women who gave birth prematurely to the data set. In future studies, more extensive research is planned to reach an error-free model (100% accuracy) with different machine learning algorithms and techniques.

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