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Approach to the diagnosis of cesarean delivery using bio- inspired models

Aproximación al diagnóstico del parto por cesárea mediante modelos bio-inspirados

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Abstract

In 2021, the cesarean section-related maternal mortality rate in Colombia was 46.4%. Efforts to reduce this rate have focused on monitoring maternal health, but the high volume of data and patient load complicate comprehensive symptom tracking. This study introduces a bio-inspired model for classifying cesarean deliveries using demographic information and electrohystereographic (EHG) biosignals from the mother-child dyad. The implemented classifiers include K-nearest neighbors (KNN), multilayer perceptron (MLP), support vector machines (SVM), and deep learning algorithms.

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For demographic data analysis, KNN achieved a sensitivity (S) of 100% and a specificity (ES) exceeding 80%, while SVM recorded an S of 75% and an ES of 83.3%. In EHG analysis, MLP demonstrated an S of 82.3% and an ES of 85.7%, followed by deep learning with an S of 72.8%. This model facilitates early detection of cesarean births by integrating maternal history and fetal behavior data.

Keywords: Artificial Intelligence, Bio-Inspired, Cesarean Section, Classification, Electrohystereography (EHG).

Resumen

La tasa de mortalidad materna por cesárea de Colombia en 2021 es 46,4 %, para disminuirlo, profesionales de la salud dan seguimiento a las gestantes, sin embargo, la densidad de información y el volumen de pacientes hace complejo tener en cuenta la sintomatología. Este artículo desarrolla un modelo bio-inspirado para la clasificación de parto por cesárea, basado en información demográfica y la bioseñal Electrohistereograma (EHG) del binomio madre-hijo. Los clasificadores son k vecinos más cercanos (KNN), perceptrón multicapa (MLP), máquinas de vectores de soporte (SVM) y aprendizaje profundo. Finalmente, se calcula el rendimiento. El mejor desempeño del análisis de datos demográficos se obtiene con: KNN con sensibilidad (S) del 100 % y especificidad (ES) de más del 80 % junto a SVM con S del 75 % y ES del 83,3 %. El mayor rendimiento en el análisis del EHG son MLP con S de 82.3 % y ES de 85.7 %. Esta herramienta brinda apoyo a la detección temprana de nacimientos por cesárea, teniendo en cuenta los antecedentes de la gestante y el comportamiento del feto.

Palabras clave: Inteligencia Artificial, Bio-Inspirado, Cesárea, Clasificación, Electrohistereografía (EHG).

1. Introduction

UN Millennium Development Goal No. 5 aims to reduce maternal mortality, which is exacerbated by the risks associated with cesarean section deliveries, the leading cause of these deaths. In 2015, it was proposed that this rate should not exceed 15 % in Colombia [2]. However, despite significant efforts, the prevalence of cesarean section-related deaths in the country in 2021 was 46.4 % [3].

Artificial intelligence can support current methods for the early detection of cesarean deliveries. For instance, models developed for managing demographic information to predict premature births [4] or to classify pregnant women at risk of hypertensive morbidity have shown accuracies of over 80 % [5]. Another approach involves bio-signal analysis, using convolutional neural networks to detect fetal hypoxia with 6 5% accuracy based on cardiotocography signals [6]. However, these models require large databases for cross-validation and high prediction performance.

The information needed to guide the decision on whether to perform a cesarean section is often obtained during emergencies. Therefore, the primary focus of this paper is to develop a bio-inspired model using computational intelligence techniques such as KNN, MLP, SVM, and deep learning to support the pre-diagnosis of cesarean delivery. This model utilizes demographic information and EHG biosignals from the pregnant woman, enabling early diagnosis in gestation and allowing the healthcare system to develop a gestation plan accordingly. The classification results between vaginal and cesarean deliveries demonstrate the model's effectiveness, achieving a sensitivity of up to 85 %.

The paper is organized as follows: Section 2 presents key concepts, including cesarean sections, classification algorithms, and performance indicators. Section 3 details the proposed bio-inspired model. Section 4 describes the implementation process for the model. Section 5 discusses the results obtained from trials and their analysis. Finally, Section 6 presents our conclusions.

1.1. Theoretical framework

Cesarean section is a surgical intervention in which the newborn baby is extracted through an incision made in the mother's abdomen [7]. Electrohysterography is a diagnostic tool used as a non-invasive technique that measures the electrical activity of contractions using surface electrodes placed on the abdomen of the pregnant woman [8]. The k-nearest neighbor (KNN) algorithm classifies the data by calculating the distance between each unlabeled data point and all other labeled points using Euclidean distance [9]. The classification is derived using Equation (1):

$$C(x_i) = \mathrm{argmax}_k \sum_{X_j \in KNN} C(X_j, Y_k) \qquad (1)$$

where x_i is the test data, X_j is one of the k nearest neighbors in the training set, $C(X_j, Y_k)$ indicates whether X_j belongs to class Y_k.

Multilayer perceptron (MLP) is a neural network with one input layer, one output layer, and N hidden layers [10]. The connections that exist between the layers are assigned a weight, and the matrix that contains them is calculated node by node using Equation (2).

$$h_{ij} = f(\textstyle\sum_{i=1}^{n} w_{ij} x_i + b_j) \qquad (2)$$

where h_{ij} is the j-*th* node of h1 and w_{ij} is the associated weight.

Support vector machines are classifiers based on the search for a hyperplane that effectively separates the n different classes of data sets. Kernels are functions that transform a low dimensional space into a higher dimensional one; some of these are linear and polynomial kernels [11], and they are calculated as by Equation (3).

$$K_L(x_i, x_{i'}) = \langle x_i \cdot x_{i'} \rangle \, , K_P(x_i, x_{i'}) = (\langle x_i \cdot x_{i'} \rangle)^d \qquad (3)$$

where $x_i , x_{i'} \in X$ input set and d is the degree of the polynomial function.

Deep learning is a learning method designed to mimic brain functions by employing multiple layers of nonlinear processing units that extract and transform the input data. The process is iterated the number of times necessary to obtain the given accuracy and move to the next layer [12]. It allows for multiple automated learning methods to be combined.

Performance indicators are used to calculate the generalizability of a model to future unseen data. Based on this, equations (4-6) show three performance indicators, sensitivity (S), specificity (E), and accuracy (EX), considering true positives (TP), false positives (FP), false negatives (FN), true negatives (TN) [13]:

$$S = \frac{VP}{VP+FN} \quad (4) \quad \mathrm{E} = \frac{VN}{FP+VN} \quad (5) \quad \mathrm{EX} = \frac{VP-VN}{VP+VN+FP+FN} \quad (6)$$

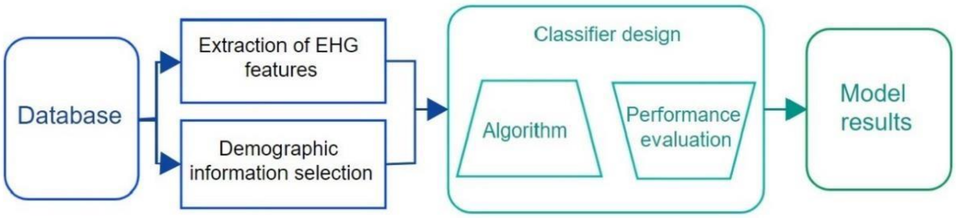
2. Methodology

Proposed bio-inspired model

Figure 1 shows the bio-inspired cesarean delivery prediction model. The dataset comprises demographic information and the EHG bio-signal, which is preprocessed to select the inputs for the classifier block. Next, the classifier is designed and developed with performance evaluation in mind. Finally, the model presents the result of the approximation. This model is intended for implementation during early pregnancy controls performed by the obstetrician.

Based on health professionals' observations and the results of this bio-inspired model, a pregnancy plan can then be proposed to preserve the mother-child binomial.

Figure 1. Block diagram of the bio-inspired model. Source: own.



Database: The information used for this project was obtained from a public database on Physionet, named the “Icelandic 16-electrode Electrohysterogram Database.” This database comprises 122 electrohysterograms (EHG) of pregnant women aged 19 to 39 years, with records and data collected both before and during labor [14].

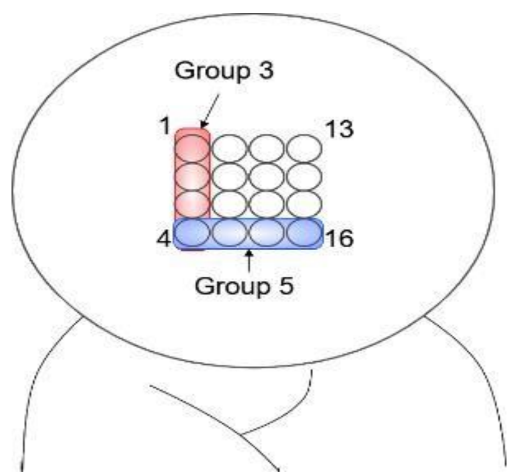
Each record includes a header file containing the expectant mother's demographic information, listed as follows: participant ID, record number, record type (labor, pregnancy), expectant mother's age (years), gestational age (weeks), body mass index (BMI) (before pregnancy and at the time when the information is recorded), placental position, number of pregnancies, parity (previous deliveries greater than 22 weeks of gestation), and previous cesarean sections (Yes, No), gestational age at delivery (weeks/days), comments for the record, comments for the delivery, and mode of delivery (vaginal delivery and cesarean section). The EHG bio-signal is described later in the document.

Preprocessing of demographic data: the selection of demographic information is guided by the structure and size of the database [15]. The following are the inclusion criteria applied: gestational age of between 32 and 38 weeks and a maximum of two records per patient, this is because this model is intended to support preventive diagnosis (if gestational age is greater than 38 weeks, delivery is close to occurring, and if it is below 32 weeks, the fetus is immature). Accordingly, the record cannot show the behavior of the mother-child binomial [16] [17]. Data that are part of patient identification and comments that do not contain medical or demographic information are omitted.

The input data include age of the pregnant woman, gestational age, body mass index (BMI) (before pregnancy and at the time of recording), placental position, number of pregnancies, parity (previous deliveries with over 22 weeks of gestation) and previous cesarean sections, gestational age at the time of delivery. The output data are mode of delivery (vaginal delivery and cesarean section), which is correlated with each of the inputs. For example, in placenta previa, delivery should be by cesarean section as the placenta obstructs the cervix [18].

EHG Preprocessing: This signal contains the data from the 16 monopolar electrodes; Figure 2 shows the distribution of the electrodes in the abdomen of the pregnant woman. To incorporate the bio-signal into the model, a pre-processing is necessary, for which the EHG is split using the windowing method [19]. This process takes a small subset of a larger dataset with a rectangular window type filter. The width used in this study is 30%, which involves truncating the dataset before and after this window.

Figure 2. Location of electrodes with groups 3,4, and 5 [14].



The time and frequency domain characteristics are calculated for each sub-window, as shown in Table 1 [20].

Table 1. Characteristics in the time and frequency domain of the EHG bio-signal [20].

Root Mean Square $RMS = \sqrt{(\frac{1}{N}\sum_{i=1}^{N} x(i)^2)}$	Mean absolute value $MAV = \frac{1}{N}\sum_{i=1}^{N}\lvert x(i)\rvert$	Variance $VAR = \frac{\sum_{i=1}^{N}(x(i)-\mu)^2}{N}$
Median frequency $MF = i_m \frac{f_s}{N}\sum_{i=1}^{i_m} P(i) = \sum_{i=i_m}^{i=N} P(i)$		Mean power $P = \lim_{L\to\infty}[\frac{1}{2L}\int_{-L}^{L}\lvert x(t)\rvert^2]\,dt$

where $x(i)$ is the segmented EHG, $i = 1,2,\ldots,N$ where N is he length of the $x(i)$, $\mu = \sum_{i=1}^{N}\frac{x(i)}{N}$ is the mean of the $x(i)$, and $P(i)$ represents the power spectrum of $x(i)$.

To define the model's input dataset, five groups of parameters were considered: Group 1 contains demographic data on the pregnant woman including age, number of deliveries, number of pregnancies, BMI, previous cesarean sections, and placental location. Group 2 contains average EHG bio-signal variables (Table 1) and demographic data. Group 3 contains EHG bio-signal variables (Table 1), where the data is an average of the electrode variables vertically (Figure 2, red electrodes). Group 4 has the root mean square of the 16 electrodes. Group 5 has bio-signal variables, taking an average of the electrode variables horizontally (Figure 2, blue electrodes).

To compare the results between bio-inspired models, the classifiers are tested with five sets of parameters. These are split into 70 % for training and 30 % for cross-validation, using two computational tools: WEKA and Python. Finally, the results are used to calculate the performance indicators.

For classification with K-Nearest Neighbors (KNN), the number of neighbors starts at 1 and increases according to performance and processing time. The implemented distance function is Euclidean, and the iterations start at 50 and increase if necessary.

The Multi-Layer Perceptron (MLP) classifier starts with 1 hidden layer and increases based on the results. The number of neurons per layer varies according to performance and processing time. The activation function for the input layer is the linear function, while for the hidden layers, it is the sigmoidal function. Values must be normalized to use this classifier.

The Support Vector Machine (SVM) classifier detects a hyperplane that separates the data, varying the kernel types between linear and polynomial.

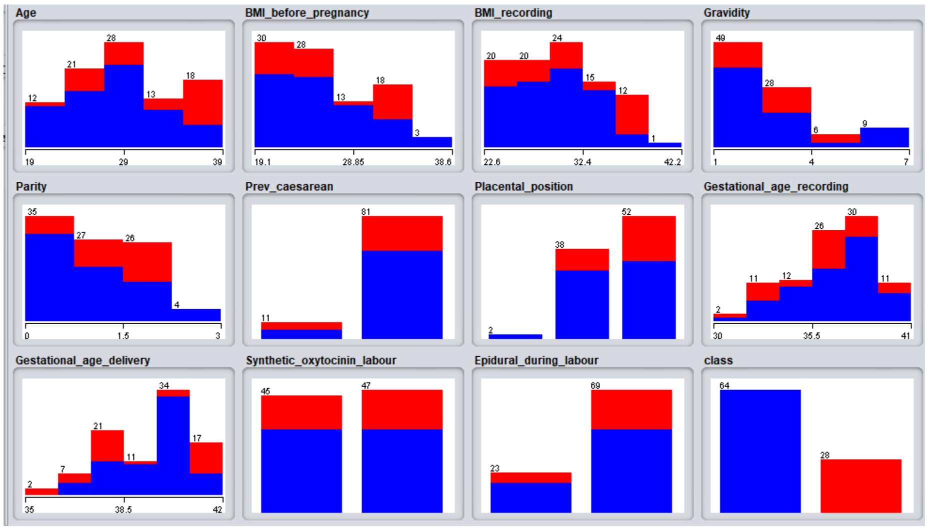
For deep learning, the training batch size varies; there are N samples for training, and the batch size is set to 5 or 10. The number of epochs per processing ranges from 50, 100, to 1000.

To clinically implement the bio-inspired model, a customized computer graphical visualization interface must be developed and designed in the Visual Studio graphical programming environment using Python. The interface must include the aforementioned classifiers and visualize the performance indicators during the training and validation stages.

3. Results and discussion

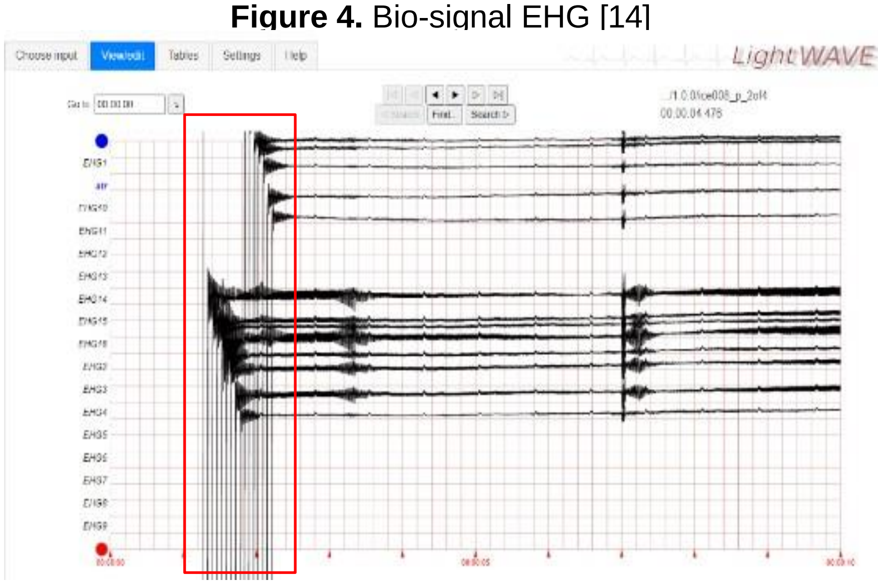
The bio-inspired model constructed classifies whether the delivery could be vaginal or by cesarean section. The demographic data were selected according to the criteria set out in Section 3. The result is illustrated in Figure 3, which shows the distribution of each of the characteristics, taking into account the two classes identified as vaginal in blue and cesarean section in red.

Figure 3. Database distribution. Source: own.



Preprocessing the signal requires the implementation of a filtering technique to reduce the noise present during the capture of the EHG bio-signal. As shown in Figure 5, this noise is present at the beginning and at the end of each recording and according to comments in the database, this is due to mother's movements and interference from poorly connected electrodes.

Figure 4. Bio-signal EHG [14]



Following the filtering step, the EHG records are represented by features in the time and frequency domain mentioned in Table 1, estimated using the windowing method, by which variables are calculated taking into account detailed information. Figure 3 shows the difference between viewing all the information of the EHG and viewing the result of the windowing.

Figure 5. Signal EHG, a) total signal, b) windowing. Source: own.

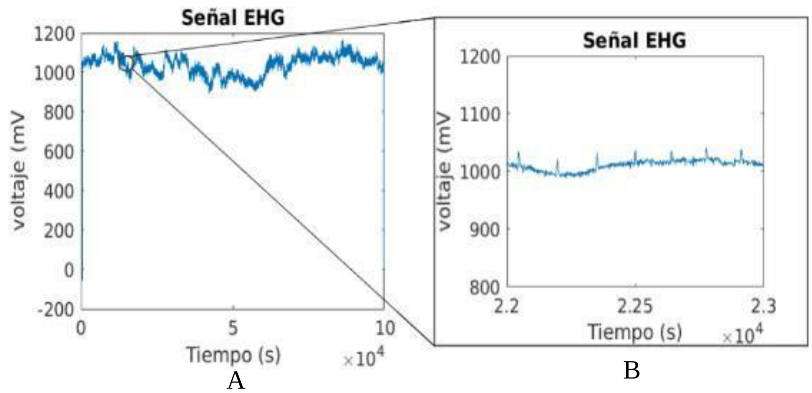


Table 2 shows the results obtained by each classifier implemented according to the group of data processed:

Table 2. Results of classifiers. S, E, and EX are in percentages (%). A= 1, 11, 13, B= 100, 128.

Group	KNN				MPL				SVM		
	K	S	E	EX	#	S	E	EX	S	E	EX
1	2	100	83.3	90	A	75	100	90	75	83.3	80
2	2	87.5	83.3	77.7	A	75.5	75	75	28	50	25
3	2	29.4	72.7	44.4	B	58.8	54.4	57.1	100	12.5	39.2
4	2	35.2	72.7	50.5	B	82.3	90.9	85.7	35.2	54.5	42.8
5	2	25	72.5	40.7	B	17,6	100	50	11.7	54.4	20.2

KNN: The number of neighbors chosen is 2. Increasing this value leads to longer processing times without significant changes in the results. The sensitivity decreases from 100% to 87.5% from Group 1 to Group 2 (Table 2). This indicates that the model better classifies patients who may suffer complications compared to those at no risk. The specificity for Group 3 is 70%; however, it decreases for Groups 1 and 2. Groups 4 and 5 have the lowest sensitivity percentages, indicating that the dataset is not sufficiently differentiable for the model to learn from trends.

MLP: The classifier is implemented with 1 and 2 hidden layers, but performance is below 50%. When the number of hidden layers exceeds 3, performance remains the same but overburdens the machine. Thus, the MLP is implemented with 3 hidden layers. For Group 1, accuracy is above 70%. Including the biological signal for Group 2 decreases accuracy, suggesting these values do not enhance the model. For Groups 3, 4, and 5, a model with 3 layers achieves accuracy percentages above 60% (Table 2).

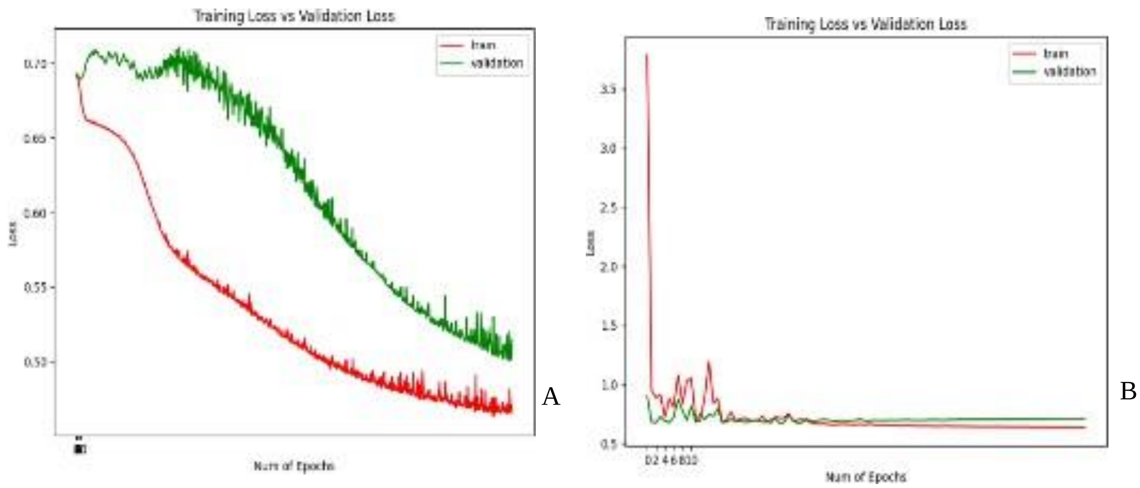
Support Vector Machine (SVM): The linear kernel has the lowest sensitivity values. However, with the polynomial kernel and Group 1, the accuracy is 75 % (Table 2).

Deep Learning: For Group 1, the model's sensitivity increases with more epochs, comparing 10 and 1000 epochs. More training epochs lead to higher accuracy, with a maximum sensitivity of 77.7 %. Group 2 achieves 75 % sensitivity with 5 and 1000 epochs.

The training loss graph shows the model's ability to fit the training data, while the validation loss indicates its ability to generalize to new data, as cross-validation uses unknown data to the model. Figure 4.A shows Group 1, where training loss adjusts faster than validation loss. The final training loss is 0.46, and the validation loss is 0.5, indicating partial overfitting. Minimizing validation loss is crucial, and some overfitting is acceptable given the data volume used for training and validation. Figure 4.B also shows partial overfitting similar to Group 1.

For Group 4, the accuracy is low, with 23.5 % sensitivity and 72.8 % specificity. Specificity increases to 81.8 % for Group 5, but sensitivity remains below 30 %.

Figure 6. Graph of losses. Original. A Group 1, B Group 2. Source: own.



The K-Nearest Neighbors (KNN) model achieves an accuracy of 90% when utilizing demographic information. However, the accuracy decreases to 77.7% when processing groups that solely contain bio-signal characteristics of Electrohysterography (EHG). This indicates that demographic information significantly enhances the model's decision-making capacity.

In a study conducted at the University of Islamabad, Pakistan, focused on classifying preterm births delivered via cesarean section, the highest sensitivity percentage of 80 % was achieved using the KNN classifier [21]. The 10 % difference between the studies is attributed to the varying types of demographic information used, with some data in the Islamabad study lacking decision-making capacity.

The difference between Group 1 (demographic information) and Group 2 (bio-signal characteristics) arises because the use of biological signals such as EHG requires a more robust database. Despite this, the percentages reported are comparable to those found in existing literature. For instance, the University of Science and Technology of Poland reported an accuracy of 96 % for predicting preterm births, using a large database with over 400 records [22].

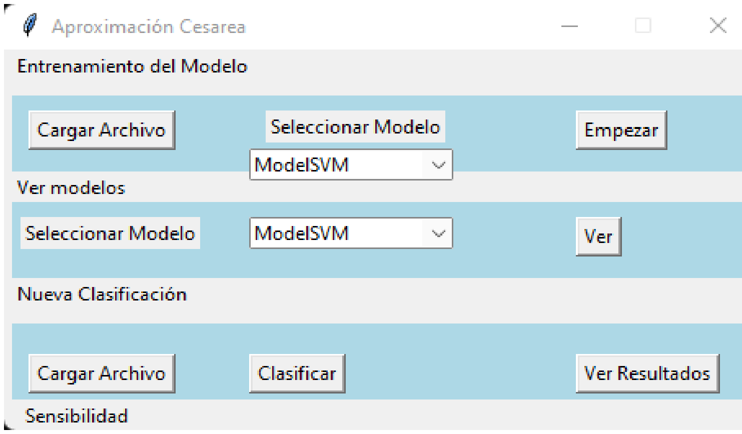
The Multilayer Perceptron (MLP) model and Group 2 show a sensitivity of 75.5 %, while Group 4 demonstrates a sensitivity of 82.3 %. In comparison, research from the Polytechnic University of Valencia [23], which used EHG bio-signals and neural networks to predict the success of labor induction, reported a sensitivity of 68.9 %. These results align with the present research, indicating that while the instrument is not a medical diagnostic tool, it can effectively support medical diagnoses.

The Support Vector Machine (SVM) model presents accuracy values below 50% for groups 2, 3, 4, and 5, but achieves over 70 % accuracy with Group 1. This aligns with methods found in literature, where results range from 50 % to 98 %, often without specifying whether validation is performed with data unknown to the model.

A study by the Technological University of Bolivar, which predicts maternal morbidity, states that the model's accuracy varies according to the gestational age when the EHG is recorded. Accuracy is 61 % in the first and second trimesters, and exceeds 70 % in the last trimester [24].

The interface developed for this project is illustrated in Figure 7. To implement the classifiers, an information loading module must be created to input a training database, which is then randomly divided. The classifier is selected, and a module is developed to classify a new patient. This application also saves the classifier, along with the results obtained during training and the classification of the new patient.

Figure 7. Graphical visualization interface. Source: own.



Technological tools, such as this bio-inspired model, enable the use of demographic information or bio-signals, like the EHG, to be implemented in medical centers equipped with the necessary technology to collect these bio-signals. Additionally, they allow health centers without such equipment to utilize this tool with information related to the pregnant woman to perform classification and provide support for preventive diagnosis, thereby reducing maternal morbidity. This research also compares different classifiers to optimize detection and allows the use of various data depending on the medical center's facilities.

4. Conclusions

The proposed bio-inspired model has been validated through the described experiments, demonstrating its effectiveness in predicting cesarean deliveries. Using the KNN classifier, the model achieves 90% accuracy with demographic information. When utilizing the MLP classifier to process EHG bio-signal information, it attains 90.9% accuracy. The next step in this implementation is to conduct clinical trials to increase patient diversity and enhance the model's adaptability.

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