

# Multistage Training of Fuzzy Cognitive Maps to Predict Preeclampsia and Fetal Growth Restriction

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**ABSTRACT** Preeclampsia (PE) and fetal growth restriction (FGR) are pregnancy complications related to placental dysfunction that pose significant challenges in terms of morbidity and mortality worldwide. Addressing these challenges involves early identification of the disease, which could reduce both the burden on healthcare systems and associated morbidity rates. In this study, we propose an innovative strategy using multistage training of fuzzy cognitive maps (FCM) to predict specific pregnancy disorders such as PE and FGR. The objective was to develop a predictive approach as a result of multistage training to simulate disease progression in a human individual. The models were rigorously evaluated for their predictive ability using datasets containing characteristics related to the mother, fetus, signs, symptoms, Doppler studies, and laboratory tests. The results conclusively reveal that multistage training better uncovers patterns in the data, leading to significantly improved predictive performance for these disorders. Convergence analysis demonstrated the stability of the FCM generated during the training stages. Also, the comparison with other machine learning models demonstrates that our approach is competitive to predict PE and FGR. The application of these models in healthcare settings holds promise as a valuable tool for the early detection of PE and FGR, contributing to the reduction of morbidity and mortality rates.

**INDEX TERMS** Preeclampsia, Fuzzy cognitive maps, Particle swarm optimization, predictive models

## I. INTRODUCTION

THE complications of pregnancy, including preeclampsia (PE) and fetal growth restriction (FGR), are important conditions for both maternal and fetal health [1]. Early detection of these conditions can guarantee the life of the mother or fetus. On the one hand, PE is a gestational disorder, which impacts from 2% to 8% of all pregnancies. It is linked to high rates of maternal and perinatal morbidity and mortality globally, mainly in low-resource countries, causing 60,000 maternal deaths and more than 500,000 premature births each year. In Latin America and the Caribbean, hypertensive disorders are responsible for almost 26% of maternal deaths [2]. It usually manifests after 20 weeks of gestation and up to six weeks postpartum, although in exceptional cases it may arise before 20 weeks [3]. On the other hand, FGR is a condition characterized by an inadequate adaptation of the mother's cardiovascular system during pregnancy. FGR is

one of the main causes of perinatal morbidity and mortality, complicating up to 10% of pregnancies [4]. In this condition, the fetus does not reach its growth potential as determined by a fetal weight below the 10th percentile for gestational age. The main risk factors for this condition are hypertension, genetic factors, drug use, smoking, cardiovascular disease, among others [5].

The pathophysiologic complexity and variability in the clinical presentation of PE and FGR represent significant challenges in the early identification and effective management of these pregnancy complications [6]. The impact of PE extends beyond gestation, because the risk of cardiovascular and neurological disease increases after pregnancy in women who have had PE [7]. On the other hand, the impact of FGR is closely related to increased perinatal morbidity and mortality.

At present, early detection of PE and FGR remains a critical challenge, and the consequences of late or incorrect diag-

nosis are devastating for both mother and fetus. Therefore, the prevailing need to improve strategies for prevention and diagnosis of PE and FGR has led to the exploration of new approaches, and in this context, the use of artificial intelligence in the field of obstetrics has opened new avenues for improving prenatal care, risk assessment, and decision making [8].

Despite the importance of the problem of PE and FGR in terms of morbidity and mortality rates, PE and FGR have been little explored using FCM. Previous studies show that PE and FGR have not been addressed using these types of techniques, which are easy to construct, interpretable and easy for medical personnel to interpret. On the other hand, the exploration of diseases affecting pregnancy has been addressed under the premise of a conventional approach. Figure 1 and 2 show the conventional FCM model architecture for PE and FGR prediction, respectively. The training of FCMs is performed in a single training step by pooling all variables.

The drawback with the conventional approach is that it does not take into account the process and evolution of the disease in the human body, which occurs in several successive stages. For example, in PE, the first stage is the maternal and fetal characteristics, which are risk factors for the development of the disease. The second stage occurs when the patient presents alterations that can be identified using studies such as Doppler. The third stage would consist of alterations in variables that can be measured using laboratory tests. This same analogy could be seen for FGR. A first stage of the disease would be the characteristics related to the mother such as age, number of pregnancies and body mass index. The second stage would consist of variables related to signs and symptoms such as edema, hypertension and proteinuria. Finally, the last stage would consist of laboratory tests such as uric acid, albumin, among others. The alterations of the variables mentioned above do not occur at the same time, so a single stage training with all of them does not represent the disease process that is taking place in the individual.

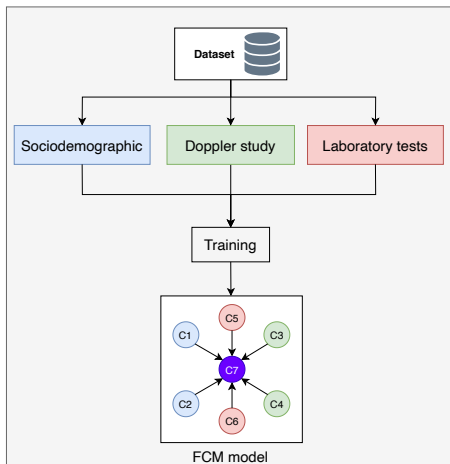


FIGURE 1. Conventional architecture of FCM model building to predict PE.

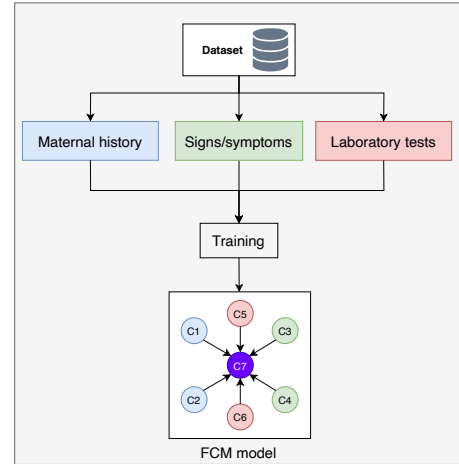


FIGURE 2. Conventional architecture of FCM model building to predict FGR.

Based on this problem, the present study proposes a multistage FCM training methodology as an innovative approach to predict PE and FGR. This methodological proposal is based on the fact that the disease process in patients is multistage; this means that variables of different nature do not develop at the same time during the disease. The disease process is dynamic and multistage training of FCMs could help to better recognize patterns in the data. Additionally, this type of training would allow better modeling of the complexity and variability inherent in PE.

The main contributions of this work are:

- A methodology for training FCMs in a multistage fashion that simulates the stages of pregnancy complications.
- The definition of a predictive model for PE detection based on FCMs using different stages for training.
- The definition of a predictive model for FGR detection based on FCMs using different stages for training.
- A comparative analysis with other machine learning (ML) techniques for predicting PE and FGR.

This paper is organized as follows: Section III presents the basic concepts related to PE and FCM. Section IV shows and describes our proposal for multistage FCM training. Section V shows the experiments and Section VI presents and analyzes the results of our proposed approach. Finally, Section VII concludes the research.

## II. RELATED WORK

### A. FCM MODELS TO PREDICT PE AND FGR

PE and FGR have been little studied using FCM-based models. However, the literature reports different frameworks using fuzzy logic to support decision-making regarding risks and other diseases occurring during pregnancy. For example, Umoh and Nyoho [9] developed a fuzzy logic model for diagnosing and monitoring risk factors in pregnancy. However, the developed model was not evaluated on a dataset. Doomath et al [10] developed a fuzzy system to predict the risk of developing postpartum hemorrhage. The results showed that

using a dataset of sociodemographic and clinical variables, the performance was good, with a sensitivity and specificity of 87.5% and 92.2%, respectively. Lakhno et al [11] proposed a fuzzy logic system using fetal descriptors based on heart rate variability. The objective was to accurately diagnose fetal distress. The results showed the performance of the developed model with an accuracy of 98.8% for fetal distress prediction and 100% for healthy pregnancy. Stylios et al [12] described some FCM architectures for medical decision support systems, including a hierarchical architecture to support the decision making of medical professionals to decide whether the delivery should be normal or a cesarean section should be performed. As in the previous work, the structure of the FCM is shown but not evaluated in datasets to know its predictive capacity.

### B. RECENT EXTENSIONS OF FCMs

FCMs have been widely used in various fields for their ability to represent and model complex systems. In recent years, several modifications and extensions have been proposed to improve the descriptive, predictive and prescriptive capabilities. For example, Kolahdoozi et al. [13] proposed an algorithm inspired by quantum computing for training FCMs in combination with the PSO algorithm. The proposed algorithm outperformed other advanced algorithms without the need to involve human knowledge. Additionally, the combined use of static and dynamic analysis allowed a better analysis of the tested case studies.

Amirkhani et al [14] presented a framework for the design of cognitive trajectory controllers using FCM. The authors used genetic algorithms to optimize the FCM. The proposed framework shows capabilities to represent causal relationships between concepts with better accuracy. Finally, the proposed approach improves controller design by integrating nonlinear control theory with computational intelligence techniques.

Hoyos et al [15] proposed an extension of FCMs for prescriptive modeling. The authors used a step-based approach to characterize the FCM in two layers according to the nature of the variables. Subsequent to the characterization, a genetic algorithm optimized the FCM to find the desired values of variables related to decision making. The approach tested in different domains demonstrated its generalization capability and its high performance in prescribing actions leading to desired outcomes within the modeled system.

Other recent extensions include hierarchical FCMs for diabetes classification [16], rule-based FCMs for financial risk management [17], hybrid FCMs with techniques such as LSTM for time series forecasting [18], and FCMs used in bioinformatics to predict AND-binding residues in protein sequence segments [19], and for the definition of a clinical decision-support system for dengue [20].

## III. THEORETICAL FRAMEWORK

### A. PE

PE is a multisystem disorder characterised by elevated blood pressure, with or without the presence of proteinuria, which usually occurs after 20 weeks gestation [21]. Signs of severity are helpful in making the diagnosis such as thrombocytopenia, elevated liver enzyme concentrations, severe persistent right upper quadrant or epigastric pain [22]. Several risk factors have been associated with the likelihood of developing PE during pregnancy, including having a previous history of PE, medical conditions such as diabetes mellitus, chronic hypertension, systemic lupus erythematosus, antiphospholipid syndrome, thrombophilias, renal disease, overweight, multifetal pregnancy, nulliparity, family history, advanced maternal age and assisted reproductive techniques [23].

### B. FGR

FGR is a condition in which a fetus does not develop as expected. Fetuses with a growth percentile less than 10 are classified in this group [24]. It is a multifactorial pathology that can be originated by different cases such as maternal, fetal and placental alterations. Fetuses with this condition have a higher probability of complications such as premature delivery, intrauterine hypoxia and perinatal mortality. Some of the maternal factors related to FGR are gestational diabetes, arterial hypertension, PE, alcohol and drug use. Fetal factors involve intrauterine infections such as toxoplasmosis or rubella. Placental factors include placental abruption and placental insufficiency [25].

### C. FUZZY COGNITIVE MAPS (FCM)

Fuzzy Cognitive Maps (FCM) is a technique developed by Kosko [26], which aims to expand the working horizon of traditional cognitive maps. Most of the knowledge within decision-making processes is represented through causal reasoning. An FCM is a directed graph with nodes symbolising concepts and arcs directed to nodes representing causal relationships. Figure 3 shows an example of an FCM with nodes and relationships between them. Mathematically, an FCM is defined as a tuple of 4 elements:

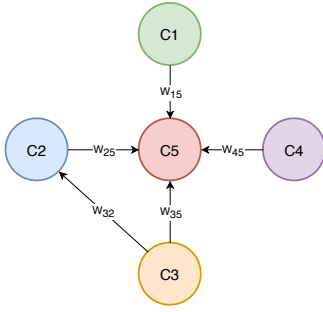
$$\Phi = \langle n, f(\cdot), r, W \rangle \quad (1)$$

where  $n$  is the number of concepts,  $W$  is the weights matrix that defines the relationships between the concepts,  $f(\cdot)$  is an activation function that will keep the values of the concepts in a range determined by  $r$ .

The inference process of FCMs consists of the successive computation of a vector of states using an initial vector  $a(0)$  and the matrix  $W$  until the system finds an equilibrium state. The following equation summarises the FCM inference or reasoning process:

$$a_j(t+1) = f\left(\sum_{i=1, i \neq j}^n W_{ij}a_i(t)\right) \quad (2)$$

where  $a_j(t+1)$  is the value of concept  $C_j$  at iteration  $t+1$ ,  $n$  is the number of concepts,  $W_{ij}$  is the value of the relation



**FIGURE 3.** Example of an FCM with 5 concepts and 5 relationships between them.

between concept  $C_i$  and concept  $C_j$ , and  $a_j(t)$  is the value of concept  $C_j$  at iteration  $t$ .

FCMs have become an important tool for representing knowledge in a more flexible way, where the uncertainty and ambiguity of human thinking can be captured. They are considered explainable and interpretable models that can provide useful information about complex systems, which has been useful in fields such as artificial intelligence, cognitive psychology and decision-making [27].

#### D. PARTICLE SWARM OPTIMIZATION (PSO)

Particle swarm optimisation (PSO) is an optimisation algorithm that evokes the behaviour of particles in nature [28]. It was developed by Kennedy and Eberhart, inspired by the social movement and group behaviour of birds and fish [28]. PSO is built around particles moving in the search space of an objective function. It is a computational model capable of iteratively optimising problems by improving a candidate solution with respect to a quality measure. PSO optimises a problem through a solution population of candidates, represented by particles, and moving these particles through the search space using mathematical formulae about particle position and velocity.

PSO is used to train the weight matrix of an FCM in which each particle  $i$  is an FCM and its position is a candidate weight matrix ( $W_i$ ). The process consists of two steps to move the particle to a new position: 1) update the velocity of the particle, 2) update the position of the particle. The first step is to update the velocity of the particle using the following equation:

$$v_i(t + 1) = v_i(t) + r_1 \cdot (W_i^{best} - W_i(t)) + r_2 \cdot (W_i^{g^{best}} - W_i(t)) \quad (3)$$

where  $v_i(t)$  is the velocity of particle  $i$  at time  $t$ ,  $r_1$  and  $r_2$  are two random values generated during the search process;  $W_i^{best}$  is the best position the particle has passed through during the search process and  $W_i^{g^{best}}$  is the best global position of the whole swarm. Once the particle velocities are updated, the positions are updated using the following equation:

$$W_i(t + 1) = W_i(t) + v_i(t) \quad (4)$$

Thus, the algorithm generates the best weight matrix ( $W_i$ ) using the above updates.

#### IV. OUR APPROACH

In this section, we present our proposed approach corresponding to multistage FCM training for disease prediction. Multi-stage FCM training is inspired by hierarchical FCM approaches [29], [30], which have interesting applications in different domains [31], [32]. Figure 4 and Figure 5 show a schematic representation of the architecture of our proposed approach with an example of the disease process. Next, we describe each of the steps required to implement our proposed methodology.

##### A. CATEGORIZATION OF AVAILABLE VARIABLES

The first step for multistage training is to characterize the variables available in the dataset. This requires knowledge of the process to be modeled and the evolution of these variables over time. For example, in a disease, the initial variables (stage 1) would be the sociodemographic variables because they are based on the patient. Within these variables we can have age and sex. When the disease begins its course, alterations begin to appear (signs and symptoms) and can be detected using studies such as Doppler. The variables related to this study constitute the second stage. Subsequent to these variables, the disease produces alterations in the organism that result in an increase or decrease of metabolites that can be detected with laboratory tests. Laboratory tests can be modeled in a third stage. Taking the above case as an example, the overall dataset can be represented as follows:

$$D = S \cup C \cup L \cup T \quad (5)$$

Where  $D$  the general dataset,  $S$  the subset of data pertaining to maternal and fetal variables,  $C$  the subset of data pertaining to Doppler variables,  $L$  the subset of data related to laboratory tests, and  $T$  is the target variable. Each of these subsets can be defined as follows:

$$S = \{C_1^s, C_2^s, C_3^s, \dots, C_j^s\} \quad (6)$$

where  $j$  is the number of maternal and fetal variables,

$$C = \{C_1^c, C_2^c, C_3^c, \dots, C_k^c\} \quad (7)$$

where  $k$  is the number of Doppler-related variables,

$$L = \{C_1^l, C_2^l, C_3^l, \dots, C_m^l\} \quad (8)$$

where  $m$  is the number of laboratory-related variables.

In the same way we express the problem for FGR. The first stage represents the variables related to the mother's history which can be expressed by the following equation:

$$H = \{C_1^p, C_2^p, C_3^p, \dots, C_h^p\} \quad (9)$$

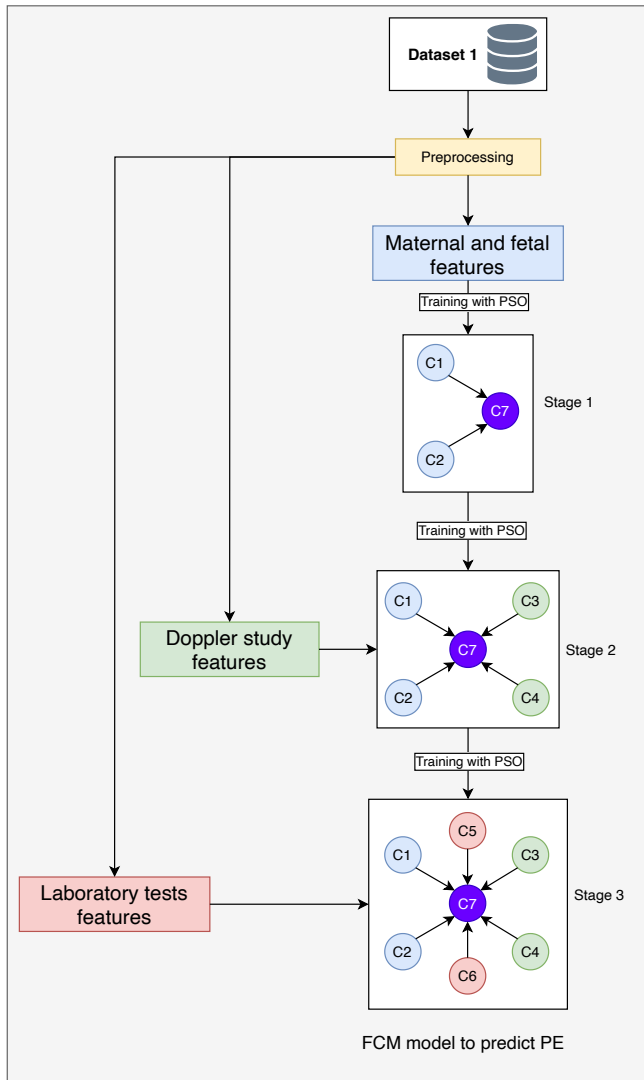


FIGURE 4. General architecture of our proposed approach for building a multistage FCM model to predict PE.

where  $h$  is the number of variables related to the mother's history to predict FGR. Then, we have the clinical manifestations in the mother, which can be represented by the following expression:

$$I = \{C_1^q, C_2^q, C_3^q, \dots, C_i^q\} \quad (10)$$

where  $i$  is the number of signs and symptoms in the mother used to predict FGR. Finally, there are alterations in laboratory tests. These variables can be expressed by:

$$V = \{C_1^r, C_2^r, C_3^r, \dots, C_n^r\} \quad (11)$$

where  $n$  is the number of laboratory-related variables used to predict FGR.

### B. MULTI-STAGE TRAINING USING PSO

The objective of multistage training is to simulate the evolution of the process to be modeled. For our example, we

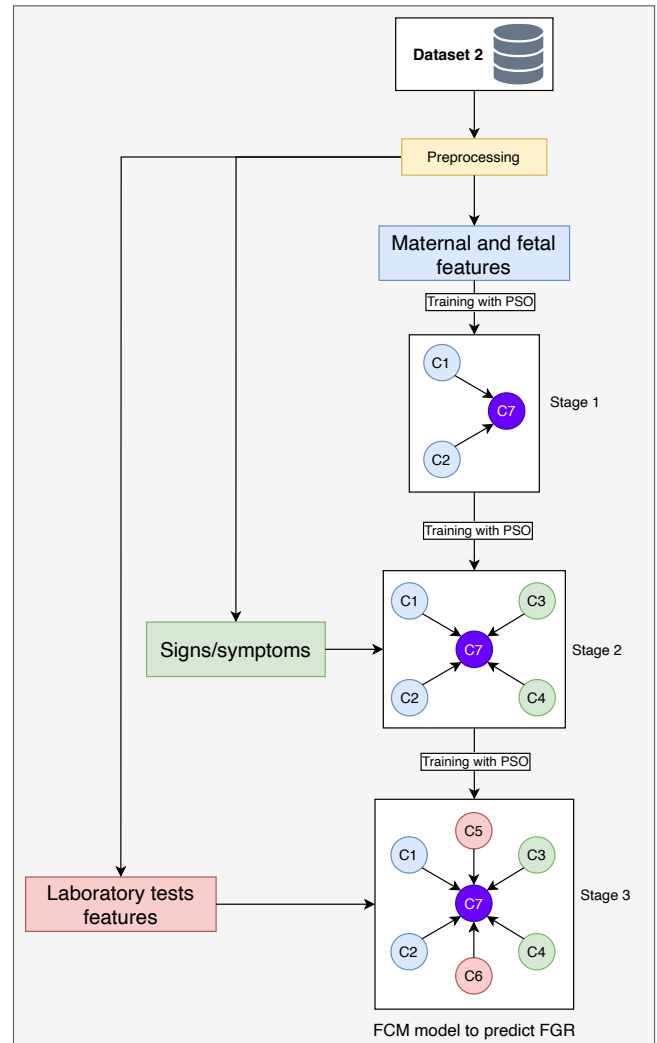


FIGURE 5. General architecture of our proposed approach for building a multistage FCM model to predict FGR.

want to simulate the evolution of the disease, and each stage is related to a type of variable characterized in the previous section. Thus, the number of stages needed for training would be determined by the number of types of variables that can be characterized. Thus, if we take, as an example, PE (see Figure 4), we can see three types of variables: maternal and fetal characteristics, Doppler characteristics, and laboratory-related characteristics. In this case, our model will be trained using three stages. For the case of FGR, three stages would also be used (see Figure 5).

For PE, in the first stage, we use the maternal and fetal variables together with the target variable, and by means of PSO, we optimize the weights or relationships between the concepts. This optimized FCM goes to the next stage (Stage 2), where the variables corresponding to the Doppler study are added. Next, an optimized FCM is generated that serves as input to the third stage, where the laboratory variables are added, which are the last to be altered when the disease is present in the patient. The aggregation of the variables for

training is given by the following equation:

$$W^A = \begin{bmatrix} 0 & W_{stage1} \\ W_{stage2} & 0 \end{bmatrix} \quad (12)$$

Where  $W^A$  is the matrix corresponding to the aggregated FCM model.  $W_{stage1}$  is the matrix corresponding to the FCM of the stage 1 variables and  $W_{stage2}$  is the matrix corresponding to the FCM with the stage 2 variables. In this way, the variables are added to form a final FCM.

For FGR, the first stage consists of the maternal and fetal characteristics in conjunction with the target variable. This first model is optimized using PSO. Subsequently, the variables associated with signs and symptoms are added to the model for further training (stage 2). Finally, the variables related to laboratory tests are added for a new training. This constitutes the third or final stage. From here the models are ready to make predictions on previously unseen data.

## V. EXPERIMENTS

To evaluate the predictive ability of our approach we used PE and FGR as case studies. Figure 4 shows a schematic representation of the architecture used for the construction of the FCM model to predict PE, while Figure 5 shows the architecture for FGR prediction.

### A. DATASETS

#### 1) Dataset 1

For the construction of the predictive model of PE, a dataset containing clinical variables related to the mother and newborn, uterine Doppler results and laboratory tests was used from a prospective study conducted at the University Medical Center Ljubljana [33]. The database information contains information from 22 pregnant women with PE and 29 women with normal pregnancy (control group), who gave their consent for the study. The dataset is available at [34]. In Table 1, we observe the information of the study variables (defined from C1 to C21) classified into 3 categories according to the training stage of the model. For stage 1, seven (7) characteristics related to the mother and newborn (C1 to C7) were used. In stage 2, variables related to the Doppler studies of the pregnant women were added (C8 to C17). For the third stage of training, laboratory test results were added (C18 - C20), and finally, the variable C21 corresponds to the classification between pregnant women with PE and those without the disease. All these variables were used for the multistage training of the FCM model.

#### 2) Dataset 2

For the prediction of FGR, a dataset containing variables related to maternal and fetal health, maternal-related signs and symptoms, and laboratory tests was used. The data came from a study conducted at the Gynecology and Obstetrics Center of Maternal and Child Health Care Hospital, Hefei, China [35]. The dataset consisted of 72 women with early PE. Table 2 shows the variables collected and classified for

each stage. For stage 1, five (5) characteristics related to the mother and newborn (C1 to C5) were used. In stage 2, variables related to signs and symptoms were added (C6 to C16). For the third training stage, laboratory test results were added (C17 to C24), and finally, variable C25 corresponds to the classification between fetuses with normal weight and fetuses with FGR. In the database, 56 records were found with FGR and 26 with normal weight.

### B. DATA PREPROCESSING

Preprocessing techniques are a preliminary step to improve data quality, accuracy, and model efficiency. In the dataset, we eliminated variables that were not considered of interest for the analysis of PE, such as patient identification. Two missing values were imputed with the arithmetic mean in the concept "mean PSV". Finally, we used the min-max normalization technique (see equation 13) to fit the data on a scale between 0 and 1. The control group was assigned the value of 0 and the PE group the number 1.

$$N_i = \frac{X_i - X_{min}}{X_{max} - X_{min}} \quad (13)$$

The normalization process was carried out in a multi-stage manner and only on the variables used in each stage. The minimum and maximum is calculated only for the variables that are incorporated in each stage of the training. When moving to the next stage and new variables are added, their own normalization is calculated. In this way, each variable is normalized in isolation, when it enters the training system, without allowing statistics of variables not yet seen to affect previous stages.

Since dataset 2 corresponding to FGR was unbalanced for the target variable, we performed Synthetic Minority Over-sampling Technique (SMOTE) [36] to generate synthetic data and thus balance the classes for a better interpretation of the results. After applying this technique, the dataset 2 contained 56 records for each class.

### C. DATA SPLITTING AND HYPERPARAMETER CONFIGURATION

To validate our approach, we employed 5-fold nested cross-validation to fit the hyperparameters and find the best model. We divided the dataset into 70% for training and the remaining 30% of the data was used for testing. Twenty percent of the training data was chosen for validation. For FCM training with PSO, we used different random values of initial population varying between 30 and 300 individuals, cognitive and social components with random values between 0.05 and 10. In the inference process, we used the hyperbolic sigmoid and hyperbolic tangent hyperbolic activation functions. Also, we tested the three inference functions: Kosko, Kosko-modified and Rescaled. Finally, the best metrics used in each case were the result of a hyperparametric grid search optimization process.

**TABLE 1.** Variables used in multistage modeling to predict PE.

Stage	Type of variable	Variable	Concept
1	Maternal and fetal variables	Maternal age	C1
		Mother's weight before pregnancy	C2
		Mother's height	C3
		Body Mass Index	C4
		Parity	C5
		Gestational age at delivery	C6
		Baby's birth weight	C7
2	Dopples-related features + Features of the stage 1	Right resistivity index (RI)-UtA	C8
		Right pulsatility index (PI)-UtA	C9
		Right peak systolic velocity (PSV)-UtA	C10
		Left RI-UtA	C11
		Left PI-UtA	C12
		Left PSV-UtA	C13
		Mean RI-UtA	C14
		Mean PI-UtA	C15
3	Laboratory tests-related features + features of the stage 2	Mean PSV-UtA	C16
		Bilateral notch	C17
		S-Flt1 (Endothelial growth factor receptor 1)	C18
		PLGF (Placental growth factor)	C19
		sFLT/PLGF	C20
	Target	C21	

**TABLE 2.** Variables used in multistage modeling to predict FGR.

Stage	Type of variable	Variable	Concept
1	Maternal and fetal variables	Maternal age	C1
		Body mass index	C2
		Gestational age of delivery	C3
		Gravidity	C4
		Parity	C5
2	Signs and symptoms + Features of the stage 1	Initial onset symptoms (IOS)	C6
		Gestational age of IOS onset	C7
		Interval from IOS onset to delivery	C8
		Gestational age of hypertension onset	C9
		Interval from hypertension onset to delivery	C10
		Gestational age of edema onset	C11
		Interval from edema onset to delivery	C12
		Gestational age of proteinuria onset	C13
		Interval from proteinuria onset to delivery	C14
		Maximum systolic blood pressure	C15
Maximum diastolic blood pressure	C16		
3	Laboratory tests-related features + features of the stage 2	Maximum values of creatinine	C17
		Maximum uric acid value	C18
		Maximum proteinuria value	C19
		Maximum total protein value	C20
		Maximum albumin value	C21
		Maximum ALT value	C22
		Maximum AST value	C23
		Maximum platelets value	C24
		Target	C25

#### D. EVALUATION

To evaluate the predictive performance of the models developed, we used three metrics: accuracy, precision, and recall. Accuracy represents the proportion of cases that the model correctly classifies as healthy, with PE, or with FGR. Precision corresponds to the number of individuals with true positive PE or FGR compared to the total number of positive values. Recall is the proportion of women with PE or the proportion of fetuses with FGR that the model has classified based on the total number of positive values. We then compared the performance of the multistage model with the conventional approach using the same classification metrics. We carried out a convergence analysis to determine the stability

of the FCMs generated at each stage. Finally, we compared the results of our proposed approach with some of the most advanced techniques currently available for predicting PE and FGR.

To determine which model performed best between the proposed approach and the conventional approach, we used the Mann-Whitney U test. Previously, the Lilliefors test was used to determine which comparison test to use because the data did not follow a normal distribution. Two hundred runs were performed for each approach. To compare our approach with other ML techniques, we again used 200 runs for each model. Our approach was compared with logistic regression (LR), random forest (RF), gradient boosting (GB), long short-

term memory (LSTM), and gated recurrent unit (GRU). The Kruskal-Wallis test was used for the comparison because the results of the runs for at least one model did not follow a normal distribution. The objective was to determine whether there were significant differences between the performance of the developed models.

## VI. ANALYSIS OF THE RESULTS

We set out to develop a multi-stage training methodology to simulate the evolution of complications in pregnancy. The multi-stage training was compared with conventional training. Table 3 shows the results of the evaluation of the models in both the proposed approach and the conventional approach.

### A. PREDICTION OF PE

The multistage FCM model for the prediction of PE was constructed with the clinical variables related to the mother and newborn, the characteristics of the Doppler studies, and variables related to laboratory tests. Table 3 shows the predictive performance of the multistage and conventional models. The results obtained show a good performance with an accuracy of 82%, while the conventional approach yielded an accuracy of 0.70%. In the other metrics, such as precision and recall, the multistage model performed better than the conventional one. If we compare these results, we notice that the multistage training performed better. This could be explained by the fact that the variables manifest themselves in the patient with PE in a staggered manner and not all at the same time, as represented in the conventional training. The best hyperparameters for PSO were an initial population of 110 individuals, a social coefficient of 2.05, and a cognitive coefficient of 2.0.

### B. PREDICTION OF FGR

The model to predict FGR was constructed using maternal and fetal variables, signs and symptoms, and laboratory tests. Table 3 shows the predictive performance of the multistage and conventional models. The accuracy of the multistage model (98%) was superior to the conventional model (93%). The results show that multistage training can better capture the functional dependencies between the predictor variables and the target variable. Similarly to PE, establishing training that simulates the disease process can better capture patterns in the data.

The models developed for FGR were superior to those developed for PE. Many factors could influence these results, such as the size of the dataset, the number of variables used for training, and the types of variables used. Regarding the dataset size, for FGR, there were more records, which could improve pattern discovery. Similarly, for FGR, there were more variables available as signs and symptoms than were not available for PE. Finally, the variables used in the FGR models are signs and symptoms, routine laboratory tests that are used in medical practice, while for PE only special laboratory tests that are not routinely performed were available. The best hyperparameters for PSO were an initial population

of 120 individuals, a social coefficient of 2.0, and a cognitive coefficient of 1.9.

### C. FIXED-POINT CONVERGENCE ANALYSIS FOR PE

Figure 6 shows the variation in the values of each concept (C1-C7 and C21) over several iterations in the first stage of training. The FCM in this stage stabilizes at 9 iterations. The behavior shows that C3 and C7 start high (0.5-0.65) and rise slightly before converging at 0.35 and 0.71, respectively. C5 shows the largest initial jump (from 0.07 to 0.49 in iteration 1), indicating strong reinforcement by its connections. Other concepts (e.g., C1, C2, C4, C6, and C8) show minor variations and stabilize between 0.33 and 0.41. The FCM in this stage reaches a clear steady state. Concepts with stronger connections (such as C5 and C7) dominate the steady state, while less influential variables remain at medium-low levels.

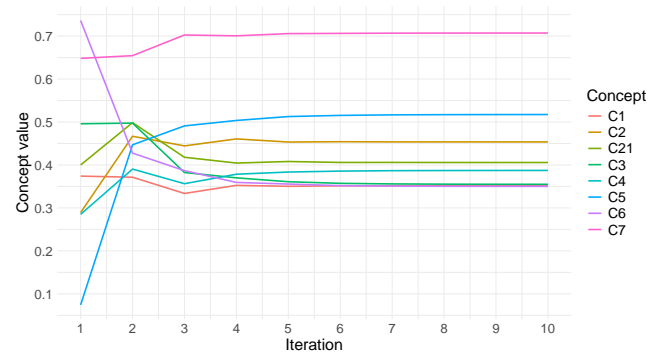


FIGURE 6. Evolution of the concepts in stage 1 to predict PE.

Figure 7 shows the variation in the values of each concept (C1-C17 and C21) over several iterations in the second stage of training. In this second stage, the FCM stabilizes at 11 iterations. Concepts with stronger connections, particularly C7 and C5, show a rapid rise in the first iterations, reaching activation levels above 0.80 (for C7) and 0.64 (for C5). Intermediate concepts such as C10 and C17 stabilize around 0.60, reflecting moderate roles within the network. Variables with minor influences, such as C12 and C8, start close to 0.13-0.16 and barely grow to 0.25-0.26, indicating low centrality. The second-stage FCM, with its 18 nodes, converges stably and predictably in 11 iterations, just two more than the first stage. The most influential nodes (especially C7, followed by C5 and C10) obtain the highest activation levels, marking potential priorities for clinical interventions or interpretations. Nodes with low final activation are candidates for having little relevance in the overall dynamics of the system.

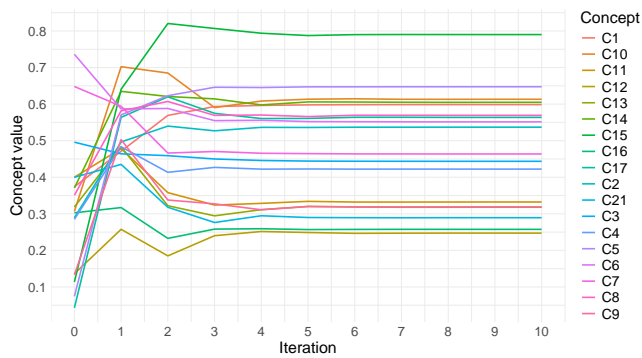
Figure 8 shows the variation in the values of each concept (C1-C21) over several iterations in the third stage of training. The FCM in the last stage, with all concepts, stabilizes after 9 iterations. Concepts C3 and C2 stand out with high final levels (0.76 and 0.73), suggesting a central role in the final network. Concepts such as C4 and C13 start low (0.12-0.13) and barely reach 0.19-0.25, indicating low residual influence. The convergence speed is comparable to stage 1, despite hav-

**TABLE 3.** Predictive performance of models trained under the multi-stage and conventional approach.

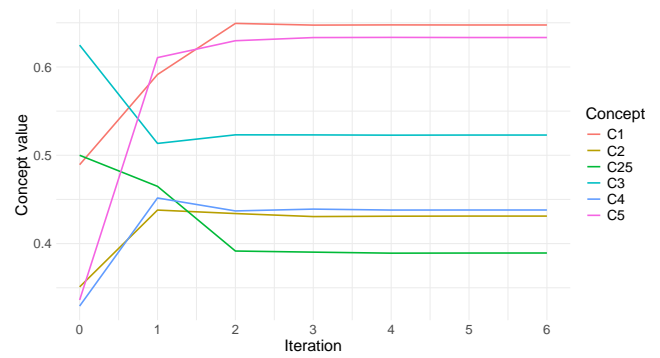
Metric	PE			FGR		
	Multistage ( $\bar{X} \pm SD$ )	Conventional ( $\bar{X} \pm SD$ )	p-value	Multistage ( $\bar{X} \pm SD$ )	Conventional ( $\bar{X} \pm SD$ )	p-value
Accuracy	0.82 ± 0.12	0.70 ± 0.24	0.023	0.98 ± 0.21	0.93 ± 0.10	0.033
Precision	0.85 ± 0.14	0.81 ± 0.11	0.041	0.97 ± 0.18	0.91 ± 0.16	0.041
Recall	0.76 ± 0.09	0.51 ± 0.14	<0.01	0.96 ± 0.06	0.93 ± 0.06	0.049

**TABLE 4.** Comparison of the predictive performance of our proposed approach with other ML techniques to predict PE.

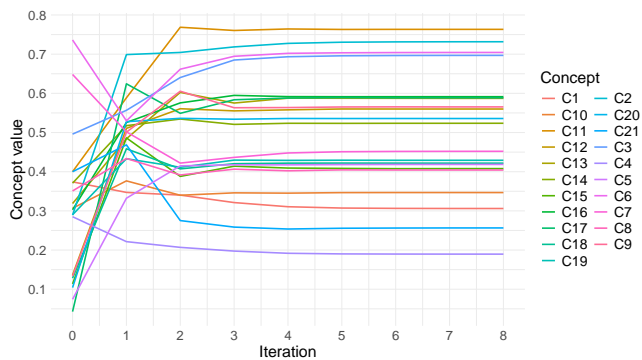
Metric	Model						p-value
	LR( $\bar{X} \pm SD$ )	RF( $\bar{X} \pm SD$ )	GB( $\bar{X} \pm SD$ )	LSTM( $\bar{X} \pm SD$ )	GRU( $\bar{X} \pm SD$ )	Our approach( $\bar{X} \pm SD$ )	
Accuracy	0.80 ± 0.18	0.81 ± 0.24	0.82 ± 0.11	0.80 ± 0.13	0.80 ± 0.22	0.82 ± 0.14	0.747
Precision	0.82 ± 0.23	0.81 ± 0.12	0.83 ± 0.19	0.82 ± 0.17	0.84 ± 0.12	0.85 ± 0.21	0.821
Recall	0.79 ± 0.12	0.83 ± 0.15	0.84 ± 0.17	0.87 ± 0.11	0.83 ± 0.14	0.76 ± 0.20	0.473



**FIGURE 7.** Evolution of the concepts in stage 2 to predict PE.



**FIGURE 9.** Evolution of the concepts in stage 1 to predict FGR.



**FIGURE 8.** Evolution of the concepts in stage 3 to predict PE.

ing a larger number of variables. The range of values upon convergence narrows (0.25-0.76), showing a greater bias toward moderate-high levels in key concepts. The final FCM design maintains stability in similar iterations, with certain concepts (especially C3 and C2) emerging as dominant nodes that could be the focus of future actions.

**D. FIXED-POINT CONVERGENCE ANALYSIS FOR FGR**

Figure 9 shows the evolution of the concepts in the first stage of the training for FGR prediction. In this stage, the FCM manages to stabilize after 6 iterations. The most strongly connected concepts, such as C1 and C5, show a rapid rise in the

first iteration, reflecting their high influenceability within the system. Most of the concepts converge in a relatively narrow range between 0.39 and 0.65, indicating an equilibrium in the system. With only six nodes, the FCM reaches its fixed point in a few iterations, indicating a well-connected and compact network for FGR analysis.

Figure 10 shows the evolution of the concepts in the second stage of training for FGR prediction. In this stage, the FCM manages to stabilize after seven iterations. Some concepts incorporated in this stage experience rapid rises in the first iteration, such as C8, C10, and C12, with values between 0.57 and 0.67, reflecting their high centrality in the generated network. Most of the nodes converge between 0.26 and 0.70, denoting a balanced but heterogeneous system. No significant oscillations or divergences occur after the last iteration. Despite increasing the number of concepts with respect to stage 1, the FCM converges with only one more iteration, demonstrating the robustness of the multi-stage network by incorporating additional variables.

Figure 11 shows the evolution of the concepts in the third and last stage of the training for FGR prediction. In this last stage, the FCM manages to stabilize after 11 iterations. Nodes with higher initial values such as C3, C7, C13 and C17 show very pronounced initial peaks before stabilizing. The final range of activations is wide from 0.08 to 0.95 reflecting the joint presence of very weak and very dominant

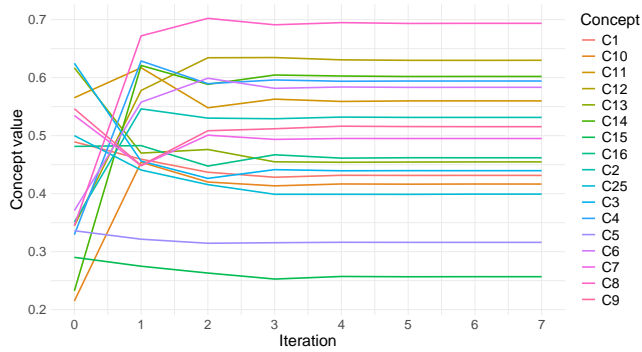


FIGURE 10. Evolution of the concepts in stage 2 to predict FGR.

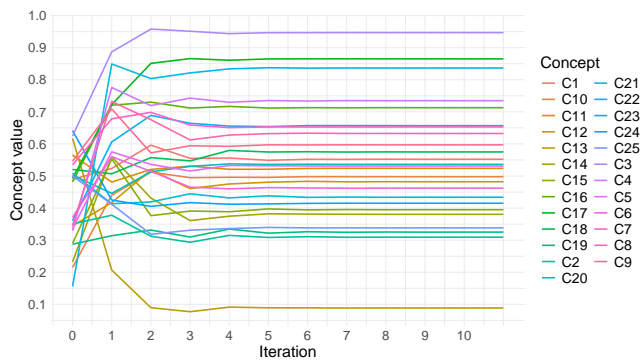


FIGURE 11. Evolution of the concepts in stage 3 to predict FGR.

nodes. After iteration 7 most of the curves exhibit near zero slopes confirming the arrival at the fixed point. However, it is at iteration 11 that the stopping criterion of  $\epsilon < 0.001$  is met. Despite increasing the complexity of the FCM by adding more concepts up to 25, which increases the number of iterations in the simulation, the FCM maintains a convergent and stable behavior.

### E. COMPARISON WITH OTHER ML APPROACHES

Table 4 shows a comparison of our proposed approach with other ML techniques for predicting PE. The results show that there are no significant differences between the accuracy, precision, and recall of the tested models (according to the statistical test). However, our approach allows for simulation of the disease process by adding variables to the training in the order in which they appear as the disease develops in the individual. Table 5 shows a comparison of our approach with other ML techniques to predict FGR. The results show that there are also no differences between the performance of the models according to the statistical test. Thus, our proposed approach generates models that are competitive for predicting PE and FGR. Additionally, our approach allows for the simulation of the disease process, which could be useful for disease analysis by medical professionals.

## VII. CONCLUSION AND FUTURE WORK

This research presents a methodology to train FCMs in a multistage fashion to predict pregnancy complications such as PE and FGR. The training of the models was developed using maternal and fetal clinical data, Doppler study variables, signs, symptoms and laboratory tests. The results showed that the performance of the trained multistage FCMs significantly improved disease classification, obtaining an accuracy of 82% for PE and an accuracy of 98% for FGR. The performance of these multistage models was superior to conventional models, which consisted of training the model in a single stage. In addition, convergence analyses demonstrated the stability of FCMs at each stage of training. The comparison of our approach with other ML techniques demonstrated that our methodology is competitive in predicting PE and FGR. The implementation of this type of methodology to develop FCM models serves as a guide for medical decision support, which would significantly improve disease prediction. Thus, timely diagnosis and treatment would play a crucial role in preventing adverse maternal-perinatal outcomes.

This research has some limitations. Our proposed approach was tested on two specific datasets due to the low availability of PE and FGR data. The application of our proposed method to data of different nature could improve the analysis of PE and FGR. In future work, the proposed methodology will be applied to the prediction and classification of other hypertensive disorders of pregnancy, using a dataset with a larger number of participants, using routine variables obtained from prenatal controls. We recommend testing our approach in other types of diseases with different evolution to validate its ability to generate predictive models with better performance.

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**TABLE 5. Comparison of the predictive performance of our proposed approach with other ML techniques to predict FGR.**

Metric	Model						p-value
	LR( $\bar{X} \pm SD$ )	RF( $\bar{X} \pm SD$ )	GB( $\bar{X} \pm SD$ )	LSTM( $\bar{X} \pm SD$ )	GRU( $\bar{X} \pm SD$ )	Our approach( $\bar{X} \pm SD$ )	
Accuracy	0.93 $\pm$ 0.25	0.97 $\pm$ 0.10	0.98 $\pm$ 0.11	0.95 $\pm$ 0.15	0.94 $\pm$ 0.32	0.98 $\pm$ 0.11	0.472
Precision	0.94 $\pm$ 0.27	0.91 $\pm$ 0.09	0.93 $\pm$ 0.26	0.96 $\pm$ 0.23	0.92 $\pm$ 0.26	0.97 $\pm$ 0.24	0.549
Recall	0.95 $\pm$ 0.12	0.96 $\pm$ 0.17	0.97 $\pm$ 0.05	0.94 $\pm$ 0.10	0.92 $\pm$ 0.16	0.96 $\pm$ 0.12	0.720

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