Time Series Forecasting Approach for Predictive Modeling of Next Menstrual Cycle Length

Paulina Julia C. de Oliveira
Computational Intelligence Laboratory
Federal University Rural of the Semi-Arid
Pau dos Ferros RN, Brazil
paulina.oliveira@alunos.ufersa.edu.br

Caio M. V. Cavalcante
Computational Intelligence Laboratory
Federal University Rural of the Semi-Arid
Pau dos Ferros RN, Brazil
caio.cavalcante@alunos.ufersa.edu.br

Rosana C. B. Rego
Departament of Engineering and Technology
Federal University Rural of the Semi-Arid
Pau dos Ferros RN, Brazil
rosana.rego@ufersa.edu.br

Abstract—A proper forecast of the menstrual cycle is meaningful for women's health, as it allows individuals to take preventive actions to minimize cycle-associated discomforts. In addition, precise prediction can be useful for planning important events in a woman's life, such as family planning. In this work, we explored the use of machine learning techniques to predict regular and irregular menstrual cycles. We implemented some time series forecasting algorithm approaches, such as AutoRegressive Integrated Moving Average, Huber Regression, Lasso Regression, Orthogonal Matching Pursuit, and Long Short-Term Memory Network. Moreover, we generated synthetic data to achieve our purposes. The results showed that it is possible to accurately predict the onset and duration of menstrual cycles using machine learning techniques.

I. INTRODUCTION

The menstrual cycle is the time from the first day of a woman's period to the day before her next period [1]. It differs from woman to woman, in addition, it is connected to physical and mental well-being [2]. The correct knowledge of cycle variations is crucial to understanding reproductive health and defining multidimensional well-being in women [2]. Some phases constitute the menstrual cycle, such as the menstrual phase or period, follicular phase, ovulation phase, and luteal phase, sequentially [3]. The length of each phase can vary from woman to woman, and it can modify over time. In this way, a cycle is considered regular when it varies from 21 to 35 days, counting from the first day of one period to the first day of the next [3]. In a regular cycle, the period can endure between three and five days [3]. The luteal phase, usually, will be fourteen days long, and the follicular phase will also be fourteen days long [3]. However, not all women will have this menstrual pattern. During the woman's life, the periods can alter, i. e., they may stay longer or get lighter [4]. The periods will persist until menopause, which usually happens when women are in their late 50s [3]. Moreover, the cycle can be irregular. A cycle is considered irregular when most of the previous cycles are outside regular intervals, i.e., there is no visible pattern in the variation [5].

Irregular cycles are common and usually not a cause for worry. Factors that can contribute to irregular periods include: natural hormonal changes, hormonal birth control, stress, resistance exercise, and weight loss [6]. For instance, for a woman in perimenopause irregularity of periods is extremely common. However, an irregular cycle may be a sign of either early ovarian failure or polycystic ovary syndrome [5], [7]. Moreover, irregular cycles can sometimes drive pregnancy complicated, as the days a woman is ovulating can also be irregular [1]. In this way, women who hold irregular cycles and desire to become pregnant have traditionally resorted to the arduous strategy of tracking urinary luteinizing hormone (LH), measuring basal body temperature (BBT), calendars, and calculations to estimate the ovulatory window and thus maximizing their chances of getting pregnant [8]. However, manually mapping and tracking fertility through BBT and LH tests can be arduous [9].

The knowledge of the menstrual cycle allow women understanding their own body and may detected a possible menstrual disorders [10]. However, many women are troubled by an irregular or unpredictable menstrual cycle [11]. The patterns are so individual to each woman that it is hard for a human to create enough rules to capture them. In this way, machine learning (ML) techniques can be applied to predict a woman's cycle. ML and deep learning algorithms can detect each woman's unique and individual patterns and better predict the ovulation window and period. Computational intelligence can be helpful for disease diagnosis, decision support systems, and prognosis [12]–[14]. Because of this, it has become an important approach in biomedical discovery and clinical research.

ML algorithms, such as artificial neural networks (ANN), can deliver significantly better solutions than known methods to cycle predictions [15]. As described by [16], machine learning procedures enable the development of intelligence into a machine so that it can achieve better in the future using the learned experience. Moreover, machine learning appliances carry about smart change in the health industry, which includes pattern detection [17], predictions system [18], [19], image recognition [20]. In this way, in this paper, we highlighted the prediction system for the predictive modeling of healthcare,

particularly menstrual cycle length from synthetic data.

One of the prior challenges in predictive modeling for the menstrual cycle pertains to addressing the uncertainty of the data at hand, as well as ensuring the adjustment of the model output [13], [15], [21]. In manuscript [13], the authors explored uncertainty quantification when designing predictive models for healthcare, such as cycle length patterns. In the same way, [15] proposed a predictive model for predicting the next menstrual cycle start date. Differently, in [21], the authors applied some machine learning models to predict polycystic ovary syndrome. Therefore, these works have demonstrated the capability of probabilistic models and machine learning algorithms to detect patterns in women's cycles.

Motivated by the above discussion, our purpose is to accurately forecast the subsequent cycle based on previously tracked cycle and periods. Thus, the main contributions of this work lie in the following:

i. Use machine learning algorithms to analyze data from previous menstrual cycles in order to identify patterns and predict the start of future cycles;

ii. Model that can accurately predict the timing and length of the menstrual cycle using only historical menstrual cycle data.

The manuscript is divided into: The introduction, where we provided background information on the problem and its significance. The related work section summarizes the relevant research on the topic. The problem formulation section describes the problem and some time series algorithm approaches. The data characteristics section describes the research design and data generation methods used in our study. The results section presents our findings, including statistical analyses and visual representations of the data. Finally, the conclusion summarizes the main findings and contributions of our study and suggests directions for future research.

II. RELATED WORK

There is a need for the development of an appropriate model for one-step-ahead forecast periods. In the last few years, the usage of web systems and apps to track periods and predict the fertile window has become popular [22], [23]. For instance, in the manuscript [24], the authors built a hybrid predictive model based on autoregressive–moving-average (ARMA) and linear mixed effect model (LMM) for forecasting menstrual cycle length in athletes. In paper [25], the authors presented a state-space modeling approach for forecasting the onset of menstruation based on basal body temperature time series data. They used the state-space model to forecast the onset of menstruation for up to three months in advance. Differently, in [26], Chen et al. proposed a mathematical model of the human menstrual cycle. The model is based on a system of differential equations that describes the changes in hormone levels in the body over the course of the menstrual cycle. The authors validated the model using data from clinical studies of the menstrual cycle and found that it accurately predicted the timing and magnitude of hormone fluctuations during the cycle.

In [27], the authors presented a mathematical model for the administration of gonadotropin-releasing hormone (GnRH) analogs in the treatment of infertility. The authors developed the model to optimize the timing and dosage of GnRH analog administration for the induction of ovulation. The model takes into account the feedback mechanisms that regulate hormone levels, as well as the effects of GnRH analogs on hormone production.

To enhance analysis, we compiled some manuscripts that modeling cycles in time series data. In Table I, we summarized the paper, the model used by authors, and the features employed.

TABLE I
RELEVANT PAPERS.

Paper	Model	Features
[24]	ARMA, LMM	Cycle lengths
[28]	Poisson model	Cycle lengths
[13]	CNN, RNN, LSTM, Poisson	Cycle lengths
[29]	Cyclic Hidden Markov Models	Cycle lengths
[30]	Natural Cycles algorithm*	Cycle lengths, BBT, LH

*Algorithm information are not provided.

The authors, in [24], employed the ARMA, and LMM models, focusing on cycle lengths as the key feature of interest. [28] used a Poisson model, with a focus on cycle lengths as well. In [13] a comparison between Convolutional Neural Network (CNN), Recurrent Neural Network (RNN), Long Short-Term Memory (LSTM), and Generalized Poisson models are made. [30] compared fertile window and cycle predicted by Natural Cycles algorithm over calendar-based methods. The Natural Cycle algorithm incorporated cycle lengths, BBT, and LH as key features for analysis.

In contrast to previous works, in this study, we implemented multiple models to forecast the menstrual cycle duration. These models include AutoRegressive Integrated Moving Average (ARIMA), Huber Regression, which is a robust regression method that provides robustness against outliers, Least Absolute Shrinkage and Selection Operator (LASSO) Regression, Orthogonal Matching Pursuit (OMP), which efficiently identifies relevant predictors, and LSTM Network.

III. PROBLEM FORMULATION

The problem formulation for predicting menstrual cycle based on only the cycle time series, involves developing a model that can accurately predict the timing and length of the menstrual cycle using only historical menstrual cycle data. The model is designed to handle both regular and irregular cycles, and may need to be personalized to the individual woman.

The menstrual cycle time series can be represented as a sequence of observations indexed by time, where each observation corresponds to a menstrual cycle. Let us denote the menstrual cycle length time series by

$$X_1 = x_1(t), \tag{1}$$

where $x_1(t)$ represents the length of the menstrual cycle at time t. Similarly, let's denote the period length time series by

$$X_2 = x_2(t), \qquad (2)$$

where $x_2(t)$ represents the length of the bleeding time at time t.

We can use a sequence-to-sequence model, where the input sequence consists of past values of X_1 and X_2, and the output sequence consists of future values of X_1 and X_2. Therefore, let us denote the input sequence $X \in R^{N \times 2}$ as

$$X = \begin{bmatrix} x_1(t-L+1) & x_2(t-L+1) \\ \vdots & \vdots \\ x_1(t) & x_2(t) \end{bmatrix}, \qquad (3)$$

where L is the length of the input sequence.

We can write the output sequence $Y R^{N \times 2}$ as

$$Y = \begin{bmatrix} x_1(t+1) & x_2(t+1) \\ \vdots & \vdots \\ x_1(t+P) & x_2(t+P) \end{bmatrix}, \qquad (4)$$

where P is the length of the output sequence. Each element of the matrices X and Y corresponds to a time step and consists of the menstrual cycle length and period length at that time step.

A. Time series algorithms approaches

The model must be able to identify the key patterns and trends in the menstrual cycle time series data, such as the length of the menstrual cycle, and the duration of menstruation. Machine learning algorithms, such as recurrent neural networks or time-series forecasting models, such as ARIMA, can be used to analyze the menstrual cycle time series and predict future menstrual cycles based on past cycles. The model can also be used to identify any irregularities or abnormalities in the menstrual cycle, which can aid in the diagnosis and treatment of reproductive health issues.

In the following sections, we discussed some models that have been utilized, including the LSTM network, ARIMA, Huber Regression, Lasso Regression, and OMP.

1) LSTM model: Long Short-Term Memory (LSTM) is a type of recurrent neural network that is generally employed for sequential data processing, such as time series analysis, and natural language processing [31]. The fundamental idea behind LSTM is the usage of memory cells, which are capable of maintaining information over long sequences [31].

We applied an LSTM network to predict the menstrual cycle time series. The LSTM model takes the input sequence X and outputs a sequence of predicted values

$$\hat{Y} = \begin{bmatrix} x_1(t+1) & x_2(t+1) \\ \vdots & \vdots \\ x_1(t+P) & x_2(t+P) \end{bmatrix}, \qquad (5)$$

with $\hat{Y} \in R^{N \times 2}$. The LSTM model can be formulated as follows:

$$h(t) = LSTM(X(t), h(t-1))$$
$$\hat{Y}(t) = linear(h(t)) \qquad (6)$$

where $h(t)$ is the hidden state at time t, which is passed to the output layer to predict the values of $\hat{Y}$, and linear is a linear transformation to map the hidden state to the output values.

The LSTM cell updates the hidden state based on the current input and the previous hidden state as follows:

$$i(t) = \varphi(W_i[h(t-1), X(t)] + b_i)$$
$$f(t) = \varphi(W_f[h(t-1), X(t)] + b_f)$$
$$o(t) = \varphi(W_o[h(t-1), X(t)] + b_o)$$
$$\hat{c}(t) = tanh(W_c[h(t-1), X(t)] + b_c) \qquad (7)$$
$$c(t) = f(t)c(t-1) + i(t)\hat{c}(t)$$
$$h(t) = o(t)tanh(c(t))$$

where $i(t)$, $f(t)$, $o(t)$ are the input, forget, and output gates, respectively, W_i, W_f, W_o, W_c are weight matrices, b_i, b_f, b_o, b_c are bias vectors, and $c(t)$ is the cell state at time t. The output layer is a linear layer that takes the hidden state $h(t)$ as input and outputs the predicted values $\hat{Y}(t)$.

2) ARIMA model: ARIMA model is a time series forecasting model that incorporates autoregression and moving average components [32]. We can expressed it as

$$\hat{Y}'_t = c + \sum(\phi_i \hat{Y}'_{t-i}) + \sum(\theta_i \epsilon_{t-i}) + \epsilon_t \qquad (8)$$

where $\hat{Y}'_t$ represents the differenced observed menstrual cycle length at time t, c is a constant term, ϕ represents the coefficient of the autoregression component at lag i. Note that, we used the past values of the differenced time series to predict future values. ϵ_t is the white noise error term at time t, and θ_i represents the coefficient of the moving average component at lag i.

ARIMA models can be used to predict the cycles patterns in a time series by incorporating seasonal differencing and seasonal autoregressive and moving average components.

3) Huber Regression: Huber regression is a robust regression that uses the Huber loss function. Unlike the squared error loss, the Huber loss function is designed to be less influenced by outliers [33]. Its definition can be expressed as follows:

$$L_\delta(Y, X\beta) = \begin{cases} \frac{1}{2}(Y - X\beta)^2 & \text{for } |Y - X\beta| \leq \delta \\ \delta(|Y - X\beta| - \frac{1}{2}\delta) & \text{otherwise.} \end{cases} \qquad (9)$$

where β is the regression coefficients, and δ is a tuning parameter, which determines the threshold beyond which the loss function transitions from squared to absolute loss, thereby controlling the model's sensitivity to outliers [33]. Therefore the problem consist in

$$min \sum_i L_\delta(Y_i, X_i\beta). \qquad (10)$$

Hence, the goal is to encounter the regression coefficients β that minimize the sum of the Huber losses between the predicted values $X_i\beta$ and the actual values Y_i.

4) Lasso regression: Unlike Huber regression, Lasso regression utilizes the L1 norm penalty (sum of absolute values) on the regression coefficient, i.e., Lasso regression promotes sparsity in the regression coefficients by adding the penalty [34]. The minimization problem for Lasso regression can be stated as follows:

$$min\frac{1}{2n}\sum_i(Y_i - X_i\alpha)^2 + \lambda\sum_j|\alpha_j|. \tag{11}$$

where λ is the regularization parameter that controls the strength of the penalty term, and α is the vector of regression coefficients.

5) Orthogonal Matching Pursuit: OMP is an applied algorithm for recovering sparse high-dimensional vectors in linear regression models [35]. The objective of OMP in cycles time series forecasting is to determine the lagged variables, i.e., the predictors that are most informative in describing the current and future values of a cycle. Therefore, given the time series X, and a set of lagged variables $\hat{Y}$ [36]:

1. Initialize the set of selected predictors $S = \emptyset$ and the residual $r = X$. Let the iteration counter $i = 1$.
2. Find $\hat{Y}_i$ that solves $max|\hat{Y}^T r_{i-1}|$ and add $\hat{Y}_i$ to the set S.
3. Let $P_i = \hat{Y}(\hat{Y}^T\hat{Y})^{-1}\hat{Y}^T$ denote the projection into the linear space spanned by the elements of $\hat{Y}$. Update $r_i = (I - P_i)X$.
4. If the stopping condition is achieved, stop the algorithm. Otherwise, set $i = i + 2$ and return to Step 2.

OMP algorithm was adjusted to combine lagged variables that capture the temporal dependencies in the data. By iteratively selecting lagged variables based on their correlations with the temporal residuals, OMP gradually determines the most informative predictors for prediction purposes in the cycle time series.

IV. DATA CHARACTERISTICS

We generated synthetic data that mimic the statistical properties, such as the distribution, variance of a real cycle. This is useful for exploring different scenarios and testing the robustness of the machine learning models to different data conditions. The data is generated from the following model:

$$\begin{aligned}\xi &= \xi_{mean} + \xi_{std} \cdot \mu_\xi \\ \varrho &= \varrho_{mean} + \varrho_{std} \cdot \mu_\varrho\end{aligned} \tag{12}$$

where ϱ represents the period length, ξ is the cycle duration in days, and μ denotes the uncertain.

According to the model, the cycle length is generated based on the mean and the standard deviation of the cycle length. The period length is generated based on the mean and the standard deviation of the period length. For analysis of the possible patterns present in regular and irregular cycles, we explored three different cases:

- **Case 1:** The period starts on the first day of the cycle, and the variation of the period length is small, i.e., $\varrho_{std} \ll \varrho_{mean}$. Therefore, it is a regular cycle.

- **Case 2:** The period starts on the last day of the cycle, and the variation of the cycle is between 28 and 35 days, and a period variation between 5 and 6 days. Therefore, it is a regular cycle.
- **Case 3:** The period starts in the middle of the cycle, and the variation of the cycle is between 28 and 49 days and a period variation between 4 and 8 days. Therefore, it is an irregular cycle.

Figures 1 and 2 show the menstrual cycle and period distribution in the three cases, respectively. As shown, in Figures 1 and 2, in case 1, the menstrual cycle duration is between 28 and 30 days, and the period duration is 5 days. A large density is concentrated in cycles of 30 days, and the period duration is 5 days. In case 2, the menstrual cycle duration is between 28 and 34 days (Figure 1), and the period duration is between 5 and 6 days (Figure 2). In case 2, we have more cycle of 28 and 34 days , and the period duration with 6 days. In case 3, the menstrual cycle duration is between 28 and 49 days (Figure 1), and the period duration is between 4 and 8 days (Figure 2).
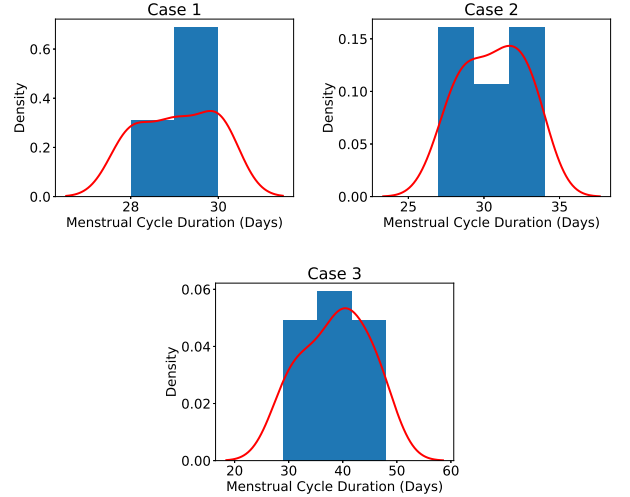

Fig. 1. Menstrual cycle distribution.

Figure 3 shows the boxplot of the menstrual cycle distribution in the three cases. As shown, in Figure 3, in case 1, the menstrual cycle duration is between 28 and 30 days, and the period duration is 5 days. In case 2, the menstrual cycle duration is between 28 and 35 days, and the period duration is between 5 and 6 days. In case 3, the menstrual cycle duration in the three cases. As shown, in Figure 3, in case 1, the menstrual cycle duration mean is 29 days, and the period duration mean is 5 days. In case 2, the menstrual cycle duration mean is 31 days, and the period duration mean is 5.5 days. In case 3, the menstrual cycle duration mean is 38 days, and the period duration mean is 6 days.

In Figures 4 (a), (b), and (c) are depicted the boxplot of the periods length. As shown, in Figure 4 (c), in case 3, the period length varies significantly from cycle to cycle. This can made it difficult to predict when the next period will start and
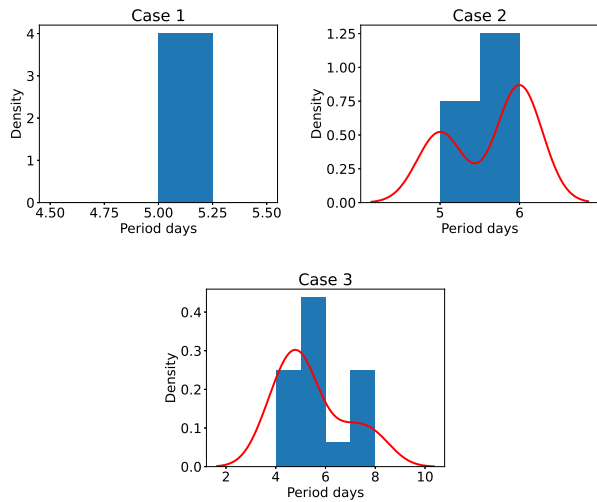
Fig. 2. Periods length distribution.

Fig. 4. Boxplot of the periods length distribution in the three cases.
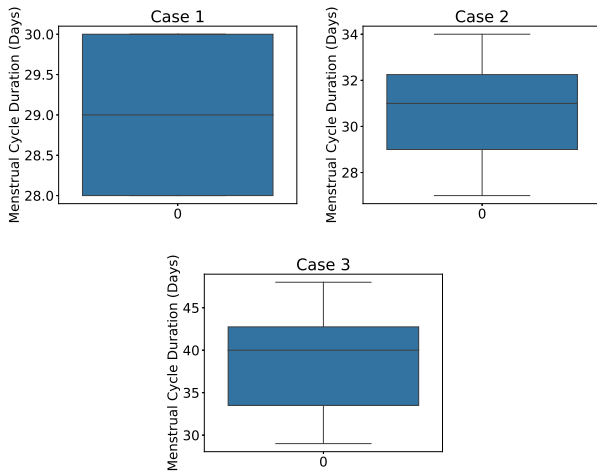

Fig. 3. Boxplot of the menstrual cycle in the three cases.

how long it will last. This variability in period length is what characterizes an irregular menstrual cycle.

With the data generated, we can now proceed with the simulation. In the following section, we will describe the simulations conducted and present the results obtained.

V. SIMULATION AND RESULTS

To perform the models' implementation, we used the TensorFlow framework version 2.12.0 for the LSTM model. For hyperparameter selection, we performed an iterative process involving experimentation and validation to fit model. We also utilized Darts library version 0.8.1 for ARIMA model implementation. Moreover, to execute Huber regression, LASSO, and OMP, we applied the PyCaret library regression module version 3.0.

We divided this section into three subsections to present the simulations conducted for three different cases: case 1 and case 2 with da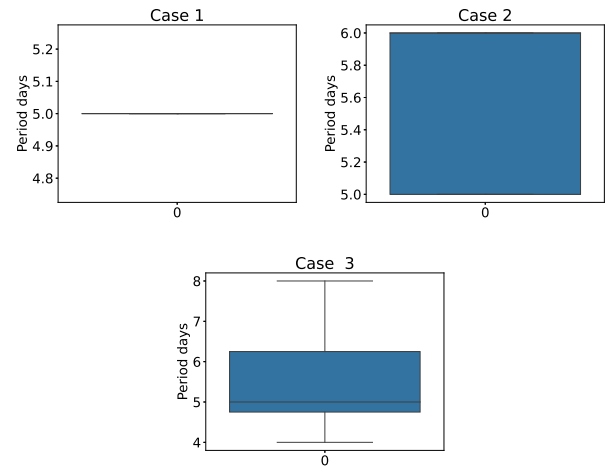tasets representing regular cycles, and case 3 with datasets representing irregular cycles. For case 1, we implemented an LSTM network with 64 units and with hyperbolic tangent activation function. This layer processes the input sequence and generates a hidden state that summarizes the information in the sequence. Moreover, we added a dropout layer with a rate of 0.05 to prevent overfitting. In the output layer a rectified linear unit activation function was used.

For cases 2 and 3, we utilized a stack of three LSTM layers with progressively decreasing numbers of units: 128, 64, and 32, respectively. These layers were interspersed with dropout layers set at a regularization rate of 0.2. The ultimate dense layer generates predictions using the rectified linear unit activation function.

The reliability of the models is evaluated using measures, such as mean absolute error (MAE), mean squared error (MSE), and root mean squared error (RMSE).

A. Case 1

Table II shows the models and their respective metrics, such as MAE, MSE, and RMSE, which were calculated based on predictions made for the next 14 cycles by each model. These metrics provide a comprehensive evaluation of the trained models. The lower the MAE, the more acceptable is the model's performance. Because it provides a good indication of how close the predictions are to the true values. Alike to MAE, a lower MSE value indicates better model performance. Also, like MSE, a lower RMSE signifies more suitable model performance. Out of all the models, LSTM stands out as having the smaller values in all the metrics, indicating its superior effectiveness to predict the regular menstrual cycle.

Figure 5 (a) depict the change in the loss function value during the training process through different epochs for the LSTM network. We needed approximately 100 epochs to the model convergence. In Figures 5 (b) and (c), the time-series of the cycles and periods are shown, respectively, and the prediction provided by LSTM, ARIMA, and LASSO models. Each model provided an identical prediction for the next cycle,

TABLE II
CASE 1 MODELS METRICS RESULTS FOR PREDICTIONS OF NEXT 14 CYCLES.

Model	MAE	MSE	RMSE
LSTM	0.3000	0.5477	0.7401
ARIMA	0.7400	0.8400	0.9165
Lasso Regression	0.7580	0.7649	0.8641
Lasso Least Angle Regression	0.7580	0.7649	0.8641
Elastic Net	0.7580	0.7649	0.8641
Dummy Regressor	0.7580	0.7649	0.8641
Light Gradient Boosting Machine	0.7580	0.7649	0.8641
Bayesian Ridge	0.7583	0.7654	0.8644
Ridge Regression	0.7882	0.8076	0.8885
Linear Regression	0.7892	0.8092	0.8894
Least Angle Regression	0.7892	0.8092	0.8894
Orthogonal Matching Pursuit	0.7892	0.8092	0.8894
Huber Regressor	0.7943	0.8174	0.8935
K Neighbors Regressor	0.8367	0.9320	0.9374
Random Forest Regressor	0.9610	1.3042	1.1017
Passive Aggressive Regressor	0.9692	1.3238	1.1040
Extra Trees Regressor	1.0076	1.3885	1.1392
AdaBoost Regressor	0.9652	1.3531	1.1162
CatBoost Regressor	1.0093	1.5354	1.1797
Gradient Boosting Regressor	1.0412	1.6650	1.2364
Decision Tree Regressor	1.0750	1.8417	1.2962
Extreme Gradient Boosting	1.1826	2.0305	1.3720

i.e., time+1. Moreover, we observed that there is a periodic pattern over time.
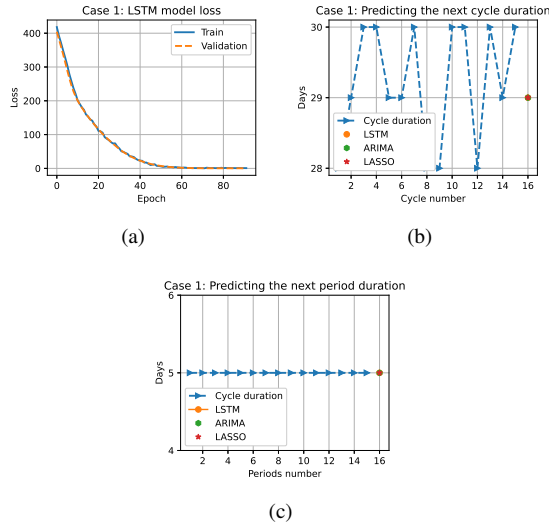

(a)

(b)

(c)

Fig. 5. (a) Evolution of the loss function across epochs for LSTM model. (b) Prediction for time+1 of cycle time series over days. (c) Period time series over days.

B. Case 2

Table III depicts the models metrics evaluation for regular cycles. In contrast to Case 1, the Case 2 dataset exhibits greater variation in cycles. Analyzing the table, different models achieve better results compared with the results in case 1. In case 2, we had models such as Huber Regressor and K Neighbors Regressor. However, the LSTM model continues to exhibit the best performance across all metrics for predictions

made for the next 14 cycles. Ridge Regression, Linear Regression, and Least Angle Regression models have the same values for MAE, MSE, and RMSE. They perform slightly worse than the Huber Regressor but still exhibit good performance.

TABLE III
CASE 2 MODELS METRICS RESULTS OF PREDICTIONS FOR THE NEXT 14 CYCLES.

Model	MAE	MSE	RMSE
LSTM	2.1000	2.5495	1.5967
Huber Regressor	1.7712	5.0785	1.9973
K Neighbors Regressor	1.8600	5.5167	2.0995
Ridge Regression	1.8115	5.1098	2.0305
Linear Regression	1.8119	5.1223	2.0275
Least Angle Regression	1.8119	5.1223	2.0275
Bayesian Ridge	1.9036	5.2605	2.0980
ARIMA	2.4000	2.7100	1.6462
Elastic Net	2.1392	5.9010	2.2964
Dummy Regressor	2.1865	5.9786	2.3316
Light Gradient Boosting Machine	2.1865	5.9786	2.3316
Lasso Least Angle Regression	2.1887	5.9879	2.3337
Lasso Regression	2.1887	5.9879	2.3337
Orthogonal Matching Pursuit	2.1008	6.1891	2.3154
Random Forest Regressor	2.2672	7.3894	2.5504
Gradient Boosting Regressor	2.7488	10.2011	3.0975
CatBoost Regressor	2.5281	8.9969	2.8520
Extra Trees Regressor	2.3502	8.5454	2.7297
Extreme Gradient Boosting	2.4686	9.0248	2.8734
AdaBoost Regressor	2.7140	10.9011	3.0415
Passive Aggressive Regressor	2.3072	7.9378	2.5390
Decision Tree Regressor	2.8667	11.5167	3.2344

Figures 6 (a), (b), and (c) present the simulation results for regular cycle data. The progression of the loss function over epochs during LSTM training is depicted in Figure 6 (a). The LSTM model took around 1600 epochs to converge. Figures 6 (b) and (c) display the time series of cycles and periods for regular cycle data, respectively. Differently from Case 1, in Case 2 each model provided a distinct prediction for the next cycle, i.e., cycle 16th, as shown in Figure 6 (b). LSTM model provided a cycle of 31 days, the ARIMA model predicted a cycle of 30 days, and differently, Huber regression predicted a cycle of 32 days. Both LSTM and ARIMA provided a correct period duration prediction, as depicted in Figure 6 (c).

C. Case 3

Table IV shows the models metrics evaluation for time series of irregular cycles. In contrast to Case 1 and Case 2, the dataset in Case 3 presents a greater variation in cycles with no perceptible patterns. Based on Table IV, the LSTM model performed better in therms of MAE, MSE, and RMSE. Both ARIMA and OMP models presented good performance, however, the ARIMA model is considered better than the OMP for the irregular cycle time series.

Figures 7 (a), (b), and (c) show the simulation results for irregular cycle data. Figure 7 (a) displays the progression of the loss function over epochs during LSTM training. Figure 7 (b) show the cycle time series and the predictions provided by models, and Figure 7 (c) depicts the period time series as a function of period number and the forecasts given by models. Among all models, LSTM provided the correct prediction.
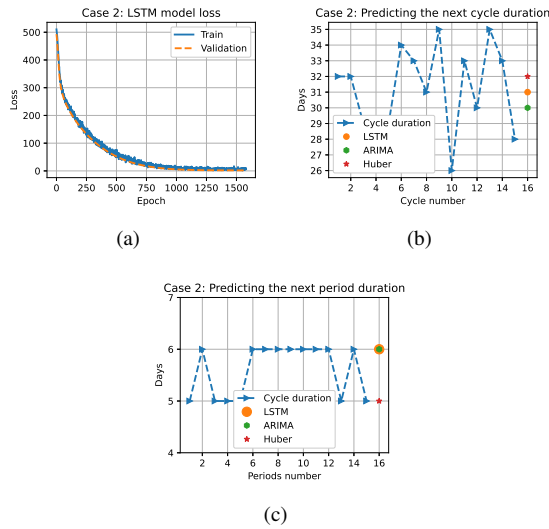
(a)   (b)

(c)

Fig. 6. (a) Progression of the loss function throughout epochs. (b) Time series representing the cycle as a function of cycle number. (c) Time series illustrating the period as a function of period number.
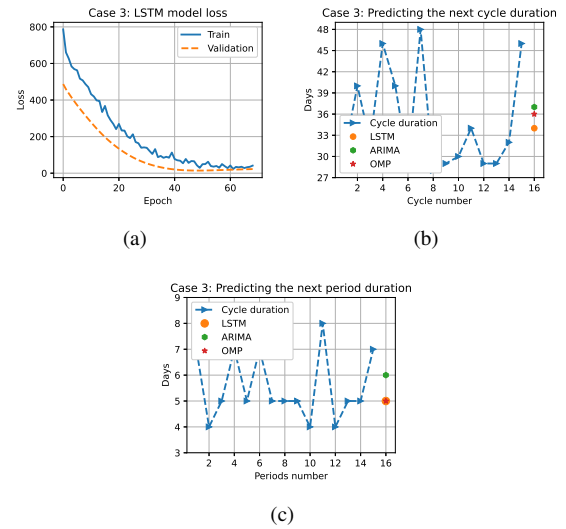

(a)   (b)

(c)

Fig. 7. (a) Evolution of the loss function over epochs. (b) Cycle time series as a function of cycle number. (c) Period time series as a function of period number.

TABLE IV
CASE 3 MODELS METRICS RESULTS OF PREDICTIONS FOR THE NEXT 14 CYCLES.

Model	MAE	MSE	RMSE
LSTM	3.4000	4.2895	2.0711
ARIMA	7.3000	7.7964	2.7922
Orthogonal Matching Pursuit	5.3373	41.1000	6.1243
Elastic Net	5.3686	41.1295	6.1588
Huber Regressor	5.5458	43.5776	6.2851
Ridge Regression	5.4826	42.5662	6.2523
Linear Regression	5.4914	42.7152	6.2604
Least Angle Regression	5.4914	42.7152	6.2604
Lasso Regression	5.4554	42.2978	6.2402
Lasso Least Angle Regression	5.4554	42.2978	6.2402
Dummy Regressor	5.4702	41.5427	6.2063
Light Gradient Boosting Machine	5.4702	41.5427	6.2063
Bayesian Ridge	5.5910	44.0523	6.3834
K Neighbors Regressor	5.6383	45.9650	6.5151
Passive Aggressive Regressor	5.6844	48.3409	6.5683
Random Forest Regressor	6.2947	59.3721	7.3739
AdaBoost Regressor	6.2856	56.1740	7.3034
CatBoost Regressor	7.2368	76.8913	8.4820
Gradient Boosting Regressor	7.2034	75.0468	8.3428
Decision Tree Regressor	7.1083	75.7250	8.3555
Extra Trees Regressor	7.1378	69.3403	8.1291
Extreme Gradient Boosting	7.5025	77.0432	8.5549

Based on the given results, for cases 2 and 3, the LSTM network model appears to be the best in terms of error metrics. Also, the ARIMA model has relatively low values for MAE, MSE, and RMSE. While not as good as the LSTM model, the ARIMA model performs better than most other models, this is due to the flexibility of the ARIMA model, it can capture both short-term and long-term dependencies in the data. However, the LSTM model can capture temporal relationships within cycle time series.

VI. CONCLUSION

In this study, we applied machine learning algorithms to predict menstrual cycle using data from generated by defined model. The algorithms can identify patterns and correlations that may not be immediately apparent to humans. This can lead to new insights and discoveries in the field of menstrual cycle prediction. Moreover, our results suggest that machine learning models can accurately predict menstrual cycle phase with small error. Our findings have important implications for women's health and may be used to inform personalized reproductive health decisions, such as family planning and fertility treatment. In addition, the models can be trained on individualized data, allowing for personalized predictions of menstrual cycle patterns. This could be particularly useful for women with irregular cycles, as traditional prediction methods may not work as well for them. Future work in this area could focus on refining our models by incorporating additional data sources, such as menstrual symptoms, hormonal data, and conducting larger-scale studies to validate our findings.

REFERENCES

[1] L. R. Campbell, A. L. Scalise, B. T. DiBenedictis, and S. Mahalingaiah, "Menstrual cycle length and modern living: a review," *Current opinion in endocrinology, diabetes, and obesity*, vol. 28, no. 6, p. 566, 2021.

[2] T. Tatsumi, M. Sampei, K. Saito, Y. Honda, Y. Okazaki, N. Arata, K. Narumi, N. Morisaki, T. Ishikawa, and S. Narumi, "Age-dependent and seasonal changes in menstrual cycle length and body temperature based on big data," *Obstetrics and Gynecology*, vol. 136, no. 4, p. 666, 2020.

[3] R. Trickey, *Women, Hormones and the Menstrual Cycle: herbal and medical solutions from adolescence to menopause*. Allen & Unwin, 2004.

[4] J. R. Bull, S. P. Rowland, E. B. Scherwitzl, R. Scherwitzl, K. G. Danielsson, and J. Harper, "Real-world menstrual cycle characteristics of more than 600,000 menstrual cycles," *NPJ digital medicine*, vol. 2, no. 1, pp. 1–8, 2019.

[5] M. Rees, S. L. Hope, and V. A. Ravnikar, *The Abnormal Menstrual Cycle*. CRC Press, 2005.

[6] M. G. Munro, H. O. Critchley, and I. S. Fraser, "The figo systems for nomenclature and classification of causes of abnormal uterine bleeding in the reproductive years: who needs them?" *American journal of obstetrics and gynecology*, vol. 207, no. 4, pp. 259–265, 2012.

[7] S. D. Harlow and S. A. Ephross, "Epidemiology of menstruation and its relevance to women's health," *Epidemiologic reviews*, vol. 17, no. 2, pp. 265–286, 1995.

[8] C. M. Røstvik, *Cash Flow: The businesses of menstruation*. UCL Press, 2022.

[9] J.-L. Yu, Y.-F. Su, C. Zhang, L. Jin, X.-H. Lin, L.-T. Chen, H.-F. Huang, and Y.-T. Wu, "Tracking of menstrual cycles and prediction of the fertile window via measurements of basal body temperature and heart rate as well as machine-learning algorithms," *Reproductive Biology and Endocrinology*, vol. 20, no. 1, pp. 1–12, 2022.

[10] B. T. Nguyen, R. D. Pang, A. L. Nelson, J. T. Pearson, E. Benhar Noccioli, H. R. Reissner, A. Kraker von Schwarzenfeld, and J. Acuna, "Detecting variations in ovulation and menstruation during the covid-19 pandemic, using real-world mobile app data," *PloS one*, vol. 16, no. 10, p. e0258314, 2021.

[11] Y. Kwak and Y. Kim, "Irregular menstruation according to occupational status," *Women & Health*, vol. 58, no. 10, pp. 1135–1150, 2018.

[12] S. Tiwari, L. Kane, D. Koundal, A. Jain, A. Alhudhaif, K. Polat, A. Zaguia, F. Alenezi, and S. A. Althubiti, "Sposds: A smart polycystic ovary syndrome diagnostic system using machine learning," *Expert Systems with Applications*, vol. 203, p. 117592, 2022.

[13] I. Urteaga, K. Li, A. Shea, V. J. Vitzthum, C. H. Wiggins, and N. Elhadad, "A generative modeling approach to calibrated predictions: a use case on menstrual cycle length prediction," in *Machine Learning for Healthcare Conference*. PMLR, 2021, pp. 535–566.

[14] J. T. Pearson, M. Chelstowska, S. P. Rowland, E. Mcilwaine, E. Benhar, E. Berglund Scherwitzl, S. Walker, K. Gemzell Danielsson, and R. Scherwitzl, "Natural cycles app: contraceptive outcomes and demographic analysis of uk users," *The European Journal of Contraception & Reproductive Health Care*, vol. 26, no. 2, pp. 105–110, 2021.

[15] K. Li, I. Urteaga, A. Shea, V. J. Vitzthum, C. H. Wiggins, and N. Elhadad, "A predictive model for next cycle start date that accounts for adherence in menstrual self-tracking," *Journal of the American Medical Informatics Association*, vol. 29, no. 1, pp. 3–11, 2022.

[16] S. A. Shinde and P. R. Rajeswari, "Intelligent health risk prediction systems using machine learning: a review," *International Journal of Engineering & Technology*, vol. 7, no. 3, pp. 1019–1023, 2018.

[17] M. Alhussein and G. Muhammad, "Voice pathology detection using deep learning on mobile healthcare framework," *IEEE Access*, vol. 6, pp. 41 034–41 041, 2018.

[18] B. Nithya and V. Ilango, "Predictive analytics in health care using machine learning tools and techniques," in *2017 International Conference on Intelligent Computing and Control Systems (ICICCS)*. IEEE, 2017, pp. 492–499.

[19] M. A. Sarwar, N. Kamal, W. Hamid, and M. A. Shah, "Prediction of diabetes using machine learning algorithms in healthcare," in *2018 24th international conference on automation and computing (ICAC)*. IEEE, 2018, pp. 1–6.

[20] W. Rahane, H. Dalvi, Y. Magar, A. Kalane, and S. Jondhale, "Lung cancer detection using image processing and machine learning healthcare," in *2018 International Conference on Current Trends towards Converging Technologies (ICCTCT)*. IEEE, 2018, pp. 1–5.

[21] A. Denny, A. Raj, A. Ashok, C. M. Ram, and R. George, "i-hope: Detection and prediction system for polycystic ovary syndrome (pcos) using machine learning techniques," in *TENCON 2019-2019 IEEE Region 10 Conference (TENCON)*. IEEE, 2019, pp. 673–678.

[22] R. A. Setton, C. H. Tierney, and T. Tsai, "The accuracy of websites and cellular phone applications in predicting the fertile window [12g]," *Obstetrics & Gynecology*, vol. 127, p. 62S, 2016.

[23] M. Deverashetti, K. Ranjitha, and K. Pradeepthi, "Security analysis of menstruation cycle tracking applications using static, dynamic and machine learning techniques," *Journal of Information Security and Applications*, vol. 67, p. 103171, 2022.

[24] T. de Paula Oliveira, G. Bruinvels, C. R. Pedlar, B. Moore, and J. Newell, "Modelling menstrual cycle length in athletes using state-space models," *Scientific reports*, vol. 11, no. 1, pp. 1–14, 2021.

[25] K. Fukaya, A. Kawamori, Y. Osada, M. Kitazawa, and M. Ishiguro, "The forecasting of menstruation based on a state-space modeling of basal body temperature time series," *Statistics in Medicine*, vol. 36, no. 21, pp. 3361–3379, 2017.

[26] C. Chen and J. P. Ward, "A mathematical model for the human menstrual cycle," *Mathematical medicine and biology: a journal of the IMA*, vol. 31, no. 1, pp. 65–86, 2014.

[27] S. Röblitz, C. Stötzel, P. Deuflhard, H. M. Jones, D.-O. Azulay, P. H. van der Graaf, and S. W. Martin, "A mathematical model of the human menstrual cycle for the administration of gnrh analogues," *Journal of theoretical biology*, vol. 321, pp. 8–27, 2013.

[28] K. Li, I. Urteaga, A. Shea, V. J. Vitzthum, C. H. Wiggins, and N. Elhadad, "A generative, predictive model for menstrual cycle lengths that accounts for potential self-tracking artifacts in mobile health data," *arXiv preprint arXiv:2102.12439*, 2021.

[29] E. Pierson, T. Althoff, and J. Leskovec, "Modeling individual cyclic variation in human behavior," in *Proceedings of the 2018 World Wide Web Conference*, 2018, pp. 107–116.

[30] T. K. Kleinschmidt, J. R. Bull, V. Lavorini, S. P. Rowland, J. T. Pearson, E. B. Scherwitzl, R. Scherwitzl, and K. G. Danielsson, "Advantages of determining the fertile window with the individualised natural cycles algorithm over calendar-based methods," *The European Journal of Contraception & Reproductive Health Care*, vol. 24, no. 6, pp. 457–463, 2019.

[31] S. Hochreiter and J. Schmidhuber, "Long short-term memory," *Neural computation*, vol. 9, no. 8, pp. 1735–1780, 1997.

[32] C. Chatfield, *Time-series forecasting*. CRC press, 2000.

[33] P. J. Huber, "Robust estimation of a location parameter," *Breakthroughs in statistics: Methodology and distribution*, pp. 492–518, 1992.

[34] R. Tibshirani, "Regression shrinkage and selection via the lasso," *Journal of the Royal Statistical Society: Series B (Methodological)*, vol. 58, no. 1, pp. 267–288, 1996.

[35] S. Kallummil and S. Kalyani, "Signal and noise statistics oblivious orthogonal matching pursuit," in *International Conference on Machine Learning*. PMLR, 2018, pp. 2429–2438.

[36] T. T. Cai and L. Wang, "Orthogonal matching pursuit for sparse signal recovery with noise," *IEEE Transactions on Information theory*, vol. 57, no. 7, pp. 4680–4688, 2011.