AI-Based Women's Fertility and Period Tracking System

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***Abstract*—The lack of robust and personalized systems for women's health monitoring that integrate period data with AI-based analyses can compromise user experience and limit the impact of data in promoting health. This paper proposes the development of an application for women's fertility monitoring and menstrual cycle tracking, using AI for data analysis and accurate predictions. The system integrates period data to provide personalized and useful insights for users. Grounded in machine learning theory applied to health data processing and analysis, this work utilizes AI to enhance the accuracy of data interpretation, tailoring recommendations and alerts to each user's specific profile. The proposed algorithm proved effective in providing accurate menstrual cycle predictions with 100% accuracy. The primary contribution of this study is the development of an intelligent health tool that promotes autonomy and preventive care. This system may serve as a model for future AI applications in health monitoring, providing a solid foundation for a more personalized and precise approach to women's health.**

***Index Terms*—artificial intelligence, neural networks, machine learning, period tracking.**

I. Introduction

Monitoring ovulation and the menstrual cycle can help identify signs of various health conditions, particularly disorders related to reproductive health and the endocrine system [1]. Early detection of irregularities in the cycle or ovulation may lead to timely diagnosis and treatment of these conditions [2]. Accurate prediction of the ovulation date also has a direct impact on aspects of family planning, women's health, and overall well-being. For those seeking to conceive, knowing the fertile window increases the chances of successful conception. Conversely, for women who prefer to avoid pregnancy, awareness of ovulation enables the use of natural contraceptive methods, such as the calendar method, with greater accuracy [3].

Additionally, monitoring ovulation and the menstrual cycle can provide valuable insights into reproductive health. For instance, irregularities in ovulation or the menstrual cycle may indicate underlying health conditions such as polycystic ovary syndrome (PCOS), hormonal imbalances, or other reproductive disorders [4], [5]. For individuals undergoing fertility treatment, knowing the exact ovulation date is crucial to guide medical interventions such as artificial insemination or hormonal therapies [6].

The prediction of the next menstrual cycle date can be represented by an equation, taking into account the first day of the last menstrual period and the average cycle length. However, when the cycle is irregular, the prediction cannot rely on the average, and alternative strategies become necessary [7], [8]. To calculate the fertile window, the estimation involves the average cycle length and the approximate timing of ovulation [9]. For many women with regular cycles, ovulation typically occurs around 14 days before the onset of the next menstrual period. In the case of irregular cycles, Artificial Intelligence (AI) techniques can be employed [7], [10]. In Table I, we present a summary of relevant studies, including the models used by the authors and the features utilized in their analyses.

In [11], the authors employed ARMA and Linear Mixed Models (LMM), considering cycle lengths as the primary feature. Similarly, [12] utilized a Poisson model with a focus on cycle lengths. The study by [13] conducted a comparative analysis involving Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), Long Short-Term Memory (LSTM) networks, and Generalized Poisson models, all applied to cycle length data. In [6], the authors compared the fertile window and cycle predictions from the Natural

TABLE I
SUMMARY OF RELATED WORKS, MODELS APPLIED, AND FEATURES CONSIDERED.

Paper	Model	Features
[11]	ARMA, LMM	Cycle lengths
[12]	Poisson model	Cycle lengths
[13]	CNN, RNN, LSTM, Generalized Poisson	Cycle lengths
[14]	Cyclic Hidden Markov Models	Cycle lengths
[6]	Natural Cycles algorithm*	Cycle lengths, BBT, LH
[15]	Machine learning classifier	Wrist skin temperature (WST), heart rate (HR), HRV, respiratory rate
[16]	State-space model with Bayesian filtering	Basal Body Temperature (BBT)

*Details regarding the algorithm are not disclosed.

Cycles algorithm against traditional calendar-based methods. This algorithm incorporates features such as cycle lengths, basal body temperature (BBT), and luteinizing hormone (LH) levels. In [16], the authors proposed a probabilistic approach to predict the onset of menstruation using a state-space model driven by BBT data. The study conducted by [15] leveraged data from wearable devices to identify physiological changes across the menstrual cycle and predict the fertile window. The authors used a machine learning classification model trained on features including wrist skin temperature (WST), heart rate (HR), heart rate variability (HRV), and respiratory rate.

AI can analyze menstrual cycle tracking data and symptoms, identifying patterns that may help users better understand their bodies and anticipate changes [13]. This may include alerts about when to expect menstruation or tips for managing symptoms. In this context, AI algorithms such as Random Forest (RF), Decision Tree (DT), XGBoost, Extra Trees (ET), K-Nearest Neighbors (KNN), LightGBM, Gradient Boosting Classifier (GBC), AdaBoost (Ada), Naive Bayes (NB), Quadratic Discriminant Analysis (QDA), Logistic Regression (LR), Ridge Regression (Ridge), and Linear Discriminant Analysis (LDA) have been implemented and evaluated for ovulation day prediction based on basal body temperature and cycle day. For predicting the next menstrual cycle date, the RNN model LSTM was applied, as proposed by [7].

AI algorithms, such as artificial neural networks, can offer more effective solutions than traditional methods for cycle prediction [17], [18]. According to [19], machine learning techniques enable a machine to develop intelligence by improving its outcomes over time based on past experiences. Furthermore, these technologies drive advances in healthcare, including pattern detection [20], [21], predictive systems [22], and image recognition [23]. In this article, an application is proposed to provide predictions of upcoming menstruation dates as well as the ovulation day.

The app can help users track menstrual cycles, symptoms, and emotions, fostering a deeper understanding of women's bodies. This can empower women to feel more comfortable and confident about their menstrual health and contribute to breaking the stigma surrounding menstruation. Such stigma is influenced by cultural, social, and religious factors, varying significantly across different societies. The lack of education about the menstrual cycle leads to misinformation, with myths associating menstruation with weakness or incapacity.

The menstrual product market is also surrounded by stigma, with packaging often designed to conceal the contents, reflecting the idea that menstruation should be hidden. This stigma can impact women's mental health, contributing to anxiety and depression, especially when they feel ashamed or insecure about their bodies and natural functions [24], [25]. Menstrual stigma is closely tied to gender inequality and is often perceived as a burden to be endured [25], [26]. Moreover, access to menstrual hygiene products remains a challenge in many regions, and the lack of resources can lead to the exclusion of women from school or work during their menstrual period [27]. Combating these stigmas requires education, open dialogue, and the promotion of a more positive and informed understanding of menstruation [28]. Based on these discussions, the main contributions of this work are:

i) Application of AI algorithms to analyze past menstrual cycle data and daily basal body temperature to predict the onset of the next cycle and the accurate date of ovulation.
ii) An AI model to accurately predict the timing of ovulation based on daily basal body temperature and cycle day.
iii) A mobile application for retrospective analysis of menstrual cycle data and daily basal temperature measurements, supporting the prediction of the next menstrual cycle.

This paper is organized as follows: Section 2 presents the data used and the features selected for detecting the ovulation day and the next menstrual cycle date. Section 3 discusses related methods from the literature and introduces the proposed method. Section 4 presents the developed application. Section 5 displays the results and discussion, including the explainability of the proposed model's outputs. Finally, Section 6 provides the concluding remarks.

II. DATASET

Synthetic data, replicating the statistical properties of real menstrual cycles and basal body temperature, were generated for this study. The methodology for generating basal body temperature data is detailed in Section II-A, while Section II-B describes the process used to generate cycle duration data.

A. Basal Body Temperature

BBT is the body's temperature at rest, measured immediately upon waking, before any physical activity or food intake. During the pre-ovulatory phases, BBT is generally lower (between 36.1°C and 36.4°C) [29]. Ovulation causes a sudden increase in basal temperature, which can vary from 0.2°C to 0.5°C due to the rise in progesterone hormone levels [30]. After ovulation, the temperature remains elevated until the start of the next cycle, when it drops again [31]. For this reason, basal body temperature is an attribute commonly used to detect the day of ovulation [6]. Figure 1 illustrates the variation of basal body temperature throughout the cycle. The basal temperature varies during the follicular phase and increases on the day of ovulation.

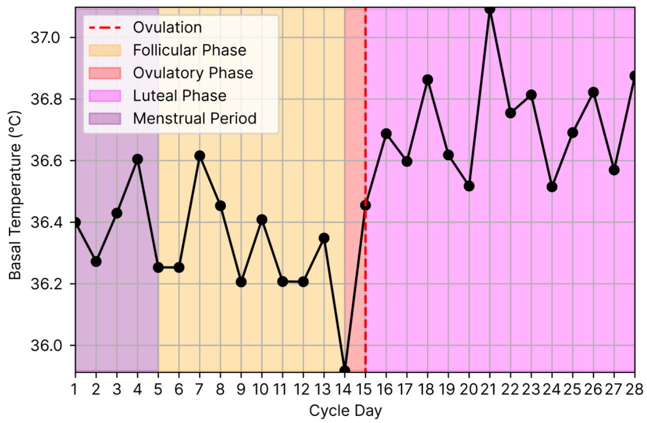

Fig. 1. Phases of a regular cycle with ovulation occurring on day 15.

The follicular phase begins on the first day of the cycle and ends on the day of ovulation. The ovulatory phase is brief, occurring on the day of ovulation itself. Finally, the luteal phase starts after ovulation and continues until the onset of menstruation, as illustrated in Figure 1.

Synthetic data simulating a woman's basal body temperature over two years, considering a typical 28-day menstrual cycle, were generated. Figure 2 shows the time series of basal body temperature. During each cycle, basal temperature is lower in the first 14 days, corresponding to the follicular phase, and slightly increases after ovulation, around day 15, indicating the transition to the luteal phase. This pattern is reproduced with random variations to reflect the natural daily fluctuation of basal body temperature.

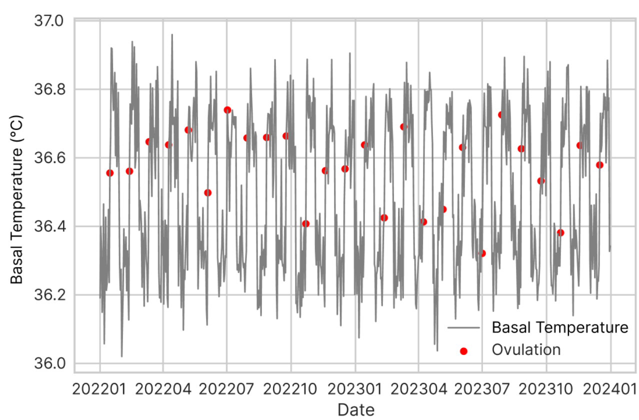

Fig. 2. Synthetic basal body temperature variation over two years for a woman.

B. Cycle Duration

To simulate the prediction of the next cycle date, synthetic data were also generated following the methodology in [7]. According to [7], the duration of each cycle is generated based on the mean and standard deviation of cycle length. Similarly, the period duration is generated based on the mean and standard deviation of the menstruation length. In this work, the case where the variation in period duration is small, i.e., $desvio \ll media$, is considered. Therefore, the cycle is regular, as illustrated in Figure 3.

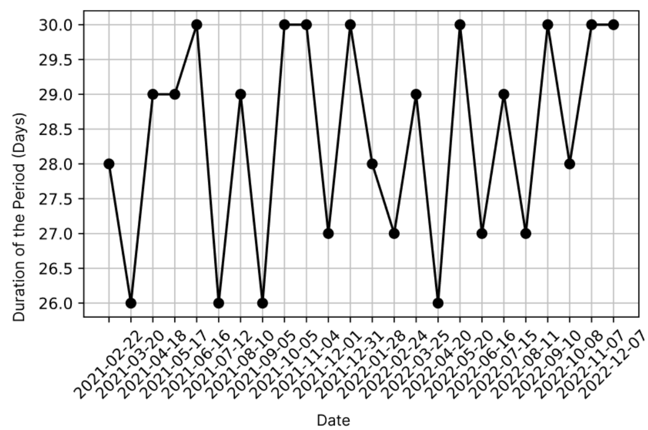

Fig. 3. Synthetic data for cycle duration according to [7].

III. Method

Ovulation typically occurs about 14 days before the start of the next menstrual cycle on average, but this number is not exact for everyone [32]. This value is an average based on a 28-day menstrual cycle, but cycle length and regularity vary significantly among individuals. For those with shorter or longer cycles, the timing of ovulation may differ. For example, in a 32-day cycle, ovulation typically occurs approximately 18 days before the next cycle, while in a 24-day cycle, it may be around 10 days prior.

To calculate the fertile window in cycles of variable length, it is common to use an approach based on averages and ranges of variation, rather than fixing an exact number of days before the next cycle. A practical way to do this is by observing cycle history and determining the shortest and longest cycles [33].

Thus, considering cycles with a duration of 28 days, the calculation of the ovulation date, approximately 14 days before the next menstruation, can be given by

$$\gamma = \delta - 14, \tag{1}$$

where γ is the ovulation date and δ is the next menstrual cycle date. Therefore, the start of the fertile window can be given by

$$period_{start} = \gamma - 5, \tag{2}$$

i.e., 5 days before ovulation. The end of the fertile window is given by

$$period_{end} = \gamma - 1. \tag{3}$$

It is important to highlight that this approach is based on the Ogino-Knaus method for regular cycles. For individuals with shorter or longer cycles, the timing of ovulation may vary. In such cases, more robust methods are necessary.

A. Ogino-Knaus Method

The Ogino-Knaus method estimates the fertile window based on the minimum and maximum cycle lengths observed over several months of monitoring [34]. Thus, the start of the fertile window can be given by

$$period_{start} = C_{min} - 18, \tag{4}$$

where C_{min} is the minimum cycle length. The end of the fertile window is given by

$$period_{end} = C_{max} - 11, \tag{5}$$

where C_{max} is the maximum cycle length. Therefore, these formulas create a broader fertile interval, covering the variation between the shortest and longest cycles, increasing the chance of correctly identifying the fertile window in irregular cycles [35]. However, individuals with irregular cycles may have difficulty accurately predicting the ovulation day based solely on a 14-day average. In this context, more robust methods are required [36].

B. Proposed Model

Individuals with irregular cycles may have difficulty accurately predicting the ovulation day based solely on a 14-day average or even the Ogino-Knaus method. For those seeking greater precision, observing signs such as basal body temperature can indicate when ovulation is near, which is more effective than counting a fixed number of days.

Thus, based on basal body temperature, the Decision Tree (DT) machine learning algorithm can help detect whether the individual is in the fertile window or not.

Given a dataset (X_i, y_i), where X_i is the basal body temperature on day i and y_i is the ovulation label, defined as

$$y_i = \begin{cases} 1, & \text{if the day is ovulation} \\ 0, & \text{otherwise} \end{cases}. \tag{6}$$

The basal temperature variation T_i between consecutive days can be calculated as follows:

$$T_i = X_i - X_{i-1}. \tag{7}$$

A decision tree can be implemented to determine the label y_i based on T_i. For this, it is necessary to split the data at each tree node. The Gini index can be used to find the best split point that separates the classes most effectively. The Gini index is given by:

$$G(S) = 1 - \sum_j p_j^2, \tag{8}$$

where p_j is the proportion of instances belonging to class j in node S. Therefore, the decision tree can learn rules based on basal temperature conditions, for example:

$$\text{If } X_i < 36.5 \Rightarrow y_i = 0 \quad \text{(not fertile)}. \tag{9}$$

$$\text{If } X_i \geq 36.6 \text{ and } T_i > 0.3 \Rightarrow y_i = 1 \quad \text{(fertile)}. \tag{10}$$

Thus, the algorithm was implemented using the Gini function to measure node impurity to improve split quality. We used a minimum of 2 samples to form a leaf node, as indicated by the Grid Search method, which was employed to find the best combination of model hyperparameters.

IV. Application

The application was developed using Python 3 and the Kivy framework, which is an open-source library aimed at creating interactive graphical user interfaces compatible with multiple platforms such as Android, iOS, Linux, and Windows.

The implemented application includes the following basic functionalities:

- Menstrual cycle prediction: Estimates upcoming menstruations based on past data, assisting with personal planning.
- Fertility and ovulation: Indicates the most probable ovulation days and fertile phases, useful for family planning.
- Alerts and reminders: Sends notifications about the start of the cycle or fertile periods, enabling more accurate tracking.

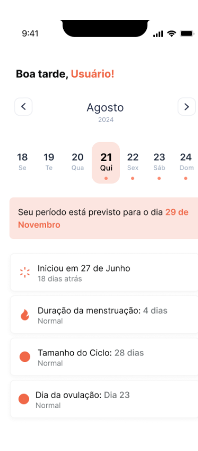

Fig. 4. Home screen.

Fig. 5. Calendar screen.

Fig. 6. Day editing screen.

Figure 4 shows the application's home screen. Upon opening the app, the user immediately sees personalized information about her menstrual cycle, such as start date, duration, cycle length, and predicted ovulation day. These data are generated by the prediction models.

Figure 5 presents an enlarged calendar view, allowing the user to have a complete monthly overview of her cycle. In this screen, cycle-related markings and events are shown in more detail, facilitating pattern recognition. Finally, Figure 6 displays the calendar editing screen, where the user can customize her cycle information and provide additional data, such as basal body temperature, to improve the app's prediction accuracy.

V. Results and Discussion

To predict the ovulation date, the decision tree algorithm was used. To forecast the next cycle date, the LSTM neural network model was applied. Figure 7 shows the methodology adopted to obtain the results presented in this section. The basal body temperature and cycle day attributes were input into the decision tree model to calculate the ovulation date. The cycle length and menstruation duration attributes were input into the LSTM model to predict the next cycle date.

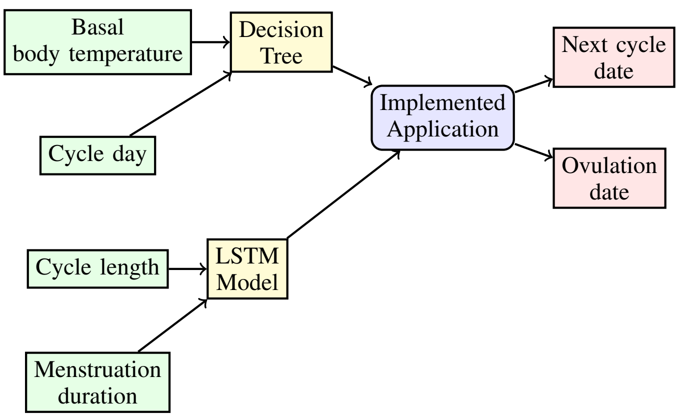

Fig. 7. Methodology applied for predicting the next cycle date and ovulation date.

Section V-A presents the results obtained with the decision tree algorithm. Section V-B presents the results obtained with the LSTM model.

A. Ovulation Prediction

The simulation was performed using Python 3 and the scikit-learn library version 1.5.2. A pipeline with several machine learning models was created using the PyCaret 3.3.2 library. The data was initially split into 70% for training and 30% for testing. Stratified K-Fold cross-validation with 10 folds was applied to preserve the class distribution in each fold. Additionally, the SMOTE technique was used to balance the classes by generating synthetic samples for the minority class.

An analysis of model performance was conducted considering two cases:

i) Case 1: basal body temperature and cycle day were used as input features;
ii) Case 2: only basal body temperature was used as an input feature.

Table II shows the classification performance of the models in Case 1, applied to the synthetic two-year basal body temperature dataset used to detect the ovulation day. The results indicate that tree-based algorithms (such as DT, AdaBoost, GBC, and XGBoost) and KNN performed best at detecting the ovulation day based on basal body temperature and cycle day. The performance of these models suggests that the pattern of basal temperature rise can be well modeled with tree-based algorithms, which are good at capturing nonlinear patterns.

TABLE II
Classification results for simulation considering the synthetic two-year basal body temperature and cycle day dataset.

Model	Accuracy	AUC	Recall	Precision	F1 Score	Time (s)
DT	1.0000	1.0000	1.0000	1.0000	1.0000	0.0480
KNN	1.0000	1.0000	1.0000	1.0000	1.0000	0.0760
NB	1.0000	1.0000	1.0000	1.0000	1.0000	0.0550
AdaBoost	1.0000	1.0000	1.0000	1.0000	1.0000	0.1280
GBC	1.0000	1.0000	1.0000	1.0000	1.0000	0.1210
XGBoost	1.0000	1.0000	1.0000	1.0000	1.0000	0.0590
LightGBM	1.0000	1.0000	1.0000	1.0000	1.0000	0.0970
RF	0.9980	1.0000	0.9500	1.0000	0.9667	0.2260
ET	0.9980	1.0000	0.9500	1.0000	0.9667	0.1670
LR	0.5784	0.6421	0.7000	0.0558	0.1026	0.4500
Ridge	0.5784	0.6421	0.7000	0.0558	0.1026	0.0590
LDA	0.5784	0.6442	0.7000	0.0558	0.1026	0.0330
QDA	0.0353	0.0000	1.0000	0.0353	0.0681	0.0330

When only basal body temperature was considered as input, the classification model performance varied significantly, and no model reached the accuracy or other ideal metrics observed when both basal body temperature and cycle day were provided. Table III shows that tree-based models performed slightly better, but excluding the cycle day as input reduced the algorithms' ability to accurately predict the ovulation day. This reinforces that, although basal body temperature contains relevant information for fertile period detection, combining it with the cycle day provides an advantage for model accuracy.

TABLE III
Model performance for Case 2.

Model	Accuracy	AUC	Recall	Precision	F1 Score	Time (s)
RF	0.7294	0.7623	0.5500	0.0617	0.1105	0.2520
DT	0.7255	0.6408	0.5500	0.0611	0.1094	0.0320
XGBoost	0.7235	0.7720	0.6000	0.0734	0.1289	0.1200
ET	0.7196	0.6806	0.5500	0.0605	0.1085	0.3010
KNN	0.7157	0.7572	0.6500	0.0798	0.1394	0.0730
LightGBM	0.7137	0.7842	0.7000	0.0815	0.1432	0.4490
GBC	0.7000	0.7720	0.7000	0.0765	0.1364	0.1430
AdaBoost	0.6431	0.7689	0.7000	0.0645	0.1171	0.1260
NB	0.6333	0.7624	0.7500	0.0694	0.1263	0.0310
QDA	0.6314	0.7624	0.7500	0.0691	0.1258	0.0310
LR	0.5392	0.5864	0.7000	0.0506	0.0940	0.5770
Ridge	0.5392	0.5864	0.7000	0.0506	0.0940	0.0300
LDA	0.5392	0.5864	0.7000	0.0506	0.0940	0.0300

The decision tree model showed the best performance compared to the other models. Thus, an analysis of the DT model was conducted. Figure 8 shows the variation of training score and cross-validation score with respect to the maximum depth of the decision tree. A maximum depth of 2 or 3 would be sufficient for this dataset.

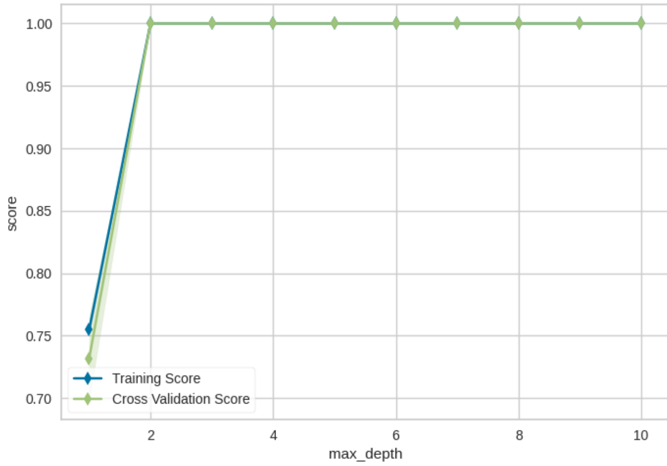

Fig. 8. Cross-validation for the decision tree.

Figure 9 shows the decision region obtained. The model separates the two classes 0 (not fertile) and 1 (fertile) with a decision region indicated by the colored areas in the background. The points are distributed in the two-dimensional space of basal body temperature and cycle day.

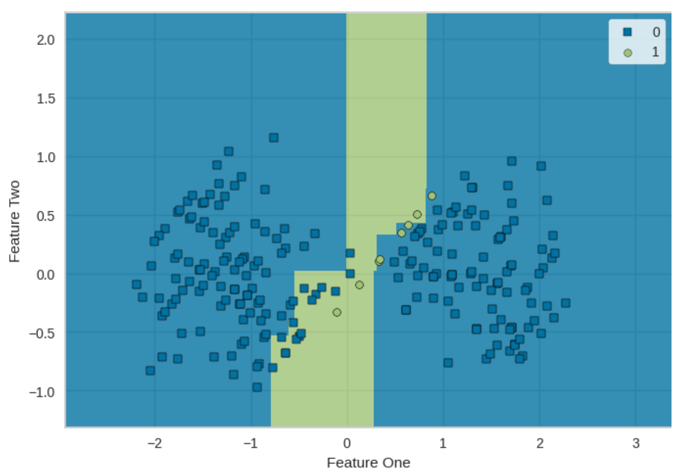

Fig. 9. Decision region obtained with the DT model.

Figure 10 shows the learning curve of the proposed model. The blue curve represents the training score (model performance on the training data). This score remains high, indicating that the model fits the training data well and achieves an accuracy close to 100%. The green curve represents the cross-validation score (model performance under cross-validation). Initially, this score is slightly lower, but it approaches the training score as the number of training instances increases. It can be concluded that increasing the training data helps reduce overfitting and improves the model's generalization.

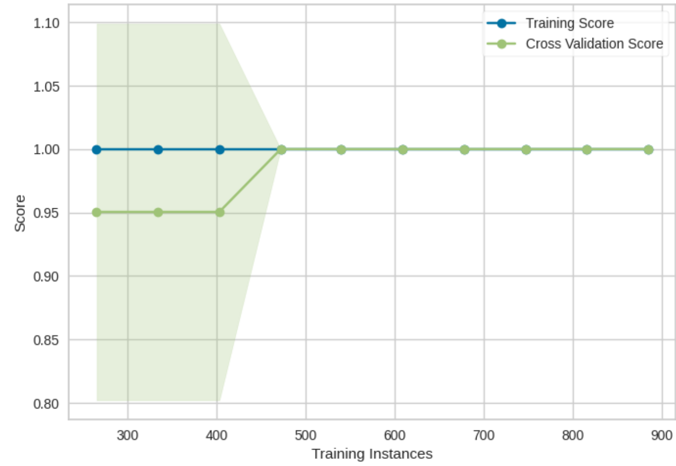

Fig. 10. Learning curve of the decision tree model.

Figures 11 and 12 show the model prediction explanation for different inputs of basal temperature and cycle day. Figure 11 shows that the model predicts the cycle is in the fertile phase with a probability of 1.00. Since the cycle day is 15 and the temperature is around 36.66°C, both values satisfy the conditions to classify the phase as fertile.

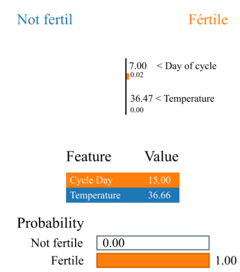

Fig. 11. Explanation of the algorithm output for basal temperature of 36.66°C and cycle day equal to 15.

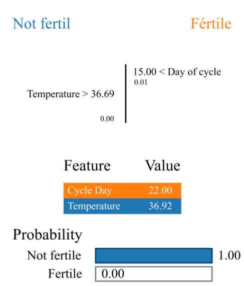

Fig. 12. Explanation of the algorithm output for basal temperature of 36.92°C and cycle day equal to 22.

In Figure 12, the model predicts the cycle is in the non-fertile phase with a probability of 1.00. The decision tree model indicates that a cycle day should be considered fertile if it falls between approximately 7 and 15. Also, the temperature should be higher than 36.48°C. However, the cycle day is 22, which is outside the fertile window identified by the model, leading to classification as non-fertile.

Figure 13 shows a comparison between the proposed algorithm and the Ogino-Knaus method. It can be seen that the Ogino-Knaus method predicted ovulation on the 14th day of the cycle, while the decision tree algorithm predicted ovulation on the 15th day of the cycle.

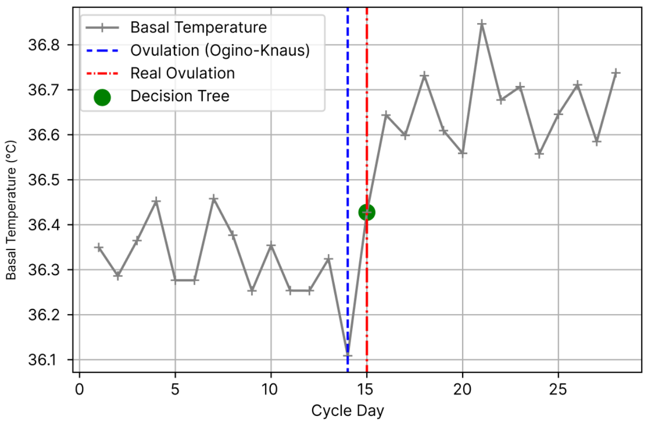

Fig. 13. Comparison between the proposed algorithm and the Ogino-Knaus method.

B. Prediction of the Next Cycle Date

For the prediction of the next cycle date, the LSTM model was used. Figure 14 shows the synthetic time series of a regular cycle and its duration in days. The model was used to predict the upcoming dates when the menstrual period will start, as shown in Figure 15.

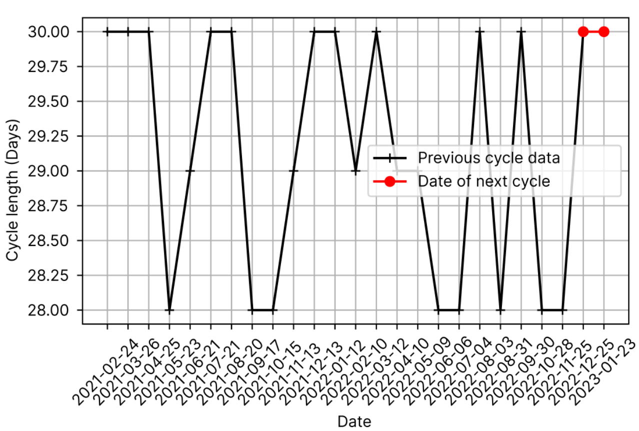

Fig. 14. Prediction of the next cycle date using the LSTM model presented in [7].

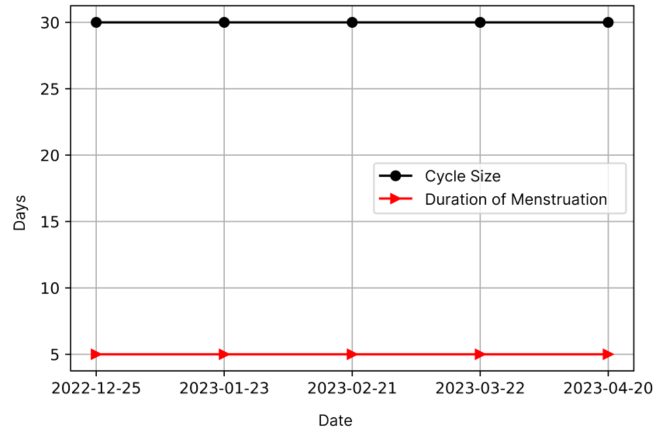

Fig. 15. Prediction of the dates for the next five cycles using the LSTM model.

Figure 16 presents the results of the prediction of a menstrual cycle with an estimated duration of 30 days, including the predicted dates for both menstruation and ovulation. The results were obtained using the DT and LSTM algorithms.

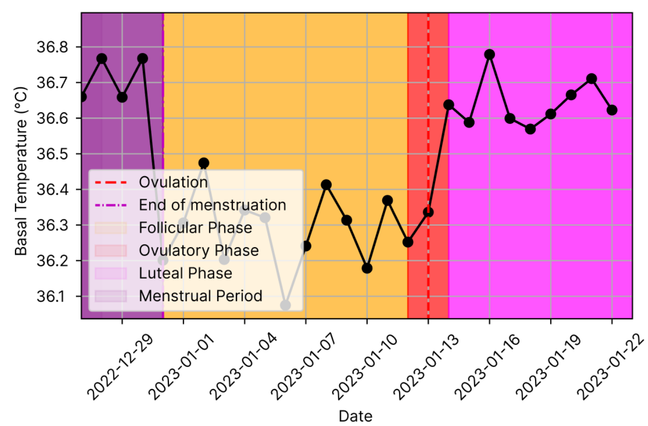

Fig. 16. Application of the decision tree and LSTM models for the prediction of ovulation and menstruation dates, respectively.

VI. Conclusion

Predicting the ovulation date is useful for family planning because it helps identify a person's fertile window, when the probability of conception is highest. This information can be used both to try to conceive and to avoid pregnancy. By applying machine learning techniques, including data preprocessing, class balancing, and cross-validation, a decision tree model was developed. The model achieved good accuracy and proved effective in predicting the ovulation day based on basal body temperature and cycle day. For predicting the date of the next menstrual cycle, the model proposed by [7] was employed. Both models were incorporated into the proposed application. Although the application is still in testing phases, it can be concluded that developing a decision support app providing accurate predictions enables women to better plan their lives. In future work, real data and additional variables, such as hormonal factors and behavioral data, will be included to further improve the model.

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