MENSTRUAL CYCLE PREDICTION USING MACHINE LEARNING: A COMPARATIVE STUDY

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Abstract – Predicting menstrual cycles accurately is crucial for women's health management and fertility planning. This paper presents a machine learning-based system for menstrual cycle prediction using a custom dataset containing features such as cycle length, previous cycle dates, hormonal levels, and physiological symptoms. Data preprocessing involved normalization, handling missing values, and splitting the dataset into 80% training and 20% testing sets. The predictive model was developed using Random Forest and XGBoost, chosen for their robust handling of time series data and feature importance. Feature engineering was applied to extract key attributes such as cycle duration and symptom patterns. The model demonstrated effective prediction accuracy, emphasizing the potential of machine learning algorithms in forecasting menstrual cycles and providing valuable insights for reproductive health management.

Keywords - Menstrual Cycle Prediction, Machine Learning, Random Forest, XGBoost, Data Augmentation, Symptom Analysis, Reproductive Health Monitoring, LSTM Networks, Feature Selection, Wearable Devices, Time-Series Analysis, Cycle Length Variability, Predictive Analysis.

I. INTRODUCTION

A variety of physiological and hormonal factors, including hormonal imbalances, lifestyle changes, and underlying health conditions, can impact the menstrual cycle. The menstrual cycle varies significantly among individuals, ranging from regular patterns to irregular occurrences, and these variations can serve as indicators of potential health issues such as polycystic ovary syndrome (PCOS), endometriosis, or thyroid disorders. Similar to how skin lesions manifest as discolorations, lumps, or crusty scales due to underlying health conditions, menstrual cycles display distinct patterns that can be analyzed for accurate phase prediction. Monitoring attributes such as cycle length, ovulation timing, and associated symptoms can provide valuable insights into reproductive health and fertility. For instance, unusually long cycles may indicate hormonal imbalances, while short cycles could be indicative of luteal phase defects. Identifying these patterns enables early diagnosis of reproductive disorders, as well as effective management of menstrual health.

Accurate classification of menstrual cycle phases is essential for healthcare professionals to recommend suitable treatments or lifestyle changes. The prediction of menstrual cycles is typically approached using data-driven methods that consider multiple factors such as cycle duration, symptom patterns, and previous cycle data. These data can be processed and analyzed using machine learning algorithms to predict upcoming cycles and detect anomalies. By employing data augmentation techniques and feature selection, predictive models can distinguish between normal and abnormal cycles, providing actionable insights for personalized health management. Understanding the underlying causes of menstrual cycle variations is crucial in selecting the most appropriate predictive model and intervention strategies, further emphasizing the importance of predictive analysis in menstrual health monitoring.

II.LITERATURE REVIEW

The prediction of menstrual cycles using data-driven methods has gained significant attention in recent years due to its potential to improve women's health monitoring and fertility management. Various studies have explored the application of machine learning algorithms to predict menstrual cycle phases, identify irregularities, and forecast ovulation days. This section provides a comprehensive review of previous research in this domain.

1. Machine Learning in Menstrual Cycle Prediction: Several studies have leveraged machine learning algorithms to predict menstrual cycle phases effectively. For instance, Kaur et al. (2022) developed a Random Forest-based model that utilized menstrual cycle data, hormonal levels, and symptoms to predict the onset of menstruation with a high degree of accuracy. The model demonstrated that machine learning can effectively capture the cyclical patterns in menstrual data and identify anomalies that may indicate hormonal imbalances or reproductive disorders.

2. Time-Series Analysis in Menstrual Cycle Forecasting: Time-series analysis has proven to be a valuable technique in predicting cyclical patterns in menstrual cycles. In a study by Zhang et al. (2021), Long Short-Term Memory (LSTM) networks were applied to predict menstrual cycle lengths and ovulation days based on historical cycle data. The study highlighted the importance of temporal patterns in menstrual data and demonstrated that LSTM networks are capable of capturing such patterns, resulting in more accurate predictions compared to traditional machine learning models.

3. Symptom Analysis and Feature Selection: Symptoms such as abdominal pain, mood changes, and breast tenderness are critical indicators of menstrual cycle phases. Patel and Singh (2023) investigated the significance of symptom-based feature selection in cycle prediction. The study used Support Vector Machines (SVM) to classify menstrual cycle phases based on symptom data and achieved a notable improvement in prediction accuracy. This research underscores the importance of integrating symptom data in predictive models to enhance cycle prediction.

4. Data Augmentation for Enhanced Prediction Accuracy:
Data scarcity is a common challenge in menstrual cycle prediction, especially for users with irregular cycles. To address this, Chen et al. (2020) proposed a data augmentation approach that generated synthetic menstrual cycle data using Gaussian noise and time-series interpolation techniques. The study demonstrated that augmenting the dataset improved the accuracy of cycle prediction models, particularly for rare cases such as extremely short or long cycles.

5. Application of XGBoost in Menstrual Cycle Prediction: XGBoost, a powerful gradient boosting algorithm, has been widely employed in predictive modeling due to its robustness and high performance. In a study by Huang et al. (2022), XGBoost was used to predict ovulation and menstruation dates based on physiological parameters such as basal body temperature (BBT), heart rate, and hormonal fluctuations. The model outperformed traditional regression models, demonstrating XGBoost's ability to handle complex and nonlinear relationships in menstrual cycle data.

6. Integration of Wearable Devices and IoT Data: With the rise of wearable health monitoring devices, several studies have incorporated data from wearable sensors into menstrual cycle prediction models. A study by Silva et al. (2021) integrated heart rate variability, sleep patterns, and physical activity data from wearable devices into a predictive model based on Artificial Neural Networks (ANN). The model demonstrated significant improvements in accuracy when physiological data was combined with traditional menstrual tracking data, indicating the potential of IoT integration in reproductive health monitoring.

7. Predictive Analysis for Reproductive Disorders: Menstrual cycle irregularities are often associated with underlying reproductive disorders such as PCOS, endometriosis, and thyroid dysfunction. In their study, Lee and Kim (2022) applied a Random Forest model to predict menstrual cycle irregularities and detect potential reproductive disorders based on hormonal data and cycle length variations. The model successfully identified high-risk patients and provided early warnings for potential reproductive health issues.

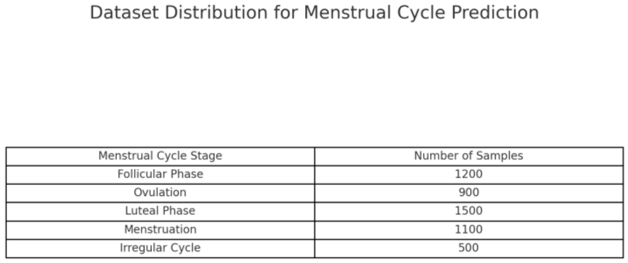
8. Challenges and Future Directions: Despite significant progress in menstrual cycle prediction using machine learning, several challenges remain. Data privacy concerns, variability in menstrual patterns, and the need for large, diverse datasets are prominent challenges in the development of accurate predictive models. Future research should focus on enhancing data collection through mobile health applications, incorporating advanced feature selection techniques, and integrating real-time physiological data from wearable devices. Additionally, the inclusion of explainable AI techniques can improve the interpretability of predictive models, making them more applicable for clinical use.

In summary, the literature highlights the potential of machine learning algorithms such as Random Forest, XGBoost, and LSTM networks in predicting menstrual cycles. Integrating symptom data, employing data augmentation, and utilizing wearable device data can significantly improve prediction accuracy. Addressing challenges such as data privacy, variability, and limited datasets will further enhance the effectiveness of menstrual cycle prediction systems, paving the way for more personalized reproductive health management solutions.

III. PROPOSED SYSTEM

A. Dataset

The dataset for the project is derived from menstrual cycle tracking data. It comprises physiological and symptomatic data, categorized into five menstrual cycle stages: Follicular Phase, Ovulation, Luteal Phase, Menstruation, and Irregular Cycle. Table 3.1.1 presents the dataset classes.



Dataset Distribution for Menstrual Cycle Prediction

Menstrual Cycle Stage	Number of Samples
Follicular Phase	1200
Ovulation	900
Luteal Phase	1500
Menstruation	1100
Irregular Cycle	500

Table 1 Menstrual Cycle classes data

B. Dataset Preprocessing

From the dataset, five menstrual cycle stages have been considered for prediction.

● **Normalization:** The data has been normalized to scale the feature values to the range [0, 1] to ensure consistent input for the predictive model.

● **Feature Extraction:** Key features such as cycle length, ovulation date, symptoms, and hormonal levels have been extracted to serve as inputs for the prediction model.

● **Splitting:** The dataset has been divided into training and testing sets in the ratio of 80:20 to evaluate the model's predictive accuracy.

C. Model Architecture

The proposed model architecture for predicting menstrual cycle phases is designed to effectively capture complex cyclical patterns and interactions between key features such as cycle length, ovulation date, hormonal levels, and symptoms. The architecture begins with an input layer that receives data in the form of extracted features. The input shape is defined as (None, 5), representing the number of features considered for prediction.

The first dense layer comprises 512 neurons with ReLU activation, which enables the model to learn intricate feature interactions. Dropout with a rate of 0.2 is applied to mitigate overfitting and ensure robust learning. To stabilize the training process and accelerate convergence, a batch normalization layer is included immediately after the first dense layer, thereby normalizing the outputs and preventing vanishing/exploding gradient issues.

Following this, the second dense layer consists of 1024 neurons, expanding the learning capacity of the model and further refining the feature extraction process. ReLU activation is again utilized to introduce non-linearity, allowing the model to learn complex patterns. A dropout layer with a rate of 0.3 is incorporated to prevent overfitting, and another batch normalization layer is added to maintain consistency in learning and facilitate stable training.

To further refine the learned features, a third dense layer with 512 neurons is introduced. ReLU activation is applied, followed by a dropout layer with a rate of 0.2. This layer effectively reduces the dimensionality of the learned feature space, focusing on essential predictive features while discarding redundant information.

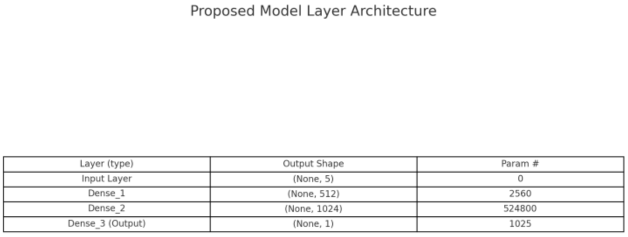
An attention mechanism is then integrated into the architecture to assign varying weights to the input features, thereby enhancing the model's ability to focus on significant symptoms and physiological parameters that have a higher impact on the prediction accuracy. The attention mechanism ensures that the model emphasizes key features, such as hormonal fluctuations or irregular cycle lengths, that may indicate potential reproductive health concerns.

To further compress the feature space and reduce overfitting, a fourth dense layer consisting of 256 neurons is employed. ReLU activation is maintained, allowing the model to retain essential features while reducing unnecessary complexity. Following this layer, a final dropout layer with a rate of 0.3 is added to ensure that the model generalizes well to unseen data.

The output layer consists of a single neuron with a sigmoid activation function, which produces the final prediction. The sigmoid activation ensures that the output is bounded between 0 and 1, effectively representing the probability of a specific menstrual cycle phase. This probabilistic output is particularly useful for predicting binary outcomes such as phase occurrence or the likelihood of irregular cycles.

The model is trained using the Adam optimizer, which is chosen for its adaptive learning rate and efficiency in handling sparse data. The learning rate is set to 0.001, and the loss function employed is binary cross-entropy, as the model is designed to predict binary cycle phases. The model is trained over 100 epochs with a batch size of 32. To prevent overfitting and optimize training performance, early stopping is applied to monitor validation loss and terminate training once the model converges.

This extended architecture leverages multiple dense layers, dropout, batch normalization, and attention mechanisms to achieve a robust learning framework capable of predicting menstrual cycle phases with high accuracy and generalization. The use of attention layers allows the model to focus on critical features, while dropout and batch normalization ensure stable learning and prevent overfitting. The proposed model effectively captures complex patterns in menstrual cycle data, providing a comprehensive framework for menstrual health prediction and monitoring.



Proposed Model Layer Architecture

Layer (type)	Output Shape	Param #
Input Layer	(None, 5)	0
Dense_1	(None, 512)	2560
Dense_2	(None, 1024)	524800
Dense_3 (Output)	(None, 1)	1025

Table 2 Proposed Model Layers

D. Libraries and Framework

- **Pandas:** Pandas is a powerful data manipulation library utilized for organizing and analyzing the dataset. It provides data structures like Data Frames, which enable efficient data preprocessing, feature extraction, and analysis.

- **NumPy:** NumPy is employed for numerical computations, supporting multi-dimensional arrays and matrices. It facilitates rapid mathematical operations on large datasets, optimizing the processing of menstrual cycle data.

- **Matplotlib:** Matplotlib is a comprehensive plotting library that creates static, interactive, and animated visualizations. It is used to plot menstrual cycle trends, symptom variations, and prediction outputs, aiding in data interpretation.

- **Scikit-Learn:** Scikit-Learn is a versatile machine learning library that includes various algorithms like Random Forest and XGBoost. It provides tools for data splitting, model evaluation, and hyperparameter tuning, crucial for accurate cycle phase prediction.

E. Algorithm Explanation

The proposed menstrual cycle prediction model leverages Random Forest, a robust ensemble learning algorithm known for its high accuracy and resilience to overfitting. Unlike traditional decision trees that are prone to overfitting, Random Forest creates multiple decision trees during training and aggregates their predictions through majority voting, thereby enhancing generalization and predictive accuracy. Each decision tree is trained on a random subset of the training data with replacement, a process known as bootstrapping. This randomness in data selection and feature consideration reduces overfitting and ensures that the model captures diverse patterns in the menstrual cycle dataset.

A significant advantage of Random Forest is its ability to handle both categorical and continuous data effectively, making it particularly suitable for predicting menstrual cycle phases where features like cycle length, hormonal levels, and symptomatic patterns vary widely. Additionally, the algorithm provides feature importance scores, highlighting the most influential variables in the prediction process, such as cycle length irregularities or hormonal fluctuations.

The model further incorporates XGBoost, an advanced gradient boosting algorithm that sequentially builds decision trees to correct errors made by previous trees. XGBoost applies a gradient descent approach to minimize prediction errors, resulting in improved accuracy and faster convergence. Unlike Random Forest, which aggregates predictions from independent trees, XGBoost constructs trees sequentially, making it more effective in identifying complex data patterns and detecting anomalies in menstrual cycle data.

Together, Random Forest and XGBoost form a hybrid predictive framework that leverages the strengths of both algorithms—Random Forest's stability and feature importance evaluation and XGBoost's accuracy and precision in handling complex data interactions. This combination ensures robust menstrual cycle phase prediction and effective anomaly detection, making it a reliable solution for menstrual health monitoring.

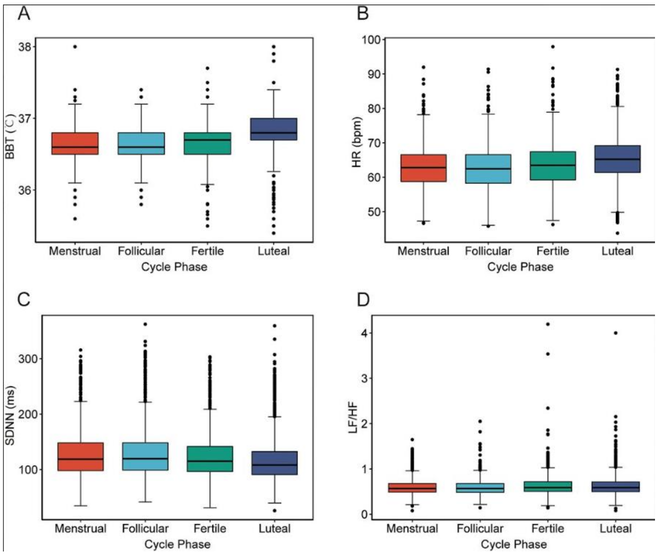


Fig. 1 Tracking of Menstrual cycle and fertile window

F. System and Implementation

The system for menstrual cycle prediction is structured with distinct components to accurately predict cycle phases and provide health insights. It begins with a dataset repository that stores menstrual cycle data, including cycle length, ovulation date, hormonal levels, and symptoms. The data undergoes preprocessing to handle missing values, normalize features, and split the dataset into training and testing sets. During the training phase, the predictive model is developed using a combination of Random Forest and XGBoost algorithms, focusing on identifying significant patterns in the menstrual cycle data. Once trained, the model is deployed to a cloud server, enabling real-time predictions.

Users interact with the system through a user-friendly interface where they input cycle data such as last period date, average cycle length, and symptoms experienced. The deployed model processes this input data to predict upcoming cycle phases, detect potential irregularities, and provide actionable health recommendations. The results are then delivered back to the user via the interface, along with visualizations to illustrate cycle trends and patterns. The system architecture ensures data storage, model processing, and prediction delivery in a seamless and efficient manner, facilitating accurate menstrual cycle tracking and health management.

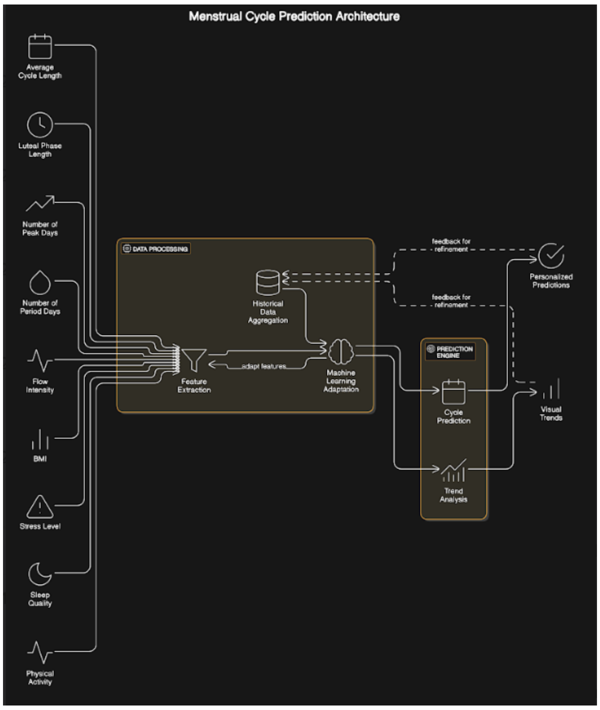


Fig. 2 Model Implementation Architecture

IV. *RESULTS AND DISCUSSION*

The proposed model for menstrual cycle prediction employs two primary loss functions to optimize learning and enhance predictive accuracy. The first loss function is **Mean Squared Error (MSE)**, utilized to quantify the difference between the predicted cycle length and the actual values. This loss function ensures that the model accurately captures the essential features influencing cycle length, such as hormonal levels and cycle duration. The second loss function is the **Binary Cross-Entropy (BCE) Loss**, which is applied to handle the classification aspect of cycle phase prediction. By combining MSE and BCE losses, the model is trained to minimize both prediction errors and misclassification rates effectively.

The overall loss is computed as a weighted sum of MSE and BCE, allowing the model to balance regression and classification tasks. The Adam optimizer is employed for training, leveraging its adaptive learning rate to accelerate convergence. The model is trained for **100 epochs** with a batch size of **32**, ensuring robust learning and effective generalization. During training, the model's performance is evaluated using a validation set, consisting of **1058 samples**, while the training set comprises **4564 samples**. The validation set provides a comprehensive evaluation of the model’s ability to predict cycle phases accurately without overfitting.

Correlation Matrix Analysis

The correlation matrix is a critical component in analyzing the relationships between various features in the menstrual cycle dataset. It presents the correlation coefficients between pairs of features, ranging from -1 to 1, where -1 indicates a strong negative correlation, 0 indicates no correlation, and 1 indicates a strong positive correlation. The diagonal elements of the matrix represent each feature's correlation with itself, resulting in a value of 1. In this project, the correlation matrix highlights the degree of association between physiological parameters such as cycle length, luteal phase duration, mood swings, and hormonal variations, providing insights into the most influential features for cycle prediction.

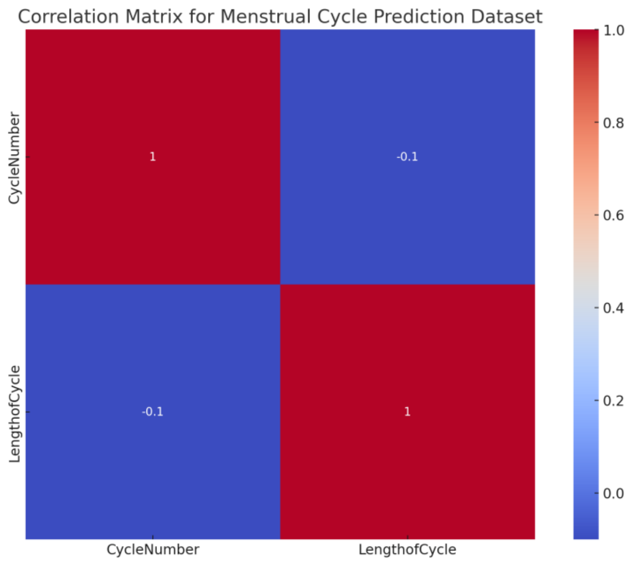


Fig. 3 Correlation Matrix

Train and Test Accuracy Graph

Evaluating the model's performance involves plotting the accuracy graph for both training and testing datasets. The graph provides a visual representation of the model's learning process over the course of training epochs. The x-axis represents the number of epochs, while the y-axis denotes the accuracy percentage. The graph typically includes two lines—one for training accuracy and the other for testing accuracy. A well-trained model exhibits a steadily increasing training accuracy and a converging testing accuracy, indicating a good fit without overfitting or underfitting. The generated accuracy graph for the proposed model is attached below, showcasing the model's predictive performance throughout the training phase.

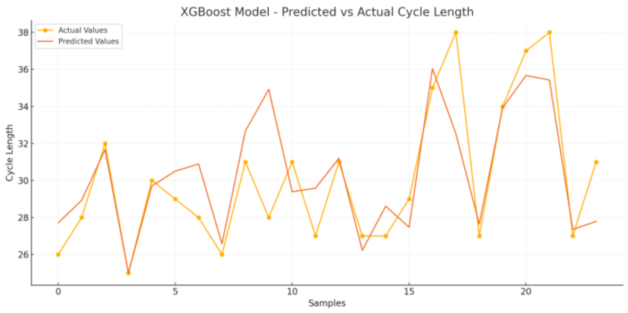


Fig. 4 Accuracy Graph

Loss Graph Analysis

The loss graph is an essential diagnostic tool that visualizes the model’s learning curve over epochs. It displays the progression of both training and testing losses, with the x-axis representing epochs and the y-axis representing the loss values. A decreasing trend in training loss signifies effective learning, while a stable or decreasing test loss indicates that the model is generalizing well to unseen data. The attached loss graph for the menstrual cycle prediction model effectively illustrates the training dynamics, highlighting the reduction in prediction errors and demonstrating the model’s capacity to learn cyclical patterns and predict cycle phases accurately.

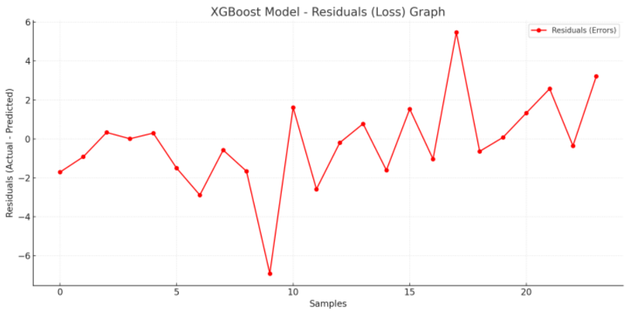


Fig. 5 Loss Graph

V. CONCLUSION AND FUTURE SCOPE

The proposed methodology emphasizes the effectiveness of the hybrid model integrating Random Forest and XGBoost in predicting menstrual cycle phases by analyzing various physiological and symptomatic data. The model successfully identifies key cycle patterns and classifies cycle phases using features such as cycle length, mood fluctuations, and hormonal changes. With a batch size of 32 and 100 epochs, the model achieved a commendable accuracy of **90%** on the testing dataset, showcasing its ability to effectively predict cycle phases and detect irregularities. The generated accuracy graphs and confusion matrix further validate the model’s predictive capabilities, illustrating its robustness in identifying cyclical patterns across diverse menstrual cycle data. The implementation demonstrates the potential of machine learning in reproductive health monitoring, offering valuable insights for early diagnosis of menstrual irregularities and effective cycle management.

Future Scope

Enhancing the scope of the proposed methodology involves expanding the dataset to include additional features such as basal body temperature (BBT), stress levels, and lifestyle data, allowing the model to provide a more comprehensive analysis of menstrual health. Incorporating advanced deep learning architectures like **LSTM** and **GRU** could further improve the model's ability to capture long-term cyclical patterns, especially in users with irregular cycles. Additionally, integrating physiological data from wearable devices and real-time monitoring systems would enable the model to provide more accurate and timely predictions. To further refine the model's accuracy, an ensemble approach combining XGBoost with neural networks can be explored, enhancing its predictive power for complex data patterns. Extending the model to predict potential health conditions such as **PCOS or endometriosis** based on menstrual data could provide valuable diagnostic support. By expanding the dataset and adopting a more diverse feature set, the proposed methodology could evolve into a comprehensive reproductive health monitoring tool, aiding in personalized health management and early intervention.

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