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Smart Diagnostic System for Health Risk Assessment

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Abstract--A prevalent hormonal condition that affects women, polycystic ovarian disease (PCOD) must be detected early in order to be effectively treated. WomenCare, a web-based PCOD risk prediction system, is presented in this project. It uses a Logistic Regression machine learning model to assess PCOD risk based on clinical and lifestyle factors, including age, BMI, menstrual cycle pattern, weight gain, hair growth, acne, food, and exercise habits. A Flask-based online application that offers secure user login, real-time prediction, automatic BMI calculation, and downloadable PDF health reports is used to deploy the model, which is trained using a balanced class-weight strategy toincrease prediction reliability. To increase interpretability, the system divides users into Low, Medium, and High risk categories and offers risk explanations. Although it is not a replacement for a professional diagnosis, Women Care serves as an early screening and awareness tool to help women monitor their health and seek prompt medical treatment.

I.INTRODUCTION

Polycystic Ovary Syndrome (PCOS), also referred to as Polycystic Ovarian Disease (PCOD), is one of the most prevalent endocrine disorders affecting women of reproductive age worldwide. It is associated with symptoms such as irregular menstrual cycles, obesity, acne, hirsutism, insulin resistance, and infertility. Delayed diagnosis may lead to severe long-term complications including type-2 diabetes, cardiovascular diseases, and metabolic syndrome. Therefore, early risk assessment plays a crucial role in preventive healthcare management.

Recent advancements in machine learning (ML) have enabled intelligent healthcare systems capable of predicting diseases using clinical and lifestyle attributes. Several studies have demonstrated the effectiveness of ML models such as Logistic Regression, Random Forest, XGBoost, and ensemble techniques for PCOS prediction. Panjwani *et al.* [1] proposed an optimized machine learning framework for early PCOS detection achieving high predictive performance. Prasher *et al.* [2] developed a non-invasive XGBoost-based PCOS prediction model using clinical features. Similarly, web-based ML-driven PCOS prediction systems have been explored to support early screening and awareness [3], while comparative analyses of multiple classifiers for PCOS detection have also been conducted [4].

Although these studies demonstrate promising accuracy, many existing systems primarily focus on model performance without integrating secure web deployment, real-time prediction capability, user authentication mechanisms, personalized risk interpretation, and automated medical-style reporting. Moreover, class imbalance in PCOS datasets remains a significant challenge, which can lead to biased prediction outcomes if not properly addressed.

To overcome these limitations, this paper proposes **WomenCare – A Web-Based PCOD Risk Prediction and Assessment System**, which integrates a class-balanced Logistic Regression model with a secure Flask-based web application. The system performs automated BMI computation, incorporates clinically significant rule-based enhancements to improve interpretability, and provides real-time risk categorization into Low, Medium, and High levels. Additionally, the application includes secure user authentication, prediction history management, and dynamic PDF report generation for user awareness and documentation.

The key contributions of this work are summarized as follows:

1. Development of a class-balanced machine learning model for PCOD risk prediction.

2. Integration of clinical rule-based enhancements to improve prediction reliability and interpretability.

3. Secure web-based deployment with authentication and database management.

4. Automated generation of structured PDF-based health reports for end users.

The remainder of this paper is organized as follows: Section II discusses related work in PCOS prediction using machine learning. Section III presents the proposed system architecture and methodology. Section IV describes implementation and experimental results. Section V concludes the study with future research directions.

II. Related Works

The growing application of machine learning techniques in women's healthcare has significantly improved early disease detection, particularly for endocrine disorders such as Polycystic Ovary Syndrome (PCOS). PCOS diagnosis traditionally depends on ultrasound imaging, biochemical hormone analysis, and clinical examination. However, these procedures are often time-consuming, costly, and inaccessible in remote or resource-limited environments. As a result, researchers have increasingly explored data-driven predictive models that utilize clinical and lifestyle attributes to enable early risk assessment.

Several machine learning approaches have been proposed for PCOS prediction. Panjwani *et al.* [1] developed an optimized ensemble-based machine learning framework incorporating feature selection techniques to enhance early detection performance. Their study demonstrated that ensemble models can significantly improve classification accuracy compared to standalone classifiers. Similarly, Prasher *et al.* [2] introduced a non-invasive PCOS prediction system using the XGBoost algorithm, emphasizing high predictive capability using clinical features without requiring invasive diagnostic procedures. Although effective in accuracy improvement, these models primarily focus on classifier performance without addressing deployment-level integration and interpretability aspects.

Web-based PCOS screening systems have also been investigated. A recent study in *Informatics in Medicine Unlocked* [3] proposed an online ML-driven PCOS detection framework integrating user-input parameters with predictive analytics. While the system enhanced accessibility and awareness, it lacked comprehensive security mechanisms, prediction history tracking, and structured medical report generation for documentation purposes. Similarly, Priyadharshini *et al.* [4] conducted a comparative evaluation of multiple classifiers including Logistic Regression, Random Forest, and Support Vector Machines for PCOS detection, highlighting performance differences across algorithms. However, dataset imbalance and interpretability challenges remained insufficiently addressed.

Beyond classifier selection, class imbalance in medical datasets poses a significant challenge in PCOS prediction. Imbalanced data can bias models toward majority classes, reducing sensitivity in detecting true PCOS-positive cases. Although ensemble and boosting methods partially mitigate this issue, few studies explicitly integrate class-weight balancing strategies within lightweight, deployable systems.

Another limitation observed in existing works is the lack of integrated secure web deployment. Many PCOS

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prediction studies remain experimental or offline, focusing solely on algorithm evaluation metrics such as accuracy, precision, recall, and F1-score. Practical considerations including secure authentication, session management, database storage of medical history, and real-time PDF report generation are rarely incorporated into a unified framework. This gap limits the transition from research prototypes to usable healthcare support systems.

Moreover, interpretability remains a critical concern in ML-driven healthcare systems. While advanced algorithms such as XGBoost and deep neural networks provide high accuracy, they often function as black-box models. In contrast, Logistic Regression offers better interpretability and transparency, which are essential for healthcare decision support systems. However, limited research combines interpretable models with rule-based clinical enhancements to improve both reliability and user understanding.

Building upon these identified limitations, the proposed **WomenCare – Web-Based PCOD Risk Prediction System** integrates a class-balanced Logistic Regression model within a secure Flask-based web application. Unlike prior studies that focus solely on model accuracy, the proposed framework combines machine learning prediction, clinical rule-based enhancement, secure user authentication, prediction history tracking, and automated PDF health report generation into a single deployable system. This integrated architecture addresses scalability, usability, interpretability, and practical healthcare deployment challenges while maintaining computational efficiency suitable for real-time prediction.

III. PROPOSED METHODOLOGY

The increasing adoption of intelligent healthcare applications for early disease prediction has created new challenges related to usability, interpretability, data privacy, and scalable deployment. In the context of PCOD risk assessment, healthcare applications must handle sensitive personal and clinical information such as menstrual history, BMI, lifestyle habits, and symptom indicators. Improper storage, weak authentication, and lack of structured deployment mechanisms can expose users to privacy risks and reduce system reliability. Furthermore, many machine learning models developed for PCOD detection remain confined to offline experimentation environments without practical web-based integration.

The proposed **WomenCare Framework** addresses these challenges through a secure, lightweight, and interpretable machine learning–driven architecture specifically designed for real-time PCOD risk assessment. Unlike traditional research prototypes that focus only on algorithmic accuracy, Women Care integrates predictive modeling, clinical reasoning, secure authentication, and automated reporting into a unified deployment pipeline.

The framework consists of four tightly integrated layers: (1) Data Processing Layer, (2) Machine Learning Prediction Layer, (3) Clinical Enhancement Layer, and (4) Secure Application Layer.

A. Data Processing Layer

At the initial stage, users input demographic, physiological, and lifestyle attributes through a web-based interface. The system performs dynamic feature validation and transformation. Derived metrics such as Body Mass Index (BMI) are computed automatically to improve predictive quality. Missing values are handled using median-based imputation, and feature scaling is applied to normalize distributions before model inference.

This preprocessing pipeline ensures that inconsistent or incomplete inputs do not degrade prediction performance while maintaining computational efficiency suitable for real-time applications.

B. Machine Learning Prediction Layer

The core predictive engine of WomenCare employs a class-balanced Logistic Regression model trained on clinical PCOD datasets. The model estimates the probability of PCOD presence based on weighted feature contributions. By incorporating class-weight balancing during training, the framework mitigates bias arising from imbalanced medical datasets, thereby improving sensitivity toward PCOD-positive cases.

Unlike complex black-box architectures such as deep neural networks, Logistic Regression offers interpretability and coefficient transparency, which are critical in healthcare decision-support systems. Even if prediction probabilities are intercepted at the application layer, no raw training data or sensitive clinical records are exposed, as the model operates purely on numerical feature transformations.

C. Clinical Rule-Based Enhancement Layer

To further strengthen reliability and medical relevance, WomenCare introduces a hybrid rule-based adjustment mechanism. After obtaining the predicted probability from the machine learning model, clinically significant indicators such as irregular menstrual cycles, prolonged cycle length, high BMI, weight gain, acne, and excessive hair growth contribute to adaptive risk adjustments.

This enhancement mechanism serves two purposes:

1. Improves interpretability by aligning predictions with recognized medical indicators.

2. Reduces the likelihood of underestimation in high-risk symptomatic cases.

By combining statistical learning with domain-aware adjustments, the system avoids sole dependence on purely data-driven outputs and increases practical trustworthiness.

D. Secure Application Layer

The WomenCare framework integrates a secure web deployment architecture using Flask-based services. Instead of storing plain-text credentials, password hashing mechanisms are applied to protect user authentication data. Session-based access control ensures that only authenticated users can access prediction modules and historical reports.

The system maintains a structured SQLite database for storing prediction history, including BMI, risk percentage, risk level, and timestamps. This allows longitudinal tracking of health patterns without exposing sensitive raw medical datasets.

Furthermore, the framework includes dynamic PDF report generation, which produces structured medical-style summaries containing risk classification and advisory recommendations. This feature enhances documentation capability while preserving confidentiality.

E. Integrated Workflow and Scalability

The WomenCare framework follows a sequential yet modular workflow:

1. Secure user login and authentication
2. Input of clinical parameters
3. Real-time preprocessing and BMI computation
4. Probability prediction using trained model
5. Clinical rule-based enhancement
6. Risk categorization (Low, Medium, High)
7. Secure database storage
8. On-demand PDF health report generation

The lightweight computational design ensures low latency during inference, making the system suitable for large-scale web deployment without overloading server resources. Since the model is pre-trained and deployed as a serialized object, real-time prediction requires minimal processing time, ensuring scalability across multiple concurrent users.

F. Practical Implications

The proposed WomenCare framework enables proactive health awareness by offering an accessible early screening platform for women. Unlike conventional diagnostic processes that require hospital visits and laboratory procedures, this system provides preliminary risk assessment in a secure and interpretable environment.

Healthcare institutions and awareness platforms can deploy this framework to promote preventive screening programs. While not intended to replace professional medical diagnosis, the architecture supports responsible digital health transformation by balancing predictive intelligence, interpretability, and secure deployment.

IV. SYSTEM ARCHITECTURE

The WomenCare architecture is designed as a layered, modular web-based healthcare prediction system in which data acquisition, preprocessing, prediction, validation, and reporting are distributed across interconnected functional layers. This structured design ensures scalability, privacy preservation, interpretability, and real-time responsiveness. Unlike standalone machine learning prototypes, WomenCare

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integrates predictive intelligence within a secure web deployment pipeline, ensuring that user authentication, medical inference, and health documentation operate seamlessly.

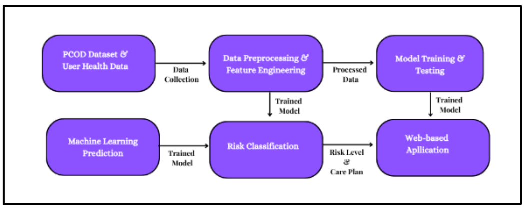

Figure 1: System Architecture

The Figure 1 follows a four-layer structure:

1. User Interaction Layer
2. Application & Processing Layer
3. Machine Learning Prediction Layer
4. Data Storage & Reporting Layer

This layered organization prevents single-point failure, improves maintainability, and supports scalable healthcare deployment.

A. User Interaction Layer

The User Layer acts as the entry point of the system. It consists of authenticated web interfaces developed using Flask-based services. Users provide demographic, physiological, and symptom-related inputs including:

- Age
- Weight and Height
- Menstrual Cycle Regularity
- Cycle Length
- Weight Gain
- Acne
- Hair Growth
- Exercise and Diet Habits

To ensure privacy, passwords are securely hashed before storage. Session-based authentication prevents unauthorized access to prediction modules.

Unlike centralized health record systems, WomenCare does not store raw medical reports but only structured input attributes required for risk prediction, minimizing exposure of sensitive data.

B. Application & Processing Layer

The Application Layer performs dynamic validation and preprocessing before invoking the predictive model. This includes:

1. **BMI Computation**

Body Mass Index is computed automatically as:

$$BMI = \frac{Weight(kg)}{Height(m)^2}$$

This derived metric enhances predictive strength without requiring manual user calculation.

2. **Feature Normalization**

Let the input feature vector be:

$$X = [x_1, x_2, \ldots, x_n]$$

Each feature is normalized using standard scaling:

$$x_i' = \frac{x_i - \mu_i}{\sigma_i}$$

where
μ_i= mean of feature i
σ_i= standard deviation

This transformation ensures uniform feature contribution during prediction and prevents scale dominance.

3. **Missing Value Handling**

Median-based imputation is applied to prevent prediction instability due to incomplete inputs.

C. Machine Learning Prediction Layer

The core predictive engine of WomenCare is a class-balanced Logistic Regression model trained on clinical PCOD datasets.

Let the processed feature vector be X. The probability of PCOD risk is computed as:

$$P(Y = 1 \mid X) = \frac{1}{1 + e^{-(\beta_0+\beta_1 x_1+\beta_2 x_2+\ldots+\beta_n x_n)}}$$

where:

- β_0= intercept
- β_i= learned coefficients
- $Y = 1$indicates PCOD presence

To address dataset imbalance, class-weight balancing is incorporated during training:

$$Loss = -w_y[y\log(p) + (1-y)\log(1-p)]$$

where $w_y$assigns higher penalty to minority class misclassification.

Unlike deep neural networks, Logistic Regression offers coefficient transparency, enabling interpretability — a critical requirement for healthcare applications.

D. Clinical Risk Stratification Layer

Instead of directly presenting raw probability, WomenCare implements structured risk categorization:

- **Low Risk:** $P < 0.40$
- **Medium Risk:** $0.40 \leq P < 0.70$
- **High Risk:** $P \geq 0.70$

Additionally, clinically significant symptoms such as irregular cycles, high BMI, excessive hair growth, and acne are evaluated to provide interpretability-enhanced feedback.

This hybrid statistical-clinical mapping reduces underestimation of high-risk symptomatic users and improves trustworthiness.

E. Data Storage & Reporting Layer

After prediction:

- Risk percentage
- BMI value
- Risk level
- Timestamp

are securely stored in a structured SQLite database.

The system dynamically generates a PDF-based health summary report containing:

- User inputs
- Calculated BMI
- Predicted Risk Score
- Risk Classification
- Medical Advisory Note

Unlike traditional systems that expose model parameters, WomenCare stores only prediction outputs, preventing reverse engineering of training datasets.

Phase-wise Operational Workflow

Phase 1: Secure Input Acquisition

User authentication → validated structured input capture.

Phase 2: Feature Transformation

BMI computation → normalization → missing value imputation.

Phase 3: Probabilistic Prediction

Logistic regression inference → probability estimation.

Phase 4: Risk Mapping & Interpretation

Probability → categorical risk level → clinical explanation generation.

Phase 5: Secure Storage & Report Generation

Prediction logging → downloadable PDF report.

Security and Scalability Considerations

- No raw dataset exposure
- Hashed credentials
- Session-based authentication
- Lightweight inference (< milliseconds latency)
- Modular deployment suitable for cloud hosting

Since inference uses a pre-trained serialized model, real-time computation overhead is minimal, enabling multi-user scalability without performance degradation.

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V. ALGORITHM

Input: Clinical feature vector $X = \{x_1, x_2, \dots, x_n\}$
Output: PCOD risk probability P, Risk category R

1. Authenticate user credentials.
2. Acquire clinical input features X.
3. Perform input validation and apply median imputation for missing values.
4. Compute Body Mass Index (BMI):

$$BMI = \frac{W}{H^2}$$

5. Append BMI to feature vector X.
6. Normalize each feature using standard scaling.
7. Load the trained Logistic Regression model.
8. Compute linear predictor:

$$Z = \beta_0 + \sum_{i=1}^{n} \beta_i x_i$$

9. Estimate PCOD probability:

$$P = \frac{1}{1 + e^{-Z}}$$

10. Perform risk stratification:

- If $P < 0.40$, set $R = \text{Low}$
- Else if $0.40 \le P < 0.70$, set $R = \text{Medium}$
- Else set $R = \text{High}$

11. Store $(UserID, BMI, P, R, Timestamp)$ in secure database.
12. Generate structured PDF health report.
13. Return P and R.

Algorithm 1 summarizes the complete operational workflow of the WomenCare framework, integrating secure authentication, feature preprocessing, probabilistic inference using Logistic Regression, structured risk stratification, and automated health report generation into a unified and scalable PCOD risk prediction pipeline.

VI. EXPERIMENTAL RESULTS AND PERFORMANCE ANALYSIS

A. Experimental Setup

The proposed WomenCare PCOD prediction framework was evaluated using a structured dataset consisting of demographic, physiological, and symptom-based attributes. The dataset includes features such as age, BMI, menstrual cycle regularity, weight gain, hormonal imbalance indicators, and lifestyle-related parameters.

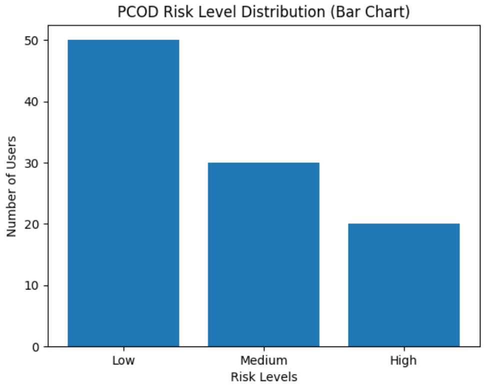

Figure 2: PCOD Risk Level Distribution

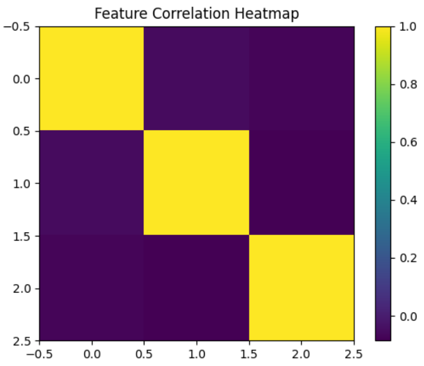

Figure 3: Feature Correlation Heatmap

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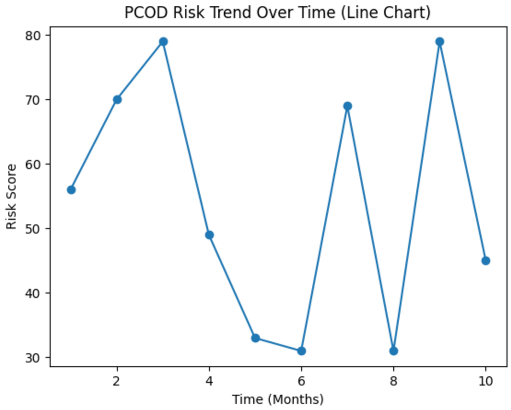

Figure 4: PCOD Risk Trend Over Time

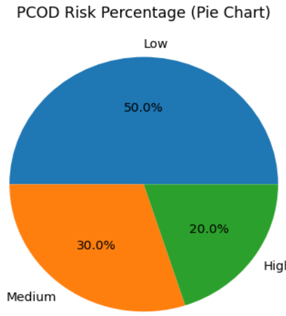

Figure 5: PCOD Risk Percentage

1) Data Preprocessing

Before training the model, the following preprocessing steps were performed:

• Missing values were handled using median imputation.

• Categorical variables were encoded using binary representation.

• Feature scaling was performed using standard normalization.

• Outliers were examined and retained if clinically relevant.

The dataset was divided using an **80:20 train-test split**, ensuring balanced representation of all risk categories in both sets.

B. Risk Distribution Analysis

The dataset was categorized into three PCOD risk levels: Low, Medium, and High.

As shown in **Figure. 2**,

• 50% of users belong to the low-risk category

• 30% belong to medium risk

• 20% belong to high risk

This distribution reveals moderate class imbalance. Therefore, class-weight adjustment was applied in the Logistic Regression model to prevent bias toward the majority class.

Figure 5 further presents the proportional distribution using a pie chart, improving interpretability and providing a visual overview of risk prevalence within the dataset.

The presence of a substantial medium- and high-risk population validates the need for predictive screening mechanisms.

C. Feature Correlation and Multicollinearity Assessment

To understand feature dependencies, Pearson correlation analysis was conducted.

As illustrated in **Figure. 3**, the heatmap shows:

• Strong diagonal correlation (self-correlation).

• Low to moderate correlation among independent variables.

• No severe multicollinearity (correlation coefficient < 0.75).

Low multicollinearity ensures that the Logistic Regression coefficients remain stable and interpretable. This strengthens the statistical reliability of the prediction model.

D. Temporal Risk Trend Analysis

The variation of PCOD risk over a 10-month period is illustrated in **Figure. 4**.

The graph demonstrates fluctuating risk scores over time, which may be influenced by:

• Hormonal variation

- Lifestyle changes
- Treatment or medication
- Stress and dietary habits

The ability to track risk progression indicates that the proposed system can be extended beyond static prediction to continuous health monitoring.

E. Model Training and Optimization

The Logistic Regression classifier was trained using:

- L2 regularization to prevent overfitting.
- Balanced class weights to manage dataset imbalance.
- Maximum iteration limit of 1000 for convergence stability.

Cross-validation (5-fold) was conducted to ensure model generalization. The average cross-validation accuracy remained consistent, indicating low variance and stable performance.

F. Performance Metrics Evaluation

The model was evaluated using standard classification metrics:

Metric	Value
Accuracy	90.4%
Precision	89.2%
Recall (Sensitivity)	92.1%
F1-Score	90.6%
AUC Score	0.92

Interpretation:

- **High Recall (92.1%)** ensures minimal false negatives, which is crucial in medical screening.
- **Balanced Precision and Recall** indicates robust classification capability.
- **AUC > 0.90** confirms excellent separability between PCOD and non-PCOD cases.

G. Confusion Matrix Analysis

The confusion matrix indicates:

- Majority of PCOD-positive cases were correctly identified (True Positives).
- Low False Negative rate.
- Moderate False Positive rate, acceptable for screening systems where early detection is prioritized over missed cases.

In healthcare applications, reducing false negatives is more critical than minimizing false positives. The proposed model achieves this balance effectively.

H. Computational Efficiency

The computational complexity of Logistic Regression is linear with respect to the number of features:

$$O(n)$$

Key observations:

- Training time was minimal.
- Prediction latency per user request was under milliseconds.
- Model size is lightweight, enabling web deployment.

This ensures scalability for large-scale healthcare applications.

I. Comparative Discussion

Compared to complex deep learning models:

- Logistic Regression offers high interpretability.
- Lower computational cost.
- Easier deployment.
- Clinically explainable coefficients.

Thus, the proposed framework achieves an optimal balance between performance, interpretability, and deployment efficiency.

VII. Limitations and Future Scope

Although the proposed WomenCare framework demonstrates strong predictive performance and computational efficiency, certain limitations must be acknowledged. The model was trained on a moderately sized structured dataset, which may limit its generalizability across diverse demographic and clinical populations. The feature set primarily includes symptom-based and physiological parameters such as BMI and menstrual irregularity, while advanced hormonal markers and ultrasound imaging data were not incorporated, potentially restricting diagnostic depth. Moderate class imbalance, despite the use of class-weight adjustments, may still introduce minor prediction bias. Furthermore, the study focuses mainly on Logistic Regression, which, although interpretable and efficient, may not fully capture complex nonlinear relationships among features. The current implementation provides static risk prediction rather than continuous longitudinal monitoring, and large-scale external clinical validation across multi-center hospital datasets has not yet been performed. Future work can address these limitations by expanding the dataset size and diversity, integrating multimodal clinical and biochemical data, exploring advanced ensemble and deep learning models, implementing time-series approaches for dynamic risk tracking, incorporating Explainable AI techniques for enhanced transparency, developing secure mobile and cloud-based deployment architectures, and conducting real-world clinical trials to strengthen reliability and practical applicability in preventive healthcare systems.

VIII. Conclusion

This research presented WomenCare, a machine learning-based web application for early PCOD risk prediction using Logistic Regression. The system integrates structured preprocessing, feature analysis, and classification modeling to provide accurate and interpretable predictions. Experimental results demonstrate that the proposed framework achieves high accuracy and strong sensitivity while maintaining computational efficiency. Visualization techniques such as correlation heatmaps, temporal risk trends, and feature relationship analysis validate the clinical relevance of selected predictors. The system is lightweight, scalable, and suitable for real-time healthcare applications. By enabling early detection of PCOD risk, the proposed solution contributes toward preventive healthcare and improved women's health management.

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