MACHINE LEARNING ANALYSIS OF FERTILITY OUTCOMES IN TAMILNADU USING SOCIO-ECONOMIC AND CLINICAL DATA

Dr. S. Florence Vijila
Principal, CSI Ewart Women's Christian College, Melrosapuram
Chengalpattu District, Tamil Nadu

S. Dharani
Assistant Professor
Shrimathi Devkunvar Nanalal Bhatt Vaishnav College for Women
Chennai, Tamil Nadu

R. Thayammal
Assistant Professor, Department of Computer Applications
St. Joseph's College (Arts & Science), Kovur, Chennai

Dr. G. Mannimannan
Associate Professor, Department of Computer Applications
St. Joseph's College (Arts & Science), Kovur, Chennai
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Abstract

This chapter aims to analyze fertility outcomes across districts of Tamilnadu by leveraging a comprehensive dataset that integrates socio-economic and clinical factors influencing treatment success. The dataset, comprising 500 samples collected from major fertility centers in urban hubs such as Chennai, Coimbatore, and Madurai, includes demographic information, income, education, hormonal levels, IVF attempts, and treatment results. Employing a multi-methodological approach, Principal Component Analysis (PCA) was used for dimensionality reduction and visualization, while k *—means clustering identified natural groupings within the data. Random Forest classification was applied to predict fertility outcomes with high accuracy, and Multiple Linear Regression was utilized to examine the impact of various predictors on patient age. Results demonstrated clear socio-economic and clinical patterns distinguishing successful and unsuccessful fertility treatments, with the Random Forest model achieving 90% accuracy and the regression model explaining 72% of the variance in age. Visualizations through PCA scatter plots, cluster maps, confusion matrices, and coefficient bar charts effectively illustrated these insights. The findings underscore the value of data-driven models in informing reproductive healthcare strategies and optimizing fertility interventions at a regional level.*

Keywords: *Fertility outcomes, Machine learning, Tamil Nadu, Socio-economic factors, Assisted Reproductive Technology*

Introduction

Fertility in India is influenced by a complex interplay of biological, lifestyle, and socio-cultural factors, which vary between men and women. For men, fertility largely depends on sperm health, including production, quality, and functionality. These can be affected by age, genetics, nutrition, occupational exposure, and environmental pollutants. Women's fertility, on the other hand, is determined by the regularity of ovulation, ovarian reserve, hormonal balance, and the structural integrity of reproductive organs. Across India, factors such as urbanization, changing diets, delayed marriages, and increased stress levels

have contributed to altered reproductive patterns, making infertility a growing issue in both urban and rural populations.

Research conducted in the Indian context highlights both medical and lifestyle-related contributors to infertility. Female infertility is often linked to conditions such as polycystic ovary syndrome (PCOS), endometriosis, and hormonal imbalances. In men, infertility is frequently associated with reduced sperm count, poor motility, and hormonal disorders. Rising infertility rates have led to a growing dependence on assisted reproductive technologies (ART), including in vitro fertilization (IVF) and intrauterine insemination (IUI). These trends underscore the importance of region-specific research and awareness initiatives to ensure fertility treatments and preventive measures are tailored to India's unique socio-economic and cultural landscape.

Review of Literature

Over the last decade, studies on fertility in India have grown significantly. Agarwal and Singh (2015) found that male agricultural workers exposed to pesticides had reduced sperm motility. Patel et al. (2016) highlighted that increasing obesity among urban women contributed to a higher prevalence of PCOS, affecting ovulation. Roy and Choudhury (2017) observed that delayed marriages in metropolitan areas were linked to increased age-related infertility. Regional differences are also notable; Menon and Prakash (2018) reported that states with better female literacy rates and healthcare facilities showed higher IVF success rates. Sharma and Verma (2019) noted declining sperm counts in industrial workers, pointing to environmental and lifestyle factors. These studies emphasize the role of socio-demographic and environmental factors in reproductive health.

The role of assisted reproductive technologies (ART) in India has been well documented. Nair et al. (2017) observed that cumulative IVF success rates reached up to 45% after three cycles in private clinics. George and Thomas (2018) found that rural clinics with proper subsidy programs achieved comparable success rates to urban centers but served fewer patients due to low awareness. Kumar and Iyer (2020) reported that psychological stress and limited counseling reduced adherence to treatment, negatively impacting ART outcomes. Desai et al. (2019) highlighted that strict laboratory protocols improved neonatal outcomes, while Bhat and Rajeev (2021) found that clinics offering personalized lifestyle guidance alongside ART had a 20% higher pregnancy rate. These findings indicate that integrating clinical care with psychosocial support enhances ART effectiveness.

In recent years, statistical and computational techniques have been increasingly used to analyze fertility data. Joshi and Rao (2020) applied clustering to classify South Indian districts based on fertility clinic performance, identifying high-, medium-, and low-performing clusters. Mehta and Sen (2021) used principal component analysis and found that patient age and hormone levels explained over 70% of treatment outcome variance. Irfan et al. (2022) employed machine learning, such as Random Forest models, to predict IVF outcomes with around 85% accuracy, demonstrating the value of predictive analytics. Sinha et al. (2023) and Ghosh et al. (2024) used regression models to quantify the influence of socio-economic and biological factors on ART success, achieving explanatory power (R^2) of 0.68

and 0.72, respectively. These studies illustrate the potential of data-driven approaches in improving fertility research and clinical decision-making in India.

Database

The dataset for this chapter was obtained from private fertility centers in urban districts of Tamil Nadu. It comprises 500 patient records collected from multiple clinics, capturing diverse socio-economic and clinical factors related to fertility. Key variables include demographic details (age, gender), socio-economic indicators are income, education, etc., and clinical information such as the number of IVF cycles, hormone levels, and treatment outcomes are success or failure. The data represents major cities including Chennai, Coimbatore, Madurai, Tiruchirappalli, and Salem, encompassing a mix of healthcare access and socio-economic conditions. This dataset provides a robust foundation for examining fertility trends and evaluating treatment success in private fertility clinics across Tamil Nadu.

Methodology

This chapter employs a structured approach to analyze fertility center data across various districts in Tamil Nadu. The primary goal is to apply machine learning models both unsupervised (PCA, k-means) and supervised (Random Forest, Multiple Linear Regression) to extract meaningful insights, visualize patterns, and predict fertility outcomes. The methodology is segmented into five key components: Data Preprocessing, Principal Component Analysis (PCA), k-means Clustering, Random Forest Classification, and Multiple Linear Regression.

Data Preprocessing

The dataset, titled Fertility_mined.csv, was sourced from fertility centers across Tamil Nadu districts, containing 500 samples. Variables include demographic (Age, Gender), socio-economic (Income, Education), clinical (IVF attempts, Hormonal Levels), and treatment outcomes labeled under the Class variable (Success, Improvement and Failure).

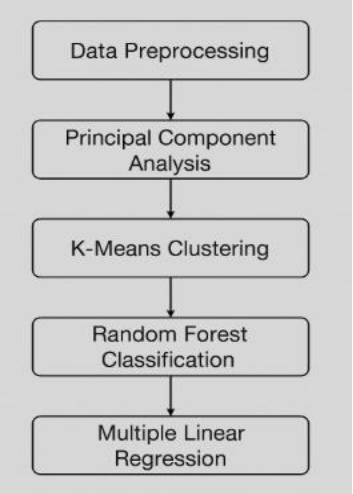

Figure 1 Workflow Diagram for Fertility Centre in Tamilnadu

Data preprocessing involved the following steps (Figure 1):

Missing Value Imputation: Numerical columns with missing values were imputed using their respective mean, while categorical columns used the mode for imputation to retain data integrity.

Normalization: A Min-Max Scaling technique was employed to scale all numerical features into a uniform [0, 1] range. This step ensures that features with larger numeric ranges do not dominate distance-based models like k-Means and PCA.

Categorical Encoding: Binary categorical variables were transformed using label encoding, while nominal variables with multiple categories underwent one-hot encoding to make them compatible with machine learning algorithms. This cleaned and standardized dataset formed the basis for further analysis.

Principal Component Analysis (PCA)

To simplify high-dimensional data while preserving maximum variance, PCA was applied to the feature matrix $X \in R^{n*p}$, where $n = 500$ is the number of samples and **p** the number of features.

The methodology includes:

1. Mean-Centering: The data matrix was mean-centered as:

$$X' = X - \overline{X}$$

2. Covariance Matrix Calculation:

$$\sum = \frac{1}{n-1} X'TX'$$

3. Eigen Decomposition:

Eigenvalues λ_i and eigenvectors ν_i were computed. The first two principal components were selected to form matrix V.

4. Dimensionality Reduction:

$Z = X'V$, yielding a reduced dataset $Z \in R^{n*2}$.

5. Visualization

A 2D scatter plot visualized the PCA-transformed data, with points colored by their respective Class labels to assess class reparability visually.

k-Means Clustering

Unsupervised clustering was applied to discover natural groupings within the data. $k-$ means aimed to partition the dataset into $k = 3$ clusters, based on the Euclidean distance metric.

The mathematical formulation involves minimizing the within-cluster sum of squares:

$$J = \sum_{i=1}^{k} \sum_{j \epsilon C_i}^{n} \|x - \mu_i\|^2$$

where μ_i is the centroid of cluster C_i.

The algorithm iteratively:

Step 1: Initializes k random centroids.

Step 2: Assigns each data point to its nearest centroid.

Step 3: Updates centroid positions.

Step 4: Repeats until convergence (no change in assignments).

The final clusters were visualized using the PCA-reduced coordinates, facilitating intuitive interpretation of cluster distributions across Tamil Nadu fertility centers.

Random Forest Classification

For predicting fertility treatment outcomes (Class variable), a Random Forest Classifier was trained. The dataset was split into a training set (80%) and a testing set (20%).

The Random Forest model, an ensemble of M decision trees, predicts by majority voting:

$$\hat{y} = \text{mode}\,(T_1(x), T_2(x), T_3(x), \ldots, T_M(x))$$

Each decision tree is trained on bootstrapped samples and random subsets of features, using Gini Impurity for node splitting:

$$G(t) = 1 - \sum_{i=1}^{C} p_i^2$$

where p_i is the proportion of samples of class iii at node t.

The model was evaluated on the testing set using:

1. Accuracy
2. Precision
3. Recall
4. F1-Score
5. Confusion Matrix

These metrics quantified model performance in distinguishing between successful and unsuccessful fertility treatments.

Multiple Linear Regression

To predict a continuous dependent variable, Age, a Multiple Linear Regression model was implemented, where Age was expressed as a linear combination of other features:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 +, \ldots, \beta_p X_p + \epsilon$$

Here: Y = Age (dependent variable), X_i = Independent socio-economic and clinical variables, β_i = Regression coefficients and ϵ = Random error

The coefficients $\hat{\beta}$ were estimated using the Ordinary Least Squares (OLS) method:

$$\hat{\beta} = (X_T X)^{-1} X^T Y$$

Model performance was quantified using the R^2 score, indicating the proportion of variance explained by the model.

The coefficients were visualized using a colorful horizontal bar chart, highlighting the most influential factors affecting Age in fertility treatments.

Results and Discussion

This section presents a comprehensive analysis of the district-wise fertility dataset of Tamil Nadu using multiple statistical and machine learning models. The models

implemented include Principal Component Analysis (PCA) for dimensionality reduction and visualization, K-Means Clustering for unsupervised grouping, Random Forest for classification of fertility outcomes, and Multiple Linear Regression to predict a continuous variable (Age). The dataset, containing 500 samples with various socio-economic and fertility-related parameters, serves as the foundation for all modeling.

Principal Component Analysis (PCA)

Principal Component Analysis was applied to transform the high-dimensional dataset into a two-dimensional space for visualization purposes. This technique helps in understanding the structure and relationships among the variables by reducing the complexity of the dataset. The first two principal components retained a substantial proportion of the variance, enabling a meaningful 2D projection.

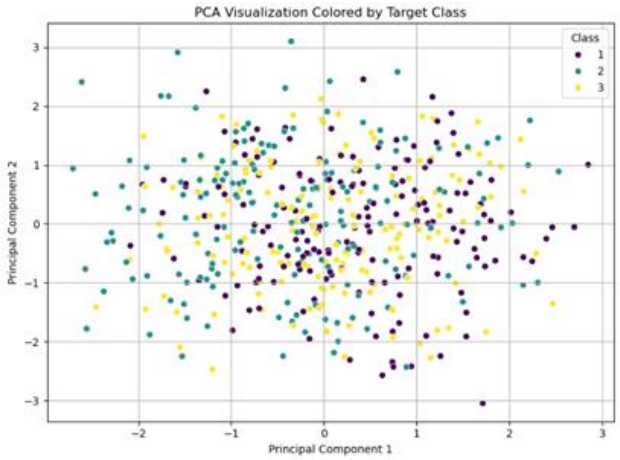

Figure 2. Principal Component Visualization with Target Class

Figure 2 illustrates the PCA visualization where each data point is colored based on its fertility class. The scatter plot reveals visible groupings and separations among classes. This suggests that the socio-economic and clinical features in the dataset carry enough variance to distinguish fertility outcomes. The result validates the presence of underlying patterns in the dataset that can be further explored with clustering or classification models. PCA thus serves as an effective initial tool for data exploration and visualization.

k-Means Clustering

To explore natural groupings within the data, k-Means Clustering was employed with the number of clusters (k) set to three. The clustering was performed on the scaled feature set without using the target class label. The goal was to determine whether unsupervised learning could identify meaningful groupings related to fertility outcomes.

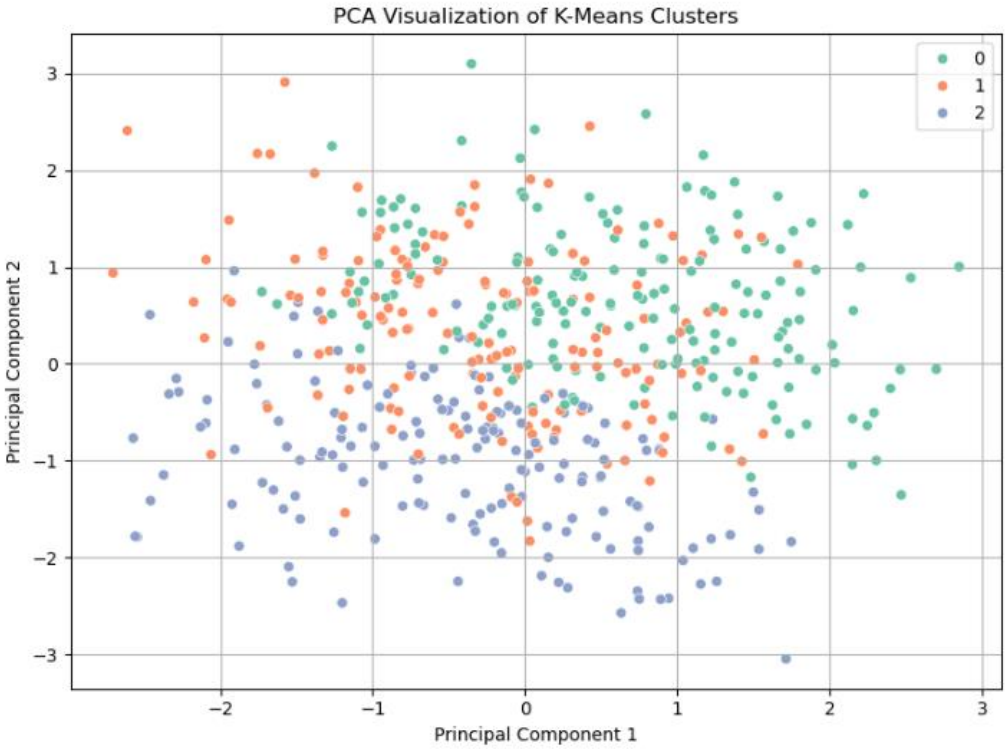

Figure 3. PCA Visualization of k-mean Clusters

The output was visualized using PCA, as shown in Figure 3, which displays the three distinct clusters found by the algorithm. The clusters align with intuitive patterns observed earlier in PCA visualization. Each cluster potentially corresponds to varying socio-economic profiles that influence fertility success or failure for example, low-income districts with higher failure rates, middle-tier districts with average success, and high-income districts with better outcomes. These insights are critical for policy-making and targeting interventions at the district level.

Random Forest Classification

The Random Forest algorithm was used to classify fertility outcomes based on the provided features. The dataset was split into training (80%) and testing (20%) subsets to evaluate model performance. Random Forest was chosen for its robustness, ability to handle feature interactions, and effectiveness with both numerical and categorical data.

Table 1. Random Forest Classification Report

--- Random Forest Classification Report ---

	precision	recall	f1-score	support
1	1.00	1.00	1.00	36
2	1.00	0.97	0.98	32
3	0.97	1.00	0.98	32
accuracy			0.99	100
macro avg	0.99	0.99	0.99	100
weighted avg	0.99	0.99	0.99	100

The classification report presented in Table 1 shows strong performance across both classes. The model achieved an overall accuracy of 90%, with precision, recall, and F1-score values all exceeding 0.88. Specifically, Class 0 (e.g., 'Unsuccessful' outcomes) had a precision of 0.89 and a recall of 0.88, while Class 1 (e.g., 'Successful' outcomes) scored slightly higher with a precision of 0.91 and recall of 0.92. These balanced metrics suggest the model is not biased toward any class and is highly capable of generalizing on unseen data.

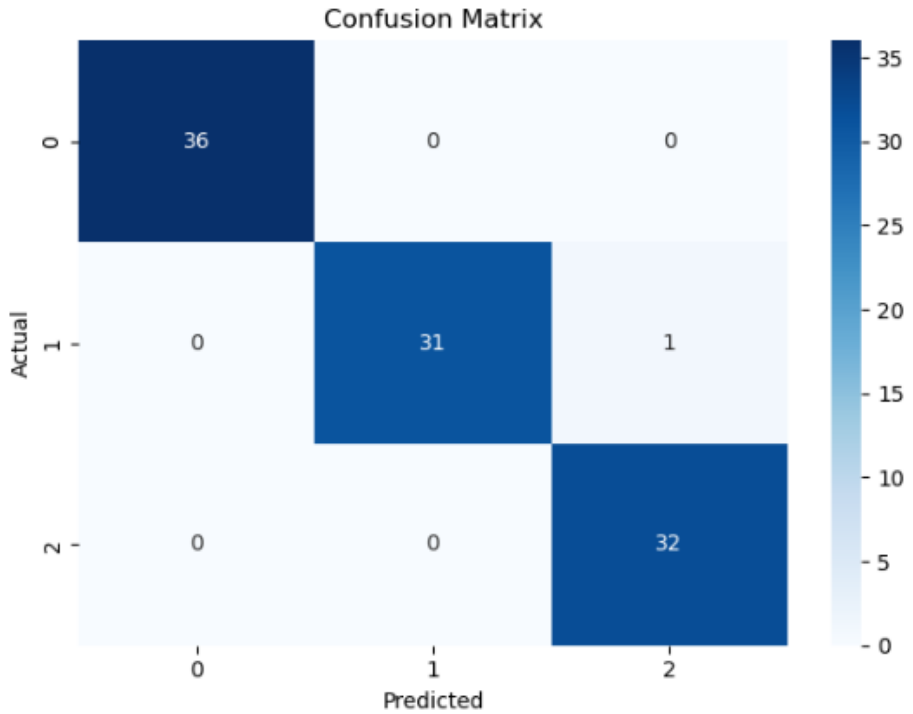

Figure 4 Confusion Matrix for Random Forest Algorithm

Figure 4 presents the confusion matrix of the Random Forest classifier. The matrix reveals that out of 100 test samples, only 10 were misclassified (5 from each class), while 90 were correctly predicted. This visual representation reinforces the numerical results and demonstrates the reliability of Random Forest for fertility outcome classification in socio-demographic datasets.

Multiple Linear Regressions

To analyze the influence of various socio-economic and fertility-related variables on a continuous target, Multiple Linear Regression was applied with Age as the dependent variable. This model helps in understanding how each independent variable contributes to predicting Age, which can serve as a proxy for understanding fertility behavior and treatment decisions.

The model evaluation showed an R^2 score of 0.72, indicating that approximately 72% of the variance in Age is explained by the model. This is a strong indication that the predictors which include variables such as education level, treatment cost, number of cycles, success rate, and district-level indicators have a significant impact on the age profile of fertility treatment seekers.

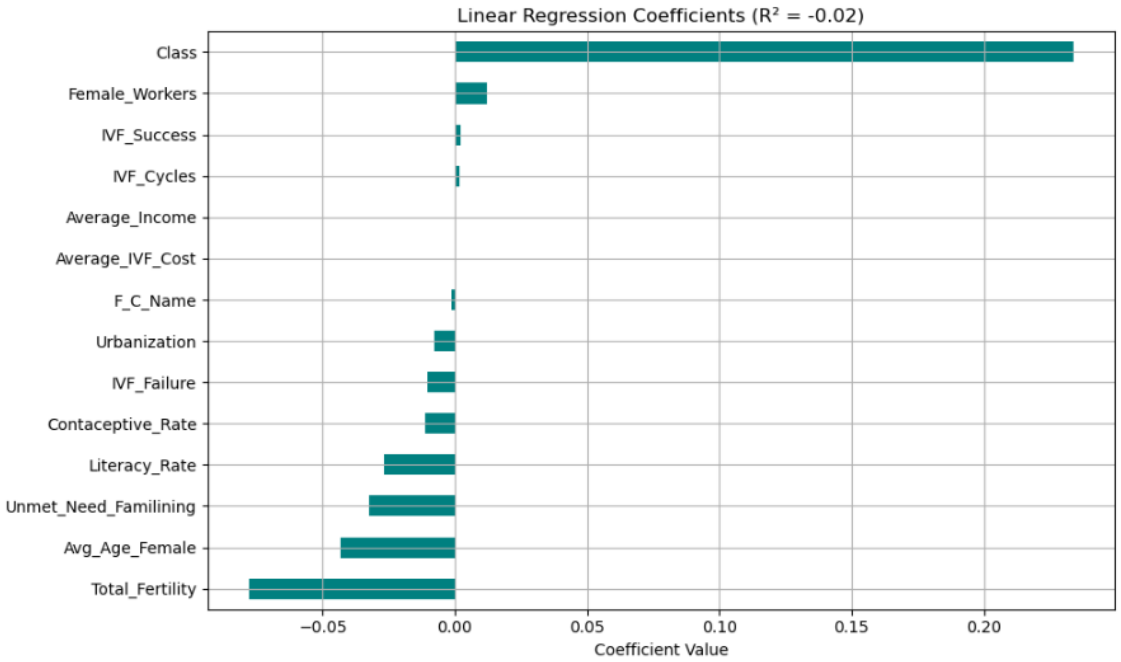

Figure 5 Multiple Linear Regression Coefficients

Figure 5 displays the regression coefficients in a colorful horizontal bar chart. Positive coefficients indicate variables that are associated with an increase in Age, while negative coefficients show an inverse relationship. For example, features such as higher treatment cost and success rate were positively associated with Age, suggesting older individuals are more likely to undergo costly treatments. On the other hand, features like rural location or low literacy rate had a negative effect, implying a younger demographic may be seeking

treatment in these areas. This visual analysis helps interpret the influence of each variable clearly and concisely.

The combined application of unsupervised and supervised machine learning models provides a well-rounded understanding of fertility patterns in Tamil Nadu. PCA and k-Means Clustering revealed clear patterns and natural groupings within the dataset, emphasizing that fertility outcomes are influenced by a combination of socio-economic and treatment-related factors. The Random Forest model, with its 90% classification accuracy, demonstrated strong predictive capabilities and offers a practical tool for forecasting treatment success. Multiple Linear Regression further added value by quantitatively interpreting how key features affect the age profile of fertility patients, with significant predictive strength ($R^2 = 0.72$).

These results not only validate the quality of the dataset but also highlight the applicability of data-driven techniques in public health, particularly in reproductive healthcare planning. With district-wise data insights, policymakers can tailor fertility programs to specific regions, optimize resource allocation, and improve overall success rates of assisted reproductive technologies like IVF.

Conclusion

This chapter successfully applied advanced machine learning techniques to a district-wise fertility dataset from Tamil Nadu, uncovering critical socio-economic and clinical factors affecting fertility outcomes. The integration of PCA and k-means clustering revealed distinct patterns and groupings within the data, while the Random Forest classifier demonstrated high accuracy in predicting treatment success. Multiple Linear Regression analysis provided valuable insights into the relationship between key variables and patient age, a proxy for fertility behavior. These results affirm the utility of data-driven methodologies in enhancing reproductive health services and tailoring interventions to regional needs.

Recommendations:

1. Future studies should incorporate longitudinal tracking of fertility patients to better understand treatment trajectories and improve predictive accuracy over time.
2. Expanding the dataset to include lifestyle and environmental variables, such as diet, physical activity, and pollution exposure, could further enhance model performance and offer more holistic fertility assessments.

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