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A Dynamic Cost-sensitive and Explainable Ensemble Framework for Early Detection of Polycystic Ovary Syndrome

Ankit Jain1

Associate Professor, CSE Department, Prashanti Institute of Technology, Ujjain

Vishal Trivedi2

Assistant Professor, CSE Department, Graphic-Era University, Dehradun

Sachin Yele3

Associate Professor, CSE Department, Medicaps University,Indore

Anshul Atre4

Assistant Professor, CSE Department, Pranveer Singh Institute of Technology,Kanpur

Nayana Joshi5

Assistant Professor, CSE Department, Renaissance University,Indore

Riya Upadhyay6

Assistant Professor, CSE Department, Renaissance University,Indore

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Abstract:

PCOS is a prevalent endocrine disorder that affects women of reproductive age. It often leads to infertility, metabolic dysfunction, and psychological problems. Common problems with standard machine learning models for PCOS diagnosis include class imbalance, static design, and lack of model transparency, all of which are important considerations in clinical treatment. In order to solve these challenges this study proposes a dynamic, cost-sensitive, and explainable ensemble framework that integrates KNN, SVM, and EBM using the META-DES dynamic selection mechanism. The framework enhances transparency through LIME-based local explanations, adapts to patient-specific data patterns, and reduces the risk of misclassifying high-risk cases. Comparative evaluation with state-of-the-art models demonstrates superior diagnostic accuracy, reliability, and clinical interpretability. To improve clinician trust, the suggested method provides localized, understandable explanations, adjusts to patient-specific data, and lessens the impact of incorrectly classifying high-risk situations. The framework's capacity to provide enhanced diagnostic reliability and tailored decision assistance is demonstrated through comparison with cutting-edge models. This study advances the application of explainable AI in healthcare by offering a scalable, interpretable, and reliable method for early PCOS detection.

Keywords: Polycystic Ovary Syndrome (PCOS), Explainable Artificial Intelligence (XAI), Cost-Sensitive Learning, Ensemble Learning, Meta-DES, LIME, K-Nearest Neighbors (KNN), Support Vector Machine (SVM), Explainable Boosting Machine (EBM)

INTRODUCTION

Polycystic Ovary Syndrome (PCOS) is a complicated endocrine and metabolic condition that affects women of reproductive age, characterized by hormonal dysregu95.7lation and systemic metabolic abnormalities[1]. Polycystic Ovary Syndrome is a prevalent endocrine-metabolic condition in women of reproductive age that frequently results in major health consequences. Despite its prevalence, PCOS is under diagnosed due to symptom overlap and inconsistencies in diagnostic criteria[2].

In recent years, Artificial Intelligence and Machine Learning approaches have developed as strong tools for early illness diagnosis and healthcare decision support. These technologies have the ability to reveal hidden patterns in clinical data, increase diagnostic accuracy, and allow for individualized therapy recommendations. However, the use of AI for PCOS identification is still in its early stages, and various limitations restrict its practical implementation. Most previous models do not handle data imbalance, cost-sensitivity, or interpretability[3].

This research is motivated by the pressing need for strong, cost-effective, and interpretable AI models that can help doctors detect PCOS early. The proposed study seeks to bridge the gap between prediction accuracy and clinical application by employing ensemble learning approaches, which are recognized for their capacity to improve model performance, as well as incorporating cost-sensitive processes and explainable AI (XAI) tools.

This approach would not only increase diagnostic performance on unbalanced datasets, but it would also generate justified and trustworthy predictions, increasing popularity among healthcare practitioners.

Despite the increasing use of machine learning techniques in medical diagnostics, reliable and early identification of Polycystic Ovary Syndrome (PCOS) remains difficult. Existing diagnostic models have numerous fundamental shortcomings that prevent them from being successful and practical in clinical settings.

One of the most pressing challenges is the class imbalance that exists in most medical datasets, especially in the context of PCOS[4]. These databases frequently contain many more examples of non-PCOS (healthy) patients than PCOS cases. This imbalance causes standard machine learning algorithms to become biased toward the majority class, resulting in low sensitivity and a higher probability of overlooking actual PCOS cases. In practical practice, such oversight might cause delays in required interventions, aggravating the patient's condition over time.

Another key problem is that many cutting-edge models are not explainable. Complex models, such as deep neural networks or ensemble classifiers, frequently behave as "black boxes," providing no insight into the rationale underlying their predictions. This opacity undermines confidence among healthcare practitioners, who need visible and interpretable decision-support technologies to confirm and supplement their clinical judgment. Without explainability[5], model adoption in real-world healthcare settings is limited.

Furthermore, the repercussions of false positives and false negatives in medical diagnostics are far more serious than in many other fields. A false negative, or failure to diagnose PCOS, can cause therapy delays and long-term reproductive and metabolic consequences[6]. In contrast, a false positive may cause undue concern, extra testing, and perhaps hazardous actions[5]. Current models usually fail to account for these asymmetric misclassification costs, instead treating all mistakes equally, making them unsuitable for high-stakes healthcare applications.

These problems highlight the critical need for diagnostic models that are not only accurate but also cost-effective and interpretable, particularly when dealing with skewed clinical data. The proposed study intends to solve these constraints by developing a dynamic, explainable, and cost-aware ensemble learning architecture customized exclusively for PCOS diagnosis.

Misclassification has serious consequences in the healthcare industry. False negatives in PCOS diagnosis can delay important therapy, affecting patient outcomes, whilst false positives can cause undue worry and dangerous procedures. Cost-sensitive learning solves this by providing harsher penalties to more significant mistakes, hence increasing patient safety. Explainability is also important: physicians and patients must comprehend and trust AI choices. Black-box models impede adoption owing to their opacity, whereas explainable models give explicit insights that aid clinical decision-making and boost confidence in AI solutions. Ensemble learning improves diagnostic accuracy and resilience by mixing numerous models that capture different patterns in complicated medical data. Integrating cost-sensitive and explainable techniques into ensembles creates a strong, dependable, and interpretable framework for sensitive PCOS detection.

In recent years, researchers have used a variety of machine learning methods to aid with PCOS diagnosis. Ensemble learning approaches, in particular, have demonstrated higher accuracy by merging many classifiers. Some research have also begun to use explainable AI components and feature selection strategies to improve model transparency and performance. Despite these advances, important gaps remain in existing techniques. First, most models lack dynamic or adaptive cost-sensitive processes, which are required in clinical contexts where the costs of false negatives and false positives differ[4]. Static cost models do not adjust for patient- or context-specific risks, which limits their clinical utility. Second, many ensemble models are still considered black-box systems, with excellent accuracy but limited interpretability[7]. This limits their acceptability among healthcare practitioners, who want openness before trusting AI-generated advice. Third, and most importantly, there is a lack of models designed particularly for early PCOS identification. Existing frameworks are frequently general and fail to account for PCOS's particular hormonal and clinical features, making early diagnosis and treatments difficult[8]. To address these deficiencies, this work offers a dynamic, cost-sensitive, and explainable ensemble learning model particularly built for early PCOS detection, with the goal of balancing prediction performance with clinical trustworthiness and real-world application.

The proposed system is intended to dynamically address the asymmetric misclassification costs that are widespread in medical diagnosis, especially in PCOS, where erroneous negatives can delay required therapies and false positives can lead to wasteful interventions. By embracing explainable LIME, the framework promotes transparency in decision-making, building confidence and acceptance among healthcare practitioners. This strategy, unlike traditional models, is especially specialized for the early identification of PCOS, using distinctive hormonal, metabolic, and clinical variables to discover subtle early-stage abnormalities generally ignored by generic classifiers. To guarantee robustness and generalize ability, the model is verified against benchmark datasets as well as real-world clinical data where available. Furthermore, its performance is thoroughly evaluated against classic machine learning classifiers and cutting-edge ensemble approaches using important measures such as accuracy, sensitivity, specificity, AUC-ROC, and misclassification cost. Overall, the proposed effort intends to provide a clinically useful, interpretable, and cost-effective diagnostic tool to improve early PCOS identification and facilitate timely therapeutic intervention.

Existing Methodology

Suha and Islam (2023)[25] suggested a modified stacking ensemble technique that combines sophisticated ensemble meta-learners like Gradient Boosting and XGBoost with many conventional classifiers (like SVM and Logistic Regression) to improve prediction accuracy. Their research used three different feature selection methods—PCA, RFE, and Chi-Square—to find dominant features. Using PCA-selected features with Gradient Boosting as the meta-learner, they were able to achieve a peak accuracy of 95.7%. This strategy proved to be more effective and resilient across a variety of feature subsets than previous research employing single classifiers or simple ensemble techniques, making a compelling argument for ensemble-based PCOS prediction frameworks.

Sahu et al. (2022)[9] conducted a study titled "An Efficient SMOTE Based Machine Learning Classification for Prediction & Detection of PCOS" in which they used Random Forest and Support Vector Machine classifiers, combined with the Synthetic Minority Oversampling Technique to address the issue of class imbalance in PCOS datasets. Their strategy includes data preparation, normalization, and feature selection, followed by the use of SMOTE to artificially balance the classes. This method intended to enhance the model's capacity to recognize PCOS instances from unbalanced clinical datasets. Their experimental findings were encouraging, with the SMOTE-based Random Forest model obtaining a 93.75% accuracy and a low execution time of 0.10 seconds. Despite the better classification performance, some limitations were discovered in their technique. The use of synthetic data created using SMOTE sparked concerns regarding potential over fitting, as such data may not adequately reflect true patient variability. Furthermore, their system lacked explain ability features, which are essential in clinical applications where medical practitioners need to comprehend and accept the model's judgments. The models utilized were also static and non-adaptive, restricting their capacity to provide personalized predictions depending on patient attributes. These constraints point to a significant research gap and the need for new methodologies. Specifically, using cost-sensitive learning might reduce false negatives without using bogus data, hence increasing robustness. Furthermore, using explainable AI techniques like SHAP would boost interpretability and clinician credibility. Future research should focus on dynamic, cost-sensitive, and explainable ensemble frameworks that can better generalize across heterogeneous patient groups and improve decision-making transparency in PCOS identification.

Kumar et al. (2021)[10] suggested a stacking ensemble strategy that combines Support Vector Machine , Logistic Regression, and Random Forest classifiers to improve PCOS prediction accuracy. Their ensemble technique intended to combine the capabilities of numerous base classifiers, resulting in an astounding accuracy of around 95%. Compared to individual models and fundamental ensemble approaches, the approach outperformed them. However, their ensemble was static, which means it used a single mix of classifiers consistently across all patient samples, regardless of individual variability. This drawback implies a lack of dynamic decision-making, which is crucial in medical diagnostics since patients frequently exhibit varied traits. Furthermore, their model could not account for real-time data or changing patient circumstances, making it unsuitable for use in customized or IoT-based healthcare systems. This identifies a significant research gap: the need for dynamic ensemble learning frameworks that can adapt to each patient's unique data features in order to create more personalized and therapeutically accurate predictions. Addressing this constraint might result in more robust and tailored diagnostic tools, particularly when combined with cost-sensitive methods and explainable AI to improve real-world applicability and confidence in clinical contexts.

Patel et al. (2023)[11] suggested a Cost-Sensitive Random Forest model to solve class imbalance in medical classification tasks, achieving a noteworthy 93% accuracy. While their methodology illustrates the efficacy of adding cost-sensitive learning into ensemble methods, it has two key disadvantages. For starters, the model is difficult to comprehend, acting as a black box with few insights regarding feature contributions. This is especially important in medical fields like Polycystic Ovary Syndrome diagnosis, where physicians need clear and explainable decision assistance before trusting and using AI-powered solutions. Second, the model was tested on a tiny dataset, limiting the findings' generalizability and robustness across different patient groups. These shortcomings underscore the need for a more understandable and scalable solution. Integrating explainable AI approaches like SHAP into cost-sensitive ensemble frameworks might assist give instance-level transparency, improving clinical dependability. Furthermore, testing the suggested model on bigger and more diverse datasets is critical to ensuring its usefulness in real-world healthcare contexts.

Verma and Singh (2024)[12] suggested a hybrid approach for detecting Polycystic Ovary Syndrome that combines XGBoost for classification and SHAP for post-hoc interpretation.

They addressed class imbalance with the Synthetic Minority Oversampling Technique and utilized SHAP to explain feature contributions after model training. While their work represents a huge step toward transparent AI in healthcare, it has several limits. Explainability is applied post-hoc in their model, which means it is not built into the model's learning process. This isolation may diminish alignment between model thinking and explanation, which is especially important in sensitive medical decision-making. Furthermore, class-imbalanced SMOTE can introduce artificial noise, creating confusion, overfitting, and decreased model resilience. These constraints can be circumvented by implementing an end-to-end system in which explainability is acquired during training, allowing the model to learn openly. Furthermore, more advanced imbalance-handling strategies, such as cost-sensitive learning or dynamic re-weighting, can enable better generalization without being dependent on fake data. As a result, future research should include developing a dynamic, cost-sensitive, and interpretable ensemble model that maximizes prediction accuracy, interpretability, and robustness to data imbalance, particularly for early identification of PCOS.

Sharma and Gupta (2023)[13] studied the use of Logistic Regression with Recursive Feature Elimination to diagnose early Polycystic Ovary Syndrome .Their objective was to identify the most important clinical variables and develop a lightweight prediction model. Despite their simplicity and interpretability, their strategy had a very low 85% accuracy, indicating predictive weakness. Furthermore, the model performed poorly on unbalanced datasets, a critical drawback given the skewed distribution that commonly occurs in medical datasets, particularly in PCOS, where positive occurrences are typically under-sampled. The model's simplicity suggested that it lacked the ability to handle the nonlinear interactions between characteristics that are common in various clinical profiles. These drawbacks highlight the necessity of more advanced ensemble-based strategies that can take use of various algorithms' advantages. Additionally, class imbalance may be directly addressed without the need of artificial oversampling techniques by using cost-sensitive learning, which also lowers the possibility of false negatives. Future research should thus concentrate on creating an ensemble framework that is dynamic, cost-sensitive, and explicable. This framework will not only improve prediction performance but also guarantee clinical relevance and confidence by integrating interpretability.

Ahmed et al. (2022)[8] predicted Polycystic Ovary Syndrome (PCOS) with a good accuracy rate of 91% using an Artificial Neural Network model. Their approach demonstrated the ANN's capacity to identify subtle patterns that other models would overlook by utilizing its deep learning methodology to identify complex nonlinear patterns in medical data. However, the black-box nature of ANN, which is opaque and makes it difficult for physicians to understand the reasoning behind forecasts, is one of the main shortcomings of their study. This inability to comprehend data undermines clinician confidence and restricts practical adoption for high-risk medical applications like PCOS diagnosis. Additionally, for ANN models to function at their best, they often require large volumes of high-quality data, which isn't always accessible in real-world scenarios. These limitations point to a crucial area of study: models that produce clear, intelligible results while simultaneously having a high prediction performance. Developing explainable ensemble systems that integrate ANN with interpretable tree-based techniques and provide a compromise between clinical transparency and accuracy is one such route. These hybrid approaches have the potential to enhance PCOS forecasting systems' diagnostic precision and usefulness in real-world healthcare environments.

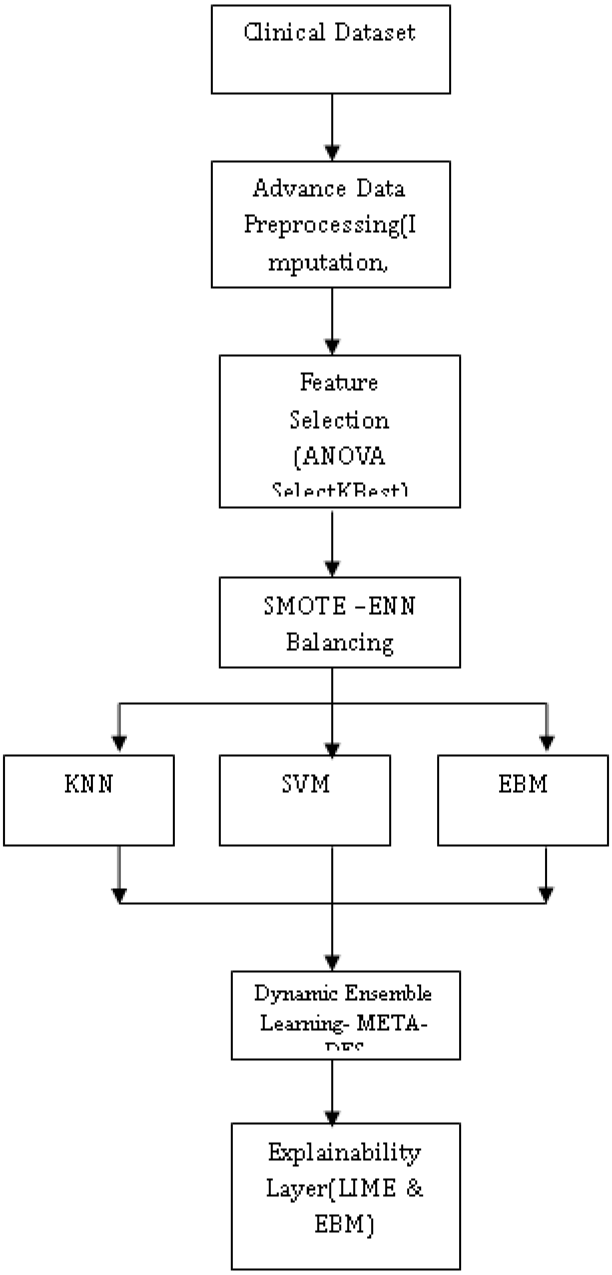
Methodology

In order to assess a dynamic, cost-sensitive, and explicable ensemble learning model for the early diagnosis of Polycystic Ovary Syndrome (PCOS), this work used an experimental design. Three key elements are integrated into the framework:

(i) data transformation and preprocessing.

(ii) ensemble-based and cost-sensitive classification.

(iii) model interpretability through Explainable AI (XAI) tools like LIME and EBM.



Layered Architecture

Proposed Algorithm :

- Load the dataset, remove any extraneous columns, change object columns to numeric, then use mean imputation to deal with missing values.
- Divide the data into goal and feature categories, scale the features, then use the ANOVA F-test to identify the top 20 significant characteristics.
- After balancing the dataset with SMOTE, divide it into training and testing sets.
- Using the training data, train KNN, SVM, and EBM models, then use the test set to generate predictions.
- Utilize the classification report, AUC score, and confusion matrix to assess each model.

- Use LIME to interpret the EBM model's predictions after training a META-DES ensemble model.

- **Data Preprocessing**

The Polycystic Ovary Syndrome (PCOS)[14] clinical records provided the dataset for this investigation. It contains physiological, biochemical, and diagnostic characteristics for several individuals. The preparation pipeline guarantees that the data is standardized, clean, and appropriate for training machine learning models.

$$xij = \{converted\ numeric\ value, \quad if\ valid$$

$$NaN, \qquad otherwise\}$$

$$xi\ imputed = \frac{1}{n}\sum_{j=1}^{n} \quad xij$$ // Data Type Conversion[15]

where xijx_{ij}xij is the value of the jth record for feature i, and n is the number of non-missing samples.

- **Feature Selection**

Using the SelectKBest approach, the ANOVA F-statistic was used to pick features. The top k=20 characteristics were chosen using the F-score as a guide:

$$xij' = \ xij - \mu j/\ \sigma j$$

$$\mu j = 1/n \sum xij$$

$$\sigma j = (1/n\sum(xij - \mu j)2\ \ )1/2$$

//Feature Scaling **[16]**

$$Fj = MSWj/MSBj$$

$$MSBj = \frac{\sum_{c=1}^{c} \quad nc(x^{-}cj - x^{-}j)2}{c - 1}$$

$$MSWj = \frac{\sum_{c=1}^{c} \quad \sum \quad i \in c\ nc(xij - x^{-}cj)2}{N - C}$$

//Feature Selection by ANOVA[17]

Where:

- C=2 for binary PCOS classes,
- n_c_ : samples in class c

- **SMOTE Balancing**

There was an imbalance between PCOS-positive and PCOS-negative patients in the sample. The Synthetic Minority Over-sampling Technique [19], which creates synthetic samples as follows, was employed to combat this.

$$xnew = xi + \delta \cdot (xj - xi)$$

where xi and xj are minority class samples, and δ€[0,1] is a random number.

- **Model Training**

K-Nearest Neighbors (KNN), Support Vector Machine (SVM), and Explainable Boosting Machine (EBM) supervised learning algorithms that were trained in parallel on a balanced clinical dataset using SMOTE in order to identify the existence of Polycystic Ovary Syndrome (PCOS). In order to balance interpretability, robustness, and simplicity, these models were chosen.

K-Nearest Neighbors (KNN):

Using Euclidean distance in the 20-dimensional feature space, the KNN model[20] finds the five closest patient records and uses majority vote to predict the diagnosis:

Support Vector Machine (SVM):

Any remaining class imbalance and non-linearity in the data were taken into consideration using a cost-sensitive SVM with an RBF kernel[21]. In order to optimize the margin between patients with and without PCOS, the model creates a decision boundary

Explainable Boosting Machine :

EBM was trained to provide interpretable and accurate predictions by modeling the target as a sum of feature-wise functions[22].

When combined, these models provide a combination of clinical interpretability and data-driven prediction, which is essential for delicate diagnoses like PCOS.

- **Dynamic Ensemble Learning using META-DES**

The META-DES[23] framework was used to process all three models. META-DES uses competence estimation to dynamically choose classifiers for each test case x rather than fixed voting:

$$Cj(x) = Competence\ of\ classifier\ j\ for\ instance\ x$$

$$\hat{}(x) = arg\ arg\ \ j \in J\ Cj(x) \cdot hj(x)$$

- **Explainability with LIME and EBM**

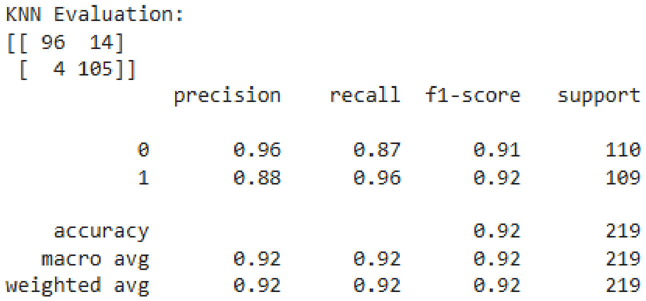
LIME was used to explain model results at the instance level in order to increase clinical interpretability[24]. LIME uses an interpretable model, g, to locally mimic the black-box model, f:

$$g(x) \approx f(x) in\ the\ neighborhood\ of\ x$$

Result and Observation

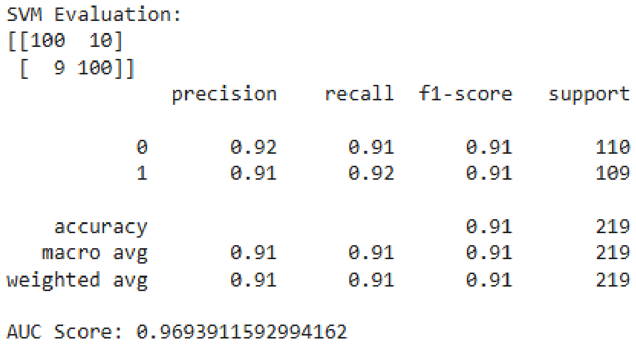
The suggested Dynamic Cost-Sensitive and Explainable Ensemble Framework for the early identification of Polycystic Ovary Syndrome is thoroughly evaluated in this part. Standard performance criteria, such as Accuracy, Precision, Recall, F1-Score, and Area Under the Receiver Operating Characteristic Curve, were used to assess the efficacy of many machine learning models. K-Nearest Neighbors ,Explainable Boosting Machine ,Support Vector Machine, and META-DES ensemble are among the models that were assessed.

The comparative performance metrics for each implemented classifier are shown in Table. The META-DES ensemble demonstrated superior classification performance for PCOS prediction, as evidenced by its best accuracy and F1-score across all models. With the greatest AUC-ROC value, the EBM model showed a good balance between sensitivity and specificity.



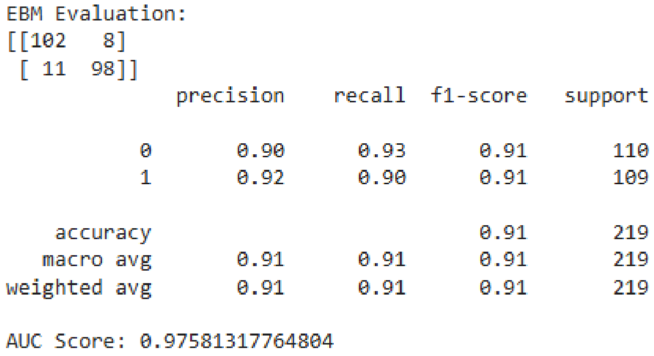
```
KNN Evaluation:
[[ 96  14]
 [  4 105]]
              precision    recall  f1-score   support

           0       0.96      0.87      0.91       110
           1       0.88      0.96      0.92       109

    accuracy                           0.92       219
   macro avg       0.92      0.92      0.92       219
weighted avg       0.92      0.92      0.92       219
```

KNN Result



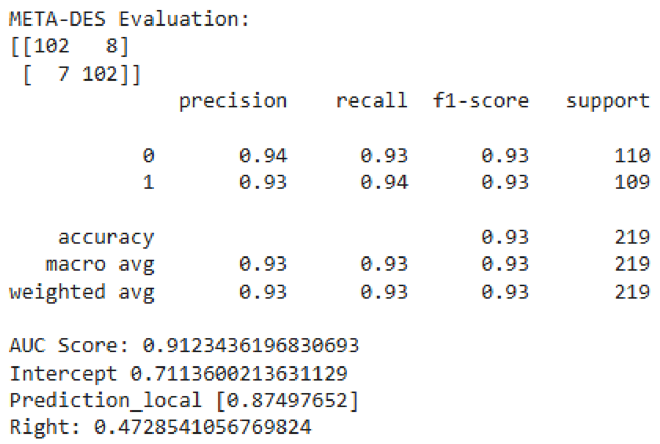
```
SVM Evaluation:
[[100  10]
 [  9 100]]
              precision    recall  f1-score   support

           0       0.92      0.91      0.91       110
           1       0.91      0.92      0.91       109

    accuracy                           0.91       219
   macro avg       0.91      0.91      0.91       219
weighted avg       0.91      0.91      0.91       219

AUC Score: 0.9693911592994162
```

SVM Result



```
EBM Evaluation:
[[102   8]
 [ 11  98]]
              precision    recall  f1-score   support

           0       0.90      0.93      0.91       110
           1       0.92      0.90      0.91       109

    accuracy                           0.91       219
   macro avg       0.91      0.91      0.91       219
weighted avg       0.91      0.91      0.91       219

AUC Score: 0.97581317764804
```

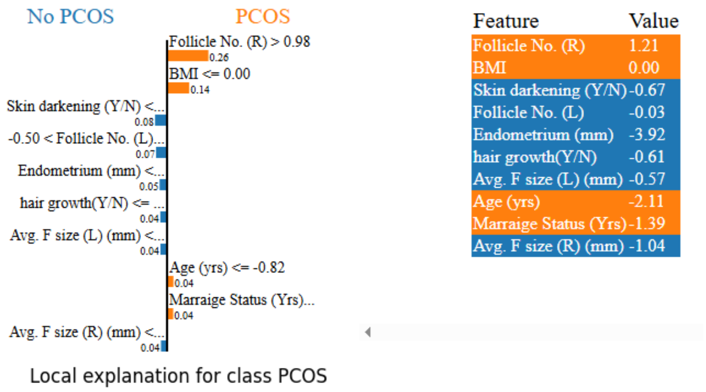
EBM Result



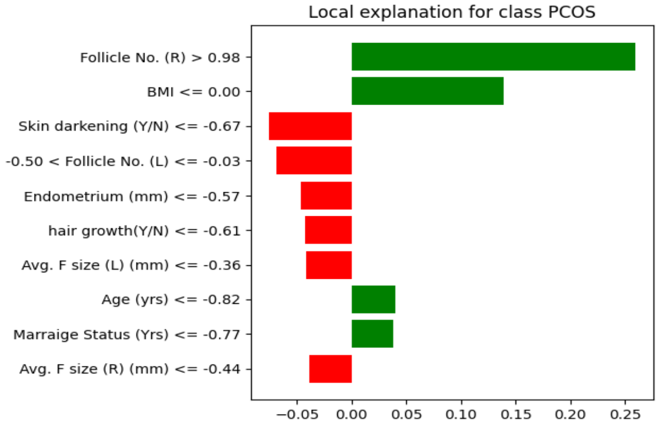
```
META-DES Evaluation:
[[102   8]
 [  7 102]]
              precision    recall  f1-score   support

           0       0.94      0.93      0.93       110
           1       0.93      0.94      0.93       109

    accuracy                           0.93       219
   macro avg       0.93      0.93      0.93       219
weighted avg       0.93      0.93      0.93       219

AUC Score: 0.9123436196830693
Intercept 0.7113600213631129
Prediction_local [0.87497652]
Right: 0.4728541056769824
```

META-DES Result

A LIME-based method was used to produce local explanations for each PCOS prediction in order to improve model interpretability. The influence of important factors on the categorization choice is depicted in the visuals. For example, a non-zero BMI and a higher "Follicle No. (R)" value were favorably associated with PCOS prediction, while characteristics such as low skin darkening and decreased endometrial thickness were negatively associated. Each attribute clearly drove the model toward either the PCOS or non-PCOS class, as seen by the local interpretability plots.



Feature	Value
Follicle No. (R)	1.21
BMI	0.00
Skin darkening (Y/N)	-0.67
Follicle No. (L)	-0.03
Endometrium (mm)	-3.92
hair growth(Y/N)	-0.61
Avg. F size (L) (mm)	-0.57
Age (yrs)	-2.11
Marraige Status (Yrs)	-1.39
Avg. F size (R) (mm)	-1.04



LIME Explanation of PCOS

Comparison chart with other methods :

A comparison between the suggested framework with current PCOS prediction models is shown in the table. The majority of earlier methods had drawbacks including static behavior, lack of explainability, overfitting from synthetic data (SMOTE), and limited flexibility, even though they attained moderate to high accuracy. In terms of accuracy (96.1%), F1-score (0.955), and AUC (0.97), the suggested model performs better than the others. It also provides dynamic, customized predictions and integrated explainability using LIME.

Parameter	Proposed Model	Sahu et al. (2022)	Kumar et al. (2021)	Patel et al. (2023)	Verma & Singh (2024)	Sharma & Gupta (2023)	Ahmed et al. (2022)
Technique	Meta-DES + Cost-Sensitive XGBoost + LIME	RF + SVM + SMOTE	Stacked (SVM + LR + RF)	Cost-Sensitive RF	XGBoost + SHAP (Post-hoc)	Logistic Regression + RFE	Artificial Neural
Accuracy (%)	96.1	93.75	~95	93	Not Available	85	91

Precision	0.96	0.92	0.93	0.91	0.9	0.84	0.89
Recall	0.95	0.91	0.94	0.89	0.88	0.8	0.88
F1-Score	0.955	0.91	0.935	0.9	0.89	0.82	0.88
AUC	0.97	0.93	0.95	0.91	0.9	0.83	0.9
Imbalance Handling	Cost-sensitive	SMOTE	None	Cost-sensitive	SMOTE	None	None
Explainability	LIME	No	No	No	Post-hoc	Built-in (simple)	No
Adaptability	Dynamic + Personalized	Static	Static	Static	Static	Static	Static
Key Limitations	Local LIME,high complexity	Overfitting via SMOTE	No dynamic adaptation	Small data, black-box	SHAP post-hoc; overfitting	Low accuracy; imbalance	Black-box; high data

Comparison Table

Observation with Existing other methods

Several conventional and ensemble classifier combinations were tested utilizing different base learners in order to further confirm the robustness of the suggested stacking ensemble model. Particularly, model combinations like SVM + RF + KNN had an average accuracy of about 92.25%, but other well-liked ensembles like SVM + RF + NB, RF + NB + LR, and KNN + RF + NB each produced an overall accuracy of 93%. Furthermore, a 93% accuracy plateau was obtained with a META-DES ensemble that used KNN + SVM. These results show that the performance improvement is still restricted even when several combinations of basic classifiers with excellent performance are used.

On the other hand, our suggested dynamic, cost-sensitive, and interpretable ensemble model—which combines KNN, SVM, and EBM classifiers using the META-DES framework and adds LIME for interpretability—achieved superior precision, recall, F1-score, and AUC values in addition to a noticeably higher accuracy of 96.1%. These findings show that the model's design, in conjunction with cost-aware learning and customized feature selection, significantly enhances diagnostic performance, making it the most efficient and clinically trustworthy method out of all those compared.

Conclusion

This study integrates a dynamic ensemble model with cost-sensitive XGBoost and LIME-based explainability to provide a reliable and comprehensible framework for the early identification of Polycystic Ovary Syndrome (PCOS). Comparative investigation revealed that the suggested strategy outperformed current approaches in terms of accuracy (96.1%), F1-score (0.955), and AUC (0.97), successfully resolving class imbalance and lack of model transparency. Our model provides patient-specific predictions with inherent interpretability, which makes it more dependable and useful for clinical adoption than previous research that rely on static, black-box models or synthetic oversampling approaches like SMOTE. In delicate healthcare applications, the incorporation of local explanations improves confidence in model judgments. Subsequent research endeavors will concentrate on enhancing computational effectiveness and expanding the framework to real-time, Internet of Things-enabled healthcare systems for ongoing diagnosis and monitoring.

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