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Research Article

An Ensemble Approach For Ultrasound-Based Polycystic Ovary Syndrome (PCOS) Classification

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ARTICLE INFO | **ABSTRACT**

Polycystic Ovary Syndrome (PCOS) is a prevalent endocrine disorder characterized by hormonal imbalances, ovulatory dysfunction, and metabolic disturbances in women of reproductive age. A novel approach for the early detection of PCOS using an innovative Ensemble Learning technique is proposed. Extreme Gradient Boosting (XGBoost), K-Nearest Neighbors (KNN), and Support Vector Machine (SVM) classifiers are combined, leveraging their complementary strengths to improve classification accuracy. A comprehensive image preprocessing pipeline, including geometric transformation, contrast enhancement, and noise reduction, is introduced to optimize feature extraction. To address class imbalance, an effective bias mitigation strategy using class weighting is implemented. The PCOSGen Dataset, comprising 3200 healthy and 1468 unhealthy ultrasound images, was used for the training and evaluation of the model. A remarkable test accuracy of 92% was achieved by the proposed ensemble, outperforming individual classifiers. Notably, feature extraction was incorporated to reduce input data dimensionality, enhancing both model interpretability and computational efficiency. This approach is made particularly suitable for real-world clinical applications, especially in resource-constrained environments. Robust performance of the model, demonstrated through comprehensive metrics including precision, recall, and F1-score, offers a promising tool for improving PCOS diagnosis using ultrasound image analysis.

Keywords: Polycystic ovary syndrome (PCOS) · Ensemble Learning ·Image Enhancement · Pregnancy · Machine Learning

Introduction

Polycystic Ovary Syndrome (PCOS) is a hormonal issue where a woman's ovaries produce more male hormones (androgens) than usual. This disrupts the normal balance and can cause the ovaries to develop small cysts, though these cysts aren't always present. Regardless of cysts, ovulation (egg release) often becomes irregular or doesn't happen at all. Normally, ovulation allows sperm to fertilize the egg. If fertilization doesn't occur, the egg is released during menstruation. In some circumstances, a woman may not produce enough of the hormones needed for ovulation. If ovulation is not successful, the ovaries may develop multiple tiny cysts. The hormones that these cysts produce are called androgens. A high testosterone level is typical in women with PCOS. This could make a woman's problems with her menstrual cycle worse.

One of the most prevalent hormonal disorders affecting women who are of reproductive age is PCOS, a serious public health concern. The World Health Organisation (WHO) estimates that 8–13% of fertile women have the illness, and up to 70 % of cases are untreated. PCOS prevalence in India ranges from 3.7 to 22.5%, according to the Indian Fertility Society.

As illustrated in Figure 1, Polycystic Ovary Syndrome (PCOS) is characterized by symptoms such as weight gain, irregular menstrual cycles, and anxiety or depression. These symptoms result from underlying hormonal imbalances and metabolic issues. The primary causes of PCOS include genetic factors, the presence of ovarian cysts, and hormonal disruptions. Understanding these elements is essential for effective management, which often involves lifestyle modifications and pharmacological treatments to regulate menstrual cycles and address metabolic complications.

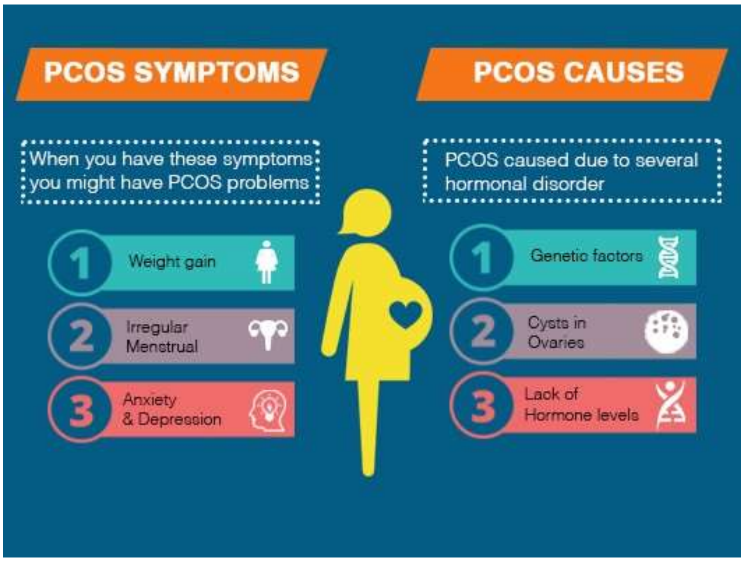

Fig.1. Symptoms and Causes of Polycystic Ovary Syndrome [11]

The classification of PCOS is crucial for several reasons: accurate classification helps in the identification of PCOS in its various forms, ensuring that women receive an appropriate diagnosis and subsequent management; different phenotypes of PCOS may respond differently to treatment, allowing for personalized treatment plans that enhance therapeutic efficacy and patient outcomes; and understanding the different phenotypes and their underlying mechanisms can drive targeted research, leading to the development of novel therapies and better understanding of the syndrome's etiology.

Over time, a number of diagnostic criteria have been proposed to classify PCOS; each has pros and cons. The 1990 NIH Criteria [3] prioritize hyperandrogenism and oligo-ovulation above polycystic ovarian morphology. To diagnose polycystic ovaries, oligo-ovulation, or hyperandrogenism, two of the three symptoms must be present, according to the most widely used set of criteria, the Rotterdam Criteria (2003) [15]. In addition to emphasizing the importance of androgen excess in the diagnosis of PCOS, the Androgen Excess and PCOS Society Criteria (2006) [2] also emphasize hyperandrogenism and ovarian dysfunction. The Rotterdam criteria can be used to differentiate between four PCOS phenotypes: Phenotype A, or Classic PCOS, is characterized by hyperandrogenism, oligo-anovulation, and polycystic ovaries; it is often associated with the most severe symptoms and elevated metabolic risk; When it comes to PCOS, phenotype B, or non-polycystic ovaries, is characterized by oligo-anovulation and polycystic ovaries without hyperandrogenism; phenotype C, or ovulatory PCOS, is characterized by polycystic ovaries and hyperandrogenism combined with regular ovulation and hyperandrogenism, usually accompanied by milder symptoms; and phenotype D, or non-hyperandrogenic PCOS, is made up of oligo-anovulation and polycystic ovaries without hyperandrogenism, typically displaying the least severe symptoms.

1 Related Work

By employing the Gabor Wavelet technique and a Competitive Neural Network (CNN) for feature extraction, [4] developed a system for classifying Polycystic Ovaries (PCO). The CNN method was used because it can combine Hemming Net and The Max Net to classify ultrasound data based on specific parameters. The Competitive Neural Network, with 32 feature vectors, processed data in 60.64 seconds with a high accuracy of 80.84% and weight and bias values of 0.002 and 0.03 correspondingly, according to the results of the system testing. In order to predict Polycystic Ovarian Disease (PCOD) in young women, [9] used a variety of ensemble learning techniques, such as Random Forest, Bagging classifier, AdaBoosting, and Gradient Boosting. With 91.7% accuracy and a 92% F1 score, the Gradient Boosting method performed the best out of all of them. [8] suggests classifying ultrasonic images using convolutional neural network (CNN) architectures, such as Inception V3, VGG16, and ResNet. Among the three, the VGG16 model had the highest accuracy.

In [5], benchmark datasets for polycystic ovarian syndrome (PCOS) were used to compare the performance of an integrated AutoML and neural network (NN) estimate based on TPOT-NN with a non-AutoML NN estimator. The results show that TPOT-NN is a useful tool, outperforming other study approaches in terms of accuracy on specific datasets. [14] incorporates convolutional neural networks (CNNs), such as ResNets, VGGNet, and Inception V3. With an accuracy of 96%, VGG19 was the most accurate of these. In addition, overfitting was addressed and model accuracy was increased by creating fresh images using a Generative Adversarial Network (GAN) technique. The goal of [10] work was to develop and apply multiple Deep Learning models. With 99% accuracy, the CNN model outperformed the Custom ResNet-50 model, which came in second at 96.7%. By comparison, the accuracy of the VGG-16 and ResNet-50 models was 58%.

With a KNN classifier, the approach suggested in [13] produced classification accuracy of more than 97%. This method promises to shorten the time needed to diagnose PCOS and increase diagnostic precision, which lowers the possibility of deadly complications brought on by a delayed diagnosis. Preprocessing, segmentation, and feature extraction using the Gabor wavelet are the first steps in the classification process in [12]. Different texture features are used to create two datasets. Testing with Neural Network-LVQ, KNN, and SVM-RBF Kernel is a part of classification. The best accuracy values obtained were 78.81% for Dataset B using KNN and 82.55% for Dataset A using SVM-RBF Kernel. With the best features, [6] suggested GIST-MDR feature extraction model produces high classifier accuracy of 93.82% for Support Vector Machine, 89.7% for Random Forest, 91.05% for Linear Discriminant Analysis, and 88.26% for Naive Bayes. [16] utilizes CNN-based image processing for feature extraction to classify cysts in the dataset. The test dataset undergoes the feature extraction process, achieving an accuracy of 85% based on performance factors. [1] highlights how crucial accurate feature selection techniques and machine learning models are for PCOS detection. By identifying features that are not important, statistical algorithms improve the accuracy of the model. With certain features, Random Forest maintains performance while cutting down on computation time, achieving 93.52% accuracy. AUC (0.82 to 0.98), a measure of the model's efficacy, shows better classification performance. The study offers strategies to maximize AUC, enhancing data-driven PCOS diagnosis.

2 Dataset

PCOSGen Dataset [7] has been used in this study. The PCOSGen dataset, which is the first of its kind, was gathered from various online sources including YouTube, ultrasoundcases info, and Kaggle. It includes various training and test datasets. 3200 and 1468 healthy and unhealthy examples, respectively, as shown in Figure 2 and 3 make up PCOSGen-train and PCOSGen-test. An accomplished gynecologist located in New Delhi, India, has assisted in medically annotating the training and testing datasets.

Fig.2. Healthy PCOSGen training images

Fig.3. Unhealthy PCOSGen training images

3 Proposed Methodology

3.1 Pre-processing

Geometric transformation: To ensure scale invariance and consistent feature extraction, all images are isotropically resampled to a fixed size (256x256 pixels). This guarantees comparable feature representations for objects of varying sizes in the original images. Isotropic resampling refers to the process of resizing the image while maintaining the aspect ratio, preventing any distortion in the object's shape due to non-uniform scaling.

Normalization: Min-max normalization is applied to linearly scale the pixel intensity values of the image to a unified range of [0, 255]. This process transforms the original data distribution to a standard range, ensuring all features operate on the same numerical scale.

Color Conversion: The image is converted from BGR (Blue, Green, Red) color space to grayscale. Grayscale images often contain sufficient information for classification, especially when dealing with objects with distinct shapes but similar colors.

Contrast Enhancement: Contrast Limited Adaptive Histogram Equalization (CLAHE) is applied to improve local contrast in the image. This enhances the visibility of features, particularly in regions with low contrast.

Noise Reduction: Morphological operations, including dilation and erosion with a small kernel (5x5), are used to remove isolated noise pixels while preserving image edges. Additionally, a Gaussian blur is applied to further reduce high-frequency noise.

Binarization: Otsu's thresholding is used to convert the grayscale image into a binary image. This step separates foreground objects from the background.

Morphological Opening: Morphological opening with a small structuring element removes small objects and further cleans the binary image.

Feature Extraction: Region properties (area, perimeter, solidity, etc.) are extracted from the labeled objects in the binary image. These properties capture the size and shape characteristics of the objects. Mean, standard deviation, and signal-to-noise ratio (SNR) are calculated from the grayscale image. These features provide information about the overall image intensity distribution. Gray Level Co-occurrence Matrix (GLCM) is computed to capture the spatial relationships between neighboring pixels. Contrast, energy, and homogeneity features are extracted from the GLCM, which quantifies the texture patterns present in the image.

Various preprocessing techniques used in this study can be seen in Figure 4.

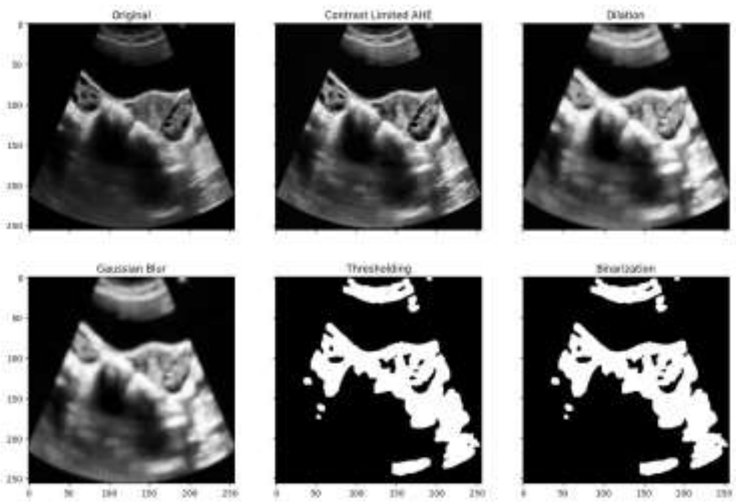

Fig.4. Image Pre-processing

3.2 Classification with Ensemble Learning

This section details the classification approach employed to identify normal and affected ovaries from the pre-processed ovarian images. An ensemble learning strategy was adopted that leverages the strengths of multiple machine learning models to achieve robust and accurate classification.

The model learns to recognize patterns in the features that differentiate healthy ovaries from affected ones based on the training data. As a result, when new, unseen ovarian images are being classified, the model can anticipate their category (affected or normal).

Individual Model Training with Bias Mitigation: There was a discernible disparity in the number of images in the training dataset between the unhealthy class (2297) and the healthy class (903) that can be seen in Figure 5. This imbalance may cause the majority class to receive preferential treatment during the learning process, which would result in the minority class (healthy ovaries) performing worse during classification.

Class weighting was used as a technique to promote more equitable learning and address this imbalance. During model training, this method gives data points from the underrepresented class—healthy ovaries—higher weights. To implement class weights, the unhealthy class was given a weight of 1 and the healthy class was given a weight of 3 (class_weights = 0: 1, 1: 3). The ultimate goal of this strategy is to enhance classification performance for both classes by encouraging the models to concentrate more on learning from the less frequent healthy class samples. A wide range of machine learning models, such as Random Forest, Logistic Regression, Gradient Boosting, XGBoost, K-Nearest Neighbors, Support Vector Machine, and Decision Tree, were used to achieve robust and accurate classification. Each model was tested using metrics like accuracy on a held-out validation set after being independently trained using bias mitigation on the pre-processed data. This evaluation assisted in determining which models were suitable for ensemble construction and in evaluating each model's efficacy for the classification.

Ensemble Learning with Hard Voting: Conventional machine learning techniques frequently depend on a single model to handle the classification task. Individual models, however, may be less effective for particular data patterns or overfit the training set. By merging the predictions from several models to produce a more reliable and accurate classifier, ensemble learning overcomes these drawbacks. Hard voting in ensemble learning is like a group decision where the most popular choice wins. Each model in the ensemble makes a prediction, and the final prediction is the class label that receives the most votes from all the models. Each trained model independently predicts the class label (normal or affected ovary) for a new, unseen image. The final predicted class for the new image corresponds to the class label receiving the most votes from the individual models in the ensemble. This voting mechanism aims to achieve a more reliable classification by incorporating the collective knowledge of the diverse models.

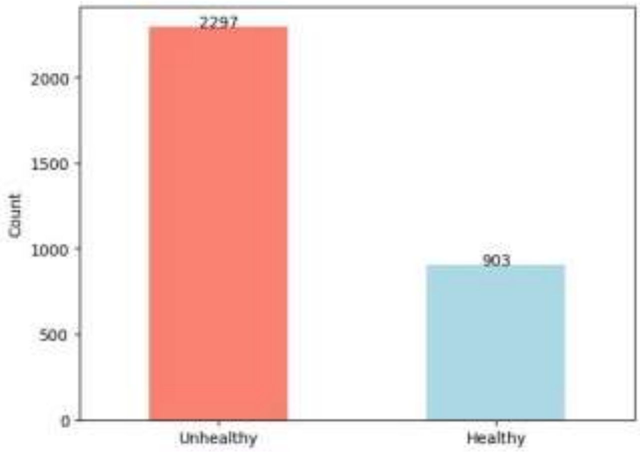

Fig.5. Distribution of Healthy and Unhealthy ovaries in the dataset.

3.3 Implementation Details

To ensure reproducibility and provide context for the computational requirements of our approach, the hardware and software tools used in this study are detailed.

Hardware: All experiments were conducted on a MacBook Pro equipped with an Apple M1 Pro chip, 32GB of unified memory, and a 1TB SSD. Efficient processing of the image dataset and training of the ensemble model were enabled by this setup.

Software: The implementation was carried out using Python 3.11 as the primary programming language. The following key libraries and frameworks were utilized:
– OpenCV for image preprocessing and feature extraction
– scikit-learn for the implementation of KNN and SVM classifiers, as well as for performance evaluation metrics
– XGBoost for the Gradient Boosting classifier
– NumPy and Pandas for data manipulation and analysis
– Matplotlib and Seaborn for data visualization and creating performance plots

3.4 Limitations and Potential Challenges Encountered

Data Imbalance: A significant challenge in the project was the disparity in the number of images between the unhealthy class (2297) and the healthy class (903). This imbalance could have led to the majority class (unhealthy ovaries) receiving preferential treatment during the learning process, resulting in poor performance for the minority class (healthy ovaries). To mitigate this, class weighting was employed, giving higher weights to the underrepresented class during model training.

Limited Generalizability: The model's generalizability could be limited by the dataset's diversity. Future work should focus on adding more ultrasound images from different stages of PCOS and various imaging conditions to enhance the model's robustness.

Real-Time Processing: Optimizing the model for real-time processing is necessary for its practical use in live ultrasound exams. This would allow immediate feedback to doctors during patient evaluations, improving the clinical workflow and decision-making.

Lack of Integration with Other Data Modalities: To provide a more comprehensive approach to PCOS diagnosis, integrating additional data modalities such as patient history, hormonal profiles, or genetic markers with ultrasound images could be explored. This multi-modal approach could enhance diagnostic accuracy and provide deeper insights into the condition.

4 Results

4.1 Evaluation Metrics and Analysis

Three important metrics are used to evaluate performance: Precision, Recall, and F1-Score.

$$\text{Precision} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Positives}}$$

$$\text{Recall} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Negatives}}$$

$$\text{F1 Score} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

4.2 Performance Evaluation

In this section, initially the effectiveness of the proposed ensemble model on both the training and testing datasets is evaluated. Table 1 displays the accuracy, precision, recall, and F1-score achieved by all the models used in the ensemble model on the training set. Among these models, Extreme Gradient Boosting (XGBoost), K-nearest neighbor (KNN), and Support Vector Machine (SVM) demonstrate superior performance across all three metrics, surpassing others. This is why ensemble model is made up of these three models.

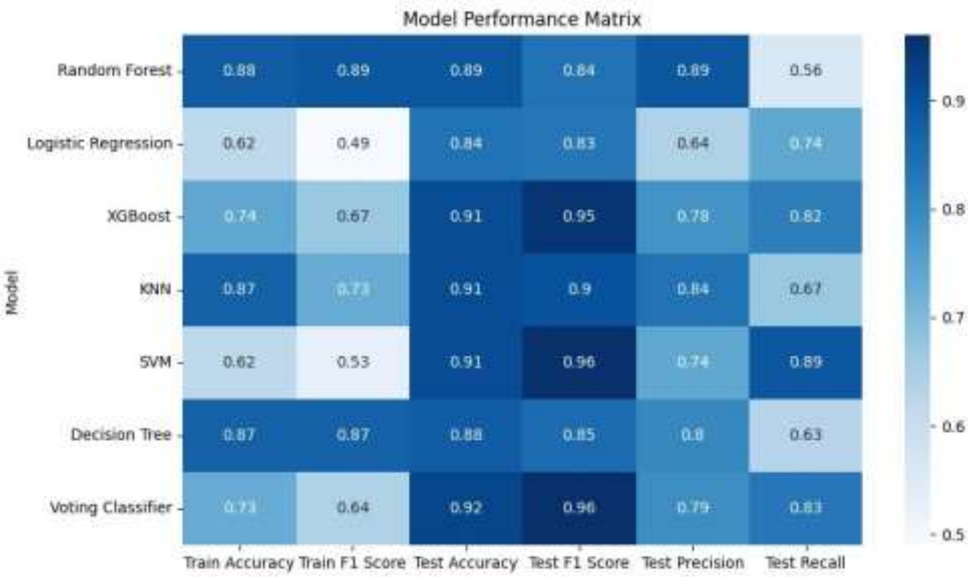

Fig.6. Model Performance Metrics

Figure 6 offers a heatmap summarizing the performance of various machine learning models used to classify ultrasound images for diagnosing Polycystic Ovary Syndrome (PCOS). The evaluated models include Random Forest, Logistic Regression, XGBoost, K-Nearest Neighbors, Support Vector Machine, Decision Tree, and a combined Voting Classifier. Each model's performance is measured using metrics like training and testing accuracy, F1 score, precision, and recall.

The heatmap uses color intensity to visually represent the metric values, with darker shades indicating better performance. This visualization allows for a quick comparison of model performance across different metrics, revealing the strengths and weaknesses of each approach in terms of training effectiveness and generalizability to unseen data.

Focusing on the most successful model, the Voting Classifier, Figure 7 presents its confusion matrix for the test dataset. This matrix reveals the number of accurate and inaccurate classifications. It details how many healthy cases (true positives: 958) and unhealthy cases (true negatives: 346) were correctly identified. However, the matrix also highlights misclassifications. In 93 instances, healthy cases were mistakenly classified as unhealthy (false positives), and in 71 instances, unhealthy cases were missed (false negatives). This confusion matrix offers valuable insights into the Voting Classifier's performance. While it demonstrates a good ability to distinguish between healthy and unhealthy cases, it also identifies areas for improvement, such as reducing false positives and false negatives.

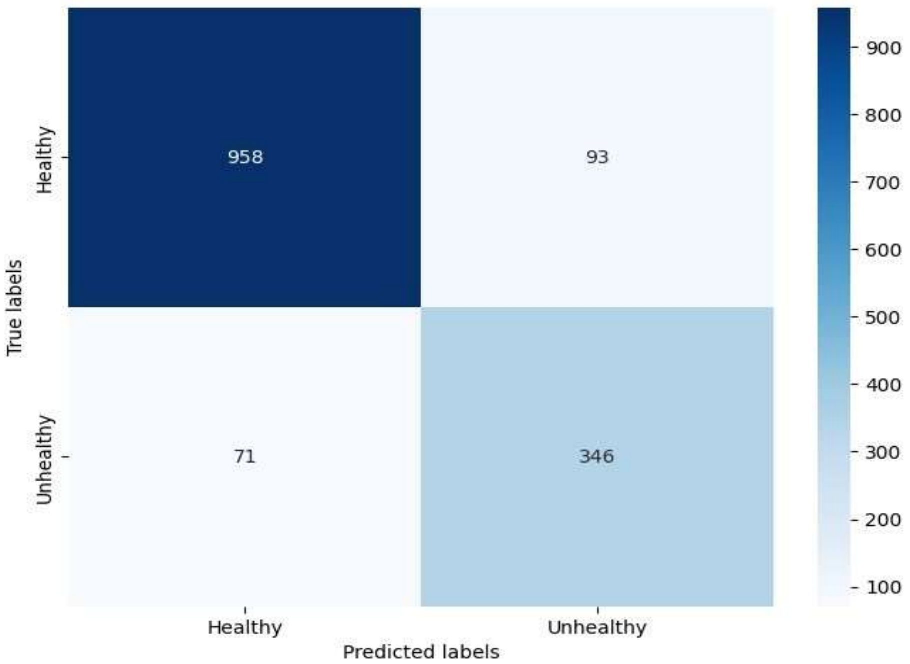

Fig.7. Confusion Matrix

In conclusion, the outcomes of the combined model in comparison to the CNN models are evaluated. The Precision, Recall, and F1-Score on the Test Set are displayed in Figure 6. Remarkably, the proposed ensemble Model surpasses all individual models. Achieving a Test accuracy of 92%, it outperforms the other three models.

4.3 Performance Comparison

To assess the effectiveness of our proposed ensemble model, we compare its performance against established models. Table 1 presents a comparison highlighting the performance of our model relative to these trained networks.

It's important to note that beyond achieving high accuracy, our proposed ensemble model offers an additional advantage in terms of training efficiency. By incorporating feature extraction, we were able to reduce the dimensionality of the input data. This not only improves the interpretability of the model but also significantly reduces training time compared to traditional ensemble models that utilize the entire feature set. This efficiency gain makes our model even more attractive for real-world applications, especially in scenarios where computational resources might be limited.

Table 1. Performance Comparison with Existing Models

Model	Test Accuracy
Competitive CNN [4]	80.84%
Ensemble Model (Random Forest, Bagging classifier, AdaBoosting, and Gradient Boosting) [9]	91.7%
SVM-RBF [12]	82.55%
CNN [16]	85%
Ensemble Model (XGBoost, KNN, and SVM)	**92%**

5 Conclusion

In this paper, we propose a new machine learning framework for Polycystic Ovary Syndrome (PCOS) classification using ultrasound images. The key is our ensemble approach which combines Extreme Gradient Boosting (XGBoost), KNearest Neighbors (KNN), and Support Vector Machine (SVM) - never been tried for PCOS before. Our ensemble with our preprocessing pipeline and class weighting to mitigate bias achieved 92% test accuracy which outperformed existing methods. Another novel part is our feature extraction to reduce input data dimensionality which makes our approach more interpretable and efficient. This is very useful for real-world clinical applications, especially in resource constraint environments - often overlooked in previous studies. This study not only advances the technical aspect of PCOS diagnosis but also bridge the gap between machine learning and clinical implementation. By demonstrating superior performance across multiple metrics and addressing real-world constraints, this study sets a new benchmark in AI-assisted PCOS diagnostics and opens avenues for future research in gynecological image analysis.

6 Future Work

While the proposed ensemble approach shows significant improvement in PCOS classification, there are many ways to further improve and expand the method. Future work can focus on adding more ultrasound images to the dataset, from different stages of PCOS and different imaging conditions to make the model more generalizable and robust. Deep learning models like Convolutional Neural Networks (CNNs) can be explored to improve feature extraction and classification, either by using pre-trained models or building custom models for PCOS detection. Explainable AI techniques can make the model's decision-making more transparent which would be very useful in clinical settings to help doctors understand and trust the model's predictions. Integrating other data modalities like patient history, hormonal profiles or genetic markers with ultrasound images can provide a more comprehensive approach to PCOS diagnosis. Optimizing the model for real-time processing can make it usable in live ultrasound exams and provide immediate feedback to doctors during patient evaluations. Longitudinal studies can be done to evaluate the model's performance in tracking PCOS over time and provide insights into disease management and treatment efficacy. By pursuing these avenues, we can work towards developing more accurate, interpretable and widely applicable AI-assisted diagnostic tools for PCOS and related conditions.

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