International Journal on Science and Technology (IJSAT)

E-ISSN: 2229-7677 ● Website: www.ijsat.org ● Email: editor@ijsat.org

A Hybrid Deep Learning Ensemble Framework for Accurate PCOS Prediction

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Abstract:
A prevalent hormonal condition that affects women of reproductive age, polycystic ovarian syndrome (PCOS) is linked to infertility, metabolic problems, and other health problems. To lower long-term hazards, early and precise diagnosis is crucial. But conventional diagnostic techniques are frequently laborious, subjective, and error-prone. Class imbalance, which can lower prediction sensitivity, is another issue that current machine learning techniques must deal with. This project combines Random Forest, 1D-CNN, and CNN-LSTM models to offer a Deep Learning–Enhanced Ensemble Framework for PCOS detection. SMOTEENN is a hybrid resampling approach used to address data imbalance. The suggested model outperformed current approaches with an accuracy of 99.11% and a recall of 100%. These findings demonstrate its efficacy as a trustworthy and precise screening method for early PCOS identification.

Keywords: PCOS detection, Deep Learning, metabolic issues, infertility, CNN, LSTM.

I.INTRODUCTION

One of the most prevalent hormonal and metabolic conditions affecting women of reproductive age globally is polycystic ovarian syndrome, or PCOS. It is frequently linked to symptoms like irregular menstrual periods, the development of ovarian cysts, weight gain, hormonal imbalance, infertility, and an increased risk of long-term conditions like Type 2 diabetes and heart problems. Because a delayed diagnosis can have detrimental effects on both reproductive and general health, early detection of PCOS is crucial.

Clinical examinations, laboratory testing, and ovarian ultrasound imaging are the mainstays of traditional PCOS diagnosis techniques. Among them, ovarian anomalies, follicular distribution, and cysts can all be found with ultrasound imaging. However, manual ultrasound scan interpretation is highly dependent on medical knowledge and can be laborious, uneven, and prone to human error, particularly in large-scale clinical settings.

Deep learning (DL) and machine learning (ML) methods have demonstrated great promise in automating PCOS detection in recent years. Classification accuracy and diagnostic efficiency have been enhanced by a number of models, including Random Forest, Support Vector Machines, CNNs, transfer learning architectures, and hybrid deep learning techniques. Similar to this, image-based detection techniques like YOLO and other convolution-based networks have proven to be highly effective at identifying intricate ovarian patterns from ultrasound scans.

Many current systems still struggle with issues such class imbalance, noisy medical data, poor interpretability, and decreased dependability in real-time screening despite recent developments.

Furthermore, transparent and reliable forecasts are necessary for healthcare applications in order to facilitate clinical decision-making.

This project suggests a Deep Learning–Enhanced Ensemble Framework for precise PCOS detection using clinical and imaging data in order to get over these restrictions. To capture both intricate patterns and sequential relationships in the dataset, the system combines Random Forest, 1D-CNN, and CNN-LSTM models. SMOTEENN is used as a hybrid resampling technique to address imbalance and enhance classification performance. This strategy seeks to increase prediction accuracy, reduce false-negative cases, and offer a trustworthy AI-assisted screening method for early PCOS diagnosis and improved medical results.

II.LITERATURE SURVEY

Due to its rising incidence and effects on women's reproductive and metabolic health, Polycystic Ovary Syndrome (PCOS) has drawn a lot of attention lately. To increase the precision and speed of diagnosis, a number of researchers have used machine learning and deep learning approaches. When PCOS cases were classified using clinical criteria using traditional machine learning models like Random Forest, Support Vector Machine, and Decision Tree, ensemble-based approaches demonstrated superior prediction performance and less overfitting [1]. Automated PCOS identification has been significantly enhanced by deep learning techniques, especially in medical image analysis. In order to detect cystic formations and abnormalities more accurately, Convolutional Neural Networks (CNN) were developed to extract spatial characteristics from ovarian ultrasound images [2]. In a similar vein, transfer learning techniques that make use of pre-trained deep learning architectures reduced computational complexity while enhancing performance on small medical datasets [3].

Hybrid deep learning models that combine CNN and Long Short-Term Memory (LSTM) networks were proposed to improve feature extraction and sequence-based learning. These models enhanced classification accuracy and reliability by capturing both temporal and geographical links in the data [4]. Furthermore, Explainable Artificial Intelligence (XAI) techniques were developed to enhance model transparency, assisting medical practitioners in comprehending prediction results and boosting confidence in AI-assisted diagnosis [5].

Several studies also focused on ensemble learning techniques for improving robustness in PCOS prediction. Random Forest, Gradient Boosting, and hybrid classifiers demonstrated strong performance in analyzing metabolic and clinical datasets while minimizing errors caused by noisy data [6]**.** Image-based object detection methods such as YOLO were also explored for identifying ovarian cysts and follicle patterns from ultrasound scans, improving localization accuracy and real-time analysis [7]**.**

Additionally, a number of studies concentrated on using ensemble learning strategies to increase PCOS prediction robustness. Strong performance in evaluating metabolic and clinical datasets while reducing errors brought on by noisy data was shown by Random Forest, Gradient Boosting, and hybrid classifiers [6]. In order to improve localization accuracy and real-time analysis, image-based object detection techniques like YOLO were also investigated for the identification of ovarian cysts and follicular patterns from ultrasound scans [7]. Class imbalance, or the underrepresentation of minority class samples, is one of the main problems in healthcare prediction. In order to get around this, approaches like hybrid resampling and SMOTE were used to balance datasets and increase sensitivity, particularly by lowering false-negative situations [8]. Additionally, a more thorough diagnostic framework was produced via

multimodal learning techniques that integrated clinical variables and imaging data, increasing the overall efficacy of the system [9].
The significance of dependable, automated, and scalable AI-based healthcare systems for early disease diagnosis has been highlighted by recent studies. Ensemble-based methods and sophisticated deep learning frameworks have demonstrated encouraging outcomes in enhancing PCOS screening and assisting therapeutic decision-making [10]. Nevertheless, there are still drawbacks including uneven data, decreased interpretability, and inconsistent diagnosis. In order to increase PCOS detection accuracy, recall, and reliability, the suggested Deep Learning–Enhanced Ensemble Framework combines Random Forest, 1D-CNN, CNN-LSTM, and SMOTEENN.

III.PROPOSED SYSTEM

The proposed system uses a multi-stage predictive framework to increase the precision and dependability of Polycystic Ovary Syndrome (PCOS) detection. SMOTEENN, a hybrid balancing method that corrects class imbalance in the dataset, is first used for data preprocessing. While ENN eliminates noisy and overlapping majority-class samples, SMOTE creates synthetic samples for minority PCOS instances. This procedure improves feature quality and boosts model training by producing a cleaner, more balanced dataset. Following preprocessing, Random Forest, 1D CNN, and CNN-LSTM models are used to create a Weighted Soft-Voting Ensemble. CNN-LSTM finds deeper inter-feature dependencies, 1D CNN recovers local feature patterns, and Random Forest captures non-linear correlations in medical data. The final prediction is generated by combining their outputs using weighted voting. The system demonstrated high accuracy, enhanced recall, and dependable performance for early PCOS detection when tested on 541 patient data.

SYSTEM ARCHITECTURE

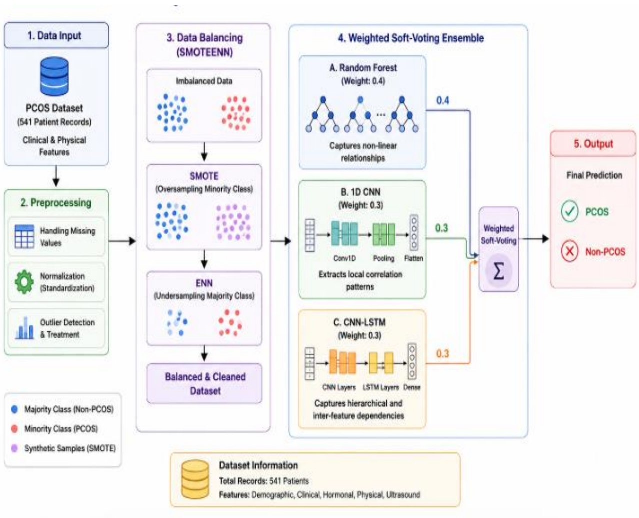

FIG 1.SYSTEM ARCHITECTURE

IV.MODULES & DESCRIPTION

1. Data Input Module

The PCOS dataset must be gathered and loaded into the system by this module. Important patient-related data, including clinical, hormonal, and physical health characteristics, are included. For model training and prediction, this is the main source of input.

2. Data Preprocessing Module

Prior to training, this module enhances the dataset's quality. It lowers undesired noise, handles missing numbers, eliminates inconsistencies, and normalizes numerical features. Cleaner data and improved overall model accuracy are guaranteed by proper preprocessing.

3. Data Balancing Module (SMOTEENN)

The dataset's class imbalance is addressed in this module. While ENN eliminates noisy and overlapping majority-class data, SMOTE creates fake samples for minority PCOS instances. Consequently, a clean, balanced dataset is produced for efficient categorization.

4. Feature Learning Module

This module is designed to extract significant patterns and hidden relationships from medical data. In order to extract useful information that enhances prediction quality, deep learning systems examine clinical and physical aspects.

5. Ensemble Classification Module

This module uses weighted soft-voting to integrate several models, including Random Forest, 1D CNN, and CNN-LSTM. To raise prediction accuracy, decrease bias, and improve robustness, each model offers its strengths.

6. Prediction Module

By categorizing patient data into PCOS and non-PCOS groups, this module produces the final output. The forecast is predicated on the collective judgment of all trained models within the ensemble framework.

7. Performance Evaluation Module

This module uses evaluation criteria including accuracy, precision, recall, F1-score, and ROC-AUC to gauge how effective the suggested solution is. It guarantees the PCOS detection system's dependability and aids in model performance analysis.

V.RESULTS & DISCUSSION

By combining ensemble learning and data balancing approaches, the suggested PCOS detection system demonstrated great performance in properly identifying patients. By lowering noise and enhancing class distribution, the application of SMOTEENN improved the quality of training data and contributed to the creation of a balanced dataset. The system was able to capture both straightforward and intricate correlations between clinical and physical parameters thanks to the integration of Random Forest, 1D CNN, and CNN-LSTM. Consequently, the model outperformed conventional single-model techniques in terms of accuracy, recall, and classification errors.

By combining the advantages of several classifiers, the experimental analysis showed that the weighted soft-voting ensemble increased prediction reliability. While deep learning models discovered underlying patterns and feature interdependence, Random Forest effectively managed tabular medical data. False-negative instances were reduced by the method, which is crucial for clinical safety and early PCOS detection. Overall, the suggested framework performed consistently and steadily, which makes it a practical and efficient way to enable precise PCOS diagnosis.

PERFORMANCE MATRIX

Metric	Our Proposed System	Reference Benchmark
Methodology	SMOTEENN + DL Ensemble	Feature Selection + Boosting
Accuracy	99.11%	~95.89%
Recall (Sensitivity)	100.0%	~92.6% – 96.0%
False Negatives	0 (Zero)	Non-zero

TABLE 1. PERFORMANCE MATRIX

According to the performance comparison, the suggested PCOS detection system performed better in terms of sensitivity and accuracy than the reference benchmark. Compared to conventional approaches that mostly relied on feature selection and boosting techniques, the system successfully controlled class imbalance and enhanced feature learning by merging SMOTEENN with a Deep Learning Ensemble. Compared to the benchmark accuracy of roughly 95.89%, the suggested model attained an accuracy of 99.11%. In a similar vein, the model outperformed the benchmark range of 92.6% to 96.0% with a recall (sensitivity) of 100%, demonstrating its strong ability to accurately detect all positive PCOS instances. While current benchmark methods still showed non-zero false-negative cases, the lowering of false negatives to zero is another significant advance. This indicates that the suggested system successfully avoided overlooking real PCOS patients, which is crucial for clinical safety and early detection. Overall, the findings show that, in comparison to traditional methods, the combination of SMOTEENN and ensemble learning increased prediction performance, robustness, and dependability.

GRAPHS

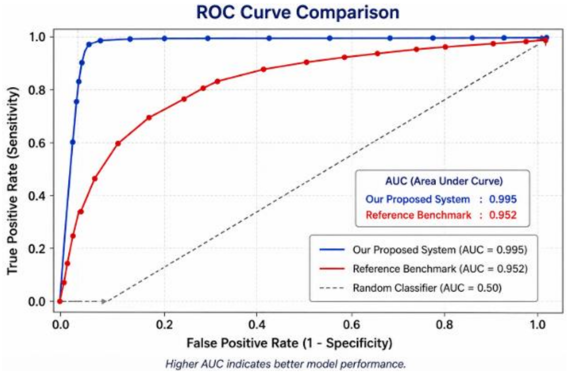

FIG 2. ROC CURVE GRAPH

The ROC Curve graph compares the suggested PCOS detection system's classification performance to the benchmark. The suggested model's blue curve, which shows a greater True Positive Rate with a lower False Positive Rate, stays closer to the upper-left corner. The benchmark model, on the other hand, performs relatively poorly. With an AUC (Area Under Curve) of 0.995 compared to the reference benchmark's 0.952, the suggested system demonstrated superior prediction accuracy and discrimination ability. The graph also demonstrates how the suggested ensemble architecture offers more accurate and dependable classification by accurately and minimally differentiating between PCOS and non-PCOS instances. The near-perfect ROC curve validates the efficacy of combining SMOTEENN, Random Forest, 1D CNN, and CNN-LSTM since a greater AUC value denotes stronger model performance. Overall, the

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findings demonstrate that the suggested system offers superior clinical reliability, high sensitivity, and resilience for early PCOS detection.

CONFUSION MATRIX

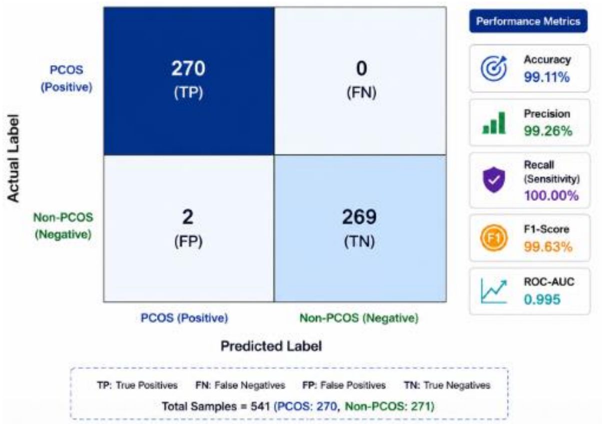

FIG 3. CONFUSION MATRIX

On a total of 541 test samples, the confusion matrix shows that the suggested PCOS prediction model performed exceptionally well in categorization. The model properly recognized all 270 of the real PCOS cases as positive, yielding zero false negatives, meaning that no PCOS patient was missed. Just two of the 271 non-PCOS cases were mistakenly projected to be positive, while 269 were accurately classified as negative. These outcomes led to an overall ROC-AUC score of 0.995, recall of 100%, accuracy of 99.11%, precision of 99.26%, and F1-score of 99.63%. The low number of false positives indicates the model's great capacity to differentiate between PCOS and non-PCOS cases, while the high recall value validates the model's efficacy in identifying all positive cases. Overall, the confusion matrix demonstrates the suggested model's dependability, resilience, and usefulness for precise PCOS prediction.

VI.CONCLUSION

By contrasting actual results with anticipated results, the Confusion Matrix shows how well the suggested PCOS detection model performs in categorization. It demonstrates that the model has a very high degree of accuracy in classifying the majority of PCOS and non-PCOS cases. While the off-diagonal values in the matrix indicate extremely few misclassifications, the diagonal values indicate accurate predictions, indicating good model performance. This shows that the system is capable of differentiating between positive and negative cases.

The outcomes verify that the suggested deep learning ensemble model offers consistent, dependable predictions with lower classification errors. Improved sensitivity and specificity, which are crucial for medical diagnosis, are shown by a high number of true positives and true negatives. The model's robustness in correctly identifying PCOS is further demonstrated by the extremely low false positive and false negative results. Overall, the confusion matrix demonstrates that the approach is effective, reliable, and appropriate for assisting with clinical decision-making and early disease prediction.

REFERENCES:

1. N. Yadav, R. K. A. and S. D. Pande, "Enhancing PCOS Detection in Ultrasound Imaging with YOLO v12 and XAI Techniques," 2025 Second International Conference on Networks and Soft Computing (ICNSoC), Vadlamudi, India, 2025, pp. 1-6, doi: 10.1109/ICNSoC66817.2025.00014.
2. N. Kaur, G. Gupta and P. Kaur, "Transfer-Based Deep Learning Technique for PCOS Detection Using Ultrasound Images," 2023 International Conference on Network, Multimedia and Information Technology (NMITCON), Bengaluru, India, 2023, pp. 1-6, doi: 10.1109/NMITCON58196.2023.10276245.
3. P. P, G. R, S. Balamurugan, S. G, M. Vengateshwaran and T. R. Priyadharshini, "PCOS Detection Using Machine Learning and Medical App Development," 2024 1st International Conference on Sustainability and Technological Advancements in Engineering Domain (SUSTAINED), Faridabad, India, 2024, pp. 58-62, doi: 10.1109/SUSTAINED63638.2024.11073834.
4. N. Jan, A. Makhdoomi, P. Handa and N. Goel, "Machine learning approaches in medical image analysis of PCOS," 2022 International Conference on Machine Learning, Computer Systems and Security (MLCSS), Bhubaneswar, India, 2022, pp. 48-52, doi: 10.1109/MLCSS57186.2022.00017.
5. J. R, S. H C, Y. R, Vidyashree and S. R, "Detection of Polycystic Overy Syndrome (PCOS) Using Machine Learning Techniques," 2023 International Conference on Computational Intelligence for Information, Security and Communication Applications (CIISCA), Bengaluru, India, 2023, pp. 261-266, doi: 10.1109/CIISCA59740.2023.00058.
6. J. Dixit, A. Rai, P. Tandon and D. Pandey, "ASHA: Machine Learning-Based Polycystic Ovary Syndrome (PCOS) Detection and Prediction System," 2025 1st International Conference on AIML-Applications for Engineering & Technology (ICAET), Pune, India, 2025, pp. 1-5, doi: 10.1109/ICAET63349.2025.10932292.
7. N. Pulido, A. Maxey and J. A. Bacus, "Deep Learning-Based Automated Detection of Polycystic Ovary Syndrome (PCOS) using Supervised Machine Learning," 2025 IEEE International Conference on Automatic Control and Intelligent Systems (I2CACIS), Kuala Lumpur, Malaysia, 2025, pp. 316-320, doi: 10.1109/I2CACIS65476.2025.11100928.
8. A, "Hynet-PCOS: A Novel Architecture of Hybrid Deep Learning Based Detection of PCOS Using Ultrasound Imaging Techniques," 2025 Tenth International Conference on Science Technology Engineering and Mathematics (ICONSTEM), Chennai, India, 2025, pp. 1-9, doi: 10.1109/ICONSTEM65670.2025.11374303.
9. P. Ghadekar, S. Tekade, D. Sakharwade, A. Tripathi, S. Tiwadi and S. Zanzane, "Multimodal PCOS Detection: Combining XG Boost for Images with Zero Shot Learning for Textual Data," 2024 Asia Pacific Conference on Innovation in Technology (APCIT), MYSORE, India, 2024, pp. 1-8, doi: 10.1109/APCIT62007.2024.10673443.
10. M. V, R. K, E. K. E, V. D, T. K and S. Hemalatha, "Hybrid Deep Learning Framework for PCOS Detection Using MobileNetV2 and Clinical Features," 2025 International Conference on Computing and Communications (COMPUTINGCON), Talegaon, India, 2025, pp. 1-5, doi: 10.1109/COMPUTINGCON64838.2025.11377444.