

An Integrated Deep Learning Approach for PCOS Diagnosis using Ultrasound images and Clinical parameters

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Abstract- Polycystic Ovary Syndrome (PCOS) is a common hormonal disorder among women of reproductive age, characterized by complex clinical symptoms and varying ultrasound findings, which often make diagnosis challenging. To address these limitations, this study proposes an integrated deep learning-based diagnostic framework that combines ovarian ultrasound images with key clinical parameters. Convolutional Neural Networks (CNNs) are utilized to automatically learn representative features from ultrasound images, enabling the identification of ovarian morphological patterns such as follicular distribution and ovarian size. Simultaneously, relevant clinical data including age, body mass index, hormonal levels, menstrual history, and metabolic indicators are analyzed using a neural network model. The learned features from both modalities are fused to improve diagnostic performance. The proposed approach minimizes reliance on subjective clinical assessment and manual feature extraction. Experimental evaluation demonstrates that the integrated model achieves superior accuracy, sensitivity, and specificity compared to single-modal diagnostic methods. This framework provides an effective and non-invasive decision-support tool for early and reliable PCOS diagnosis.

Keywords: Polycystic Ovary Syndrome (PCOS), Deep Learning, Convolutional Neural Network, Ultrasound Imaging, Clinical Parameters, Medical Diagnosis.

I. INTRODUCTION

Polycystic Ovary Syndrome (PCOS) represents one of the most common endocrine disturbances in women during their reproductive years, significantly affecting reproductive function, metabolic homeostasis, and mental well-being. The syndrome manifests through a spectrum of clinical features including irregular menstruation, elevated androgen levels, excess body weight, impaired insulin sensitivity, and reduced fertility. Timely and precise identification of PCOS is critical for implementing appropriate therapeutic interventions and mitigating the risk of severe long-term sequelae such as diabetes mellitus type 2 and cardiovascular pathologies. Nevertheless, establishing a definitive diagnosis remains problematic owing to the syndrome's heterogeneous manifestations and considerable variation in symptom presentation across individuals.

Contemporary clinical protocols for PCOS diagnosis predominantly adhere to standardized frameworks such as the Rotterdam criteria, which integrate clinical symptomatology, hormonal profiling, and ultrasonographic evaluation of ovarian morphology. Ultrasonography serves as a pivotal diagnostic modality for detecting characteristic polycystic ovarian features, including elevated antral follicle numbers and enlarged ovarian dimensions. Despite its clinical utility, ultrasound-based assessment exhibits substantial dependence on practitioner proficiency and suffers from notable inter-observer inconsistency. Furthermore, conventional manual interpretation of ultrasound imagery is labor-intensive and prone to diagnostic variability, especially in ambiguous clinical scenarios.

Recent developments in artificial intelligence and deep learning technologies have demonstrated exceptional capabilities in medical imaging analysis and automated diagnostic assistance. Convolutional

Neural Networks (CNNs) have emerged as particularly effective architectures, capable of autonomously extracting hierarchical feature representations from medical images without requiring manual feature engineering. These computational models have achieved notable success across diverse diagnostic domains, encompassing neoplasm identification, anatomical structure segmentation, and pathological classification. However, relying exclusively on ultrasound imagery for PCOS diagnosis presents inherent limitations, as biochemical markers and clinical metadata offer essential complementary information for comprehensive patient assessment. Addressing these constraints requires integrated diagnostic methodologies that synthesize imaging modalities with clinical parameters. The amalgamation of heterogeneous data sources facilitates a more holistic characterization of patient status and enhances diagnostic precision. Through the application of advanced deep learning frameworks, simultaneous analysis of ultrasound images and structured clinical records becomes feasible, thereby improving predictive performance and diminishing diagnostic uncertainty.

Driven by these clinical challenges and technological opportunities, this study introduces an integrated deep learning architecture for PCOS diagnosis that synergistically combines ovarian ultrasound imaging with pertinent clinical variables. The proposed methodology seeks to reduce subjective bias in diagnostic assessment, establish greater consistency across healthcare facilities, and provide clinicians with a robust, non-invasive decision-support mechanism. Implementation of such a system holds promise for enabling earlier PCOS detection and enhancing patient prognosis through prompt clinical management.

II. RELATED WORKS

Tariq Rahim, Ibadullah, Aimal Nazir, Muhammad Salih Tanveer, Muhammad Rohan Qureshi (2025) presented a novel Two-Stream CNN with Transformer Attention model for PCOS diagnosis from ovarian ultrasound images. Their approach splits the image into two streams for improved

feature learning and uses Multi-Head Attention to model spatial relationships, achieving high classification accuracy and F1-score, demonstrating robust performance for automated PCOS detection using deep learning. Mehtap Agirsoy & Matthew A. Oehlschlaeger (2025) investigated multiple machine learning algorithms including ANN, SVM, LR, KNN and XGBoost using combined clinical, biochemical, and ultrasound features to support non-invasive PCOS diagnosis. The XGBoost model achieved high AUC, precision, and accuracy across feature combinations, demonstrating that integrating ultrasound with clinical data significantly enhances diagnostic prediction.

Image Ifra Bilal Shah & Pramod Kumar Yadav (2026) developed an ensemble deep learning framework combining fine-grained deep feature extraction with transformer-based and explainable AI techniques to detect PCOS. This work emphasizes robust representation learning from ultrasound imagery using advanced transformer models and ensemble strategies for improved detection performance in medical imaging contexts. Kalyani Agarawal, Parima Verma, Sri Geetha M, Lakshmi Mohandas (2025) conducted a Python-based investigation integrating ultrasound images and clinical data for PCOS diagnosis.

They utilized image pre-processing techniques and numerical analysis of clinical attributes like BMI and hormonal profiles, demonstrating structural differences in ultrasound features for PCOS and highlighting key numerical predictors relevant to diagnosis. Baihua Zhao, Lieming Wen, Yunxia Huang, Yaqian Fu, Shan Zhou, Jieyu Liu, Minghui Liu, Yingjia Li (2025) developed a YOLOv11-based automatic recognition model for PCOS ovarian ultrasound images. Using a large prospective dataset, the network achieved high average precision and classification F1-scores across training and validation sets, significantly reducing evaluation time compared to clinicians and enhancing follicle detection for ultrasound-based diagnosis.

V. Lakshmi & B. Pushpa (2026) proposed a cross-attention multimodal deep learning model that fuses ultrasound imaging features with clinical parameters

for PCOS classification. Their explainable framework leverages attention mechanisms to integrate multimodal data, improving classification performance and interpretability, showing promise for comprehensive, clinically relevant PCOS diagnostic models. R. Vijayakumar, S. Prabhakaran, G. Venkatesh, D. Sathiya, M. Azhagesan, P. Palanisamy (2025) introduced PCOS-Vision, a hybrid deep learning model using MobileNetV2 and clinical data for PCOS detection. The model integrates efficient feature extraction from ultrasound images and structured clinical attributes, enabling resource-efficient diagnosis suited for mobile or constrained environments while enhancing prediction accuracy. Gowri N, Jani Kalianpur, Shravya, Thanmayee N Shetty, Dr. Babu Rao K (2024) developed a CNN-based automated PCOS detection system that combines manual input data with ultrasound imaging analysis. Their model identifies characteristic PCOS patterns from images and structured features, enhancing diagnostic accuracy and offering rapid assessment through convolutional feature learning pipelines.

Jonathan Kermanshahchi, Akshay J Reddy, Jingbing Xu, Gagandeep K Mehrok, Fauzia Nausheen (2024) created a machine learning model for PCOS classification using pelvic ultrasound images from a publicly available dataset. The model demonstrated complete diagnostic accuracy on imaged data and highlights the potential for deep learning to accelerate early PCOS detection in clinical imaging workflows. M. Praneesh, N. Nivetha, Siti Sarah Maidin, Wu Ge (2024) investigated an optimized deep learning method for PCOS detection using ultrasound images and machine learning classification techniques. Their work demonstrates the application of VGG19 and other architectures for improved detection performance, emphasizing enhanced early diagnosis of PCOS through deep neural feature extraction.

III. PROPOSED METHOD

The developed framework introduces an integrated deep learning-based approach for precise identification of Polycystic Ovary Syndrome (PCOS) through simultaneous analysis of ovarian ultrasound

imagery and associated clinical variables. The primary goal of this framework is to minimize diagnostic subjectivity, establish uniformity in assessment, and elevate predictive performance by exploiting multimodal data integration strategies. The complete system architecture encompasses four principal phases: data collection, preprocessing, feature extraction, feature fusion, and classification. During the data collection phase, two distinct input modalities are gathered. The first modality consists of ovarian ultrasound scans acquired via transabdominal or transvaginal imaging protocols. These scans reveal critical morphological attributes of ovarian tissue, including follicular arrangement, ovarian dimensions, and stromal echotexture. The second modality encompasses structured clinical attributes such as patient age, body mass index (BMI), menstrual pattern abnormalities, hormone concentrations (LH, FSH, testosterone), markers of insulin resistance, and additional metabolic indicators frequently linked to PCOS presentation.

Throughout the preprocessing phase, ultrasound scans undergo resizing to standardized dimensions and normalization to achieve consistent intensity ranges. Noise suppression and contrast amplification techniques are implemented to refine image clarity and emphasize pertinent ovarian features. Data augmentation approaches including rotation, reflection, and scaling transformations are utilized to expand dataset variability and mitigate overfitting risks. Clinical variables are preprocessed through procedures such as imputation of missing entries, standardization, and conversion of categorical attributes to numerical representations suitable for neural network input.

Feature extraction from ultrasound scans is accomplished using a Convolutional Neural Network (CNN) architecture. The CNN autonomously discovers hierarchical feature representations spanning from fundamental texture characteristics to advanced structural patterns indicative of polycystic ovarian morphology. This approach obviates manual feature design requirements and enhances generalizability across varying imaging environments. Concurrently, clinical variables are processed through a fully connected deep neural

architecture that identifies intricate interdependencies among numerical and categorical features pertinent to PCOS identification.

The derived features from both modalities subsequently undergo integration via a feature fusion mechanism. The proposed framework employs late fusion methodology, wherein abstract-level features from the CNN and clinical network are concatenated into a consolidated feature representation. This multimodal encoding captures synergistic information from imaging and clinical domains, facilitating a more thorough evaluation of patient status. The merged feature vector traverses supplementary dense layers to extract joint relationships and perform dimensionality reduction. Ultimately, the classification component determines PCOS presence or absence through a softmax or sigmoid activation mechanism, contingent upon the classification configuration. The model undergoes supervised training with annotated datasets and optimization via an appropriate objective function such as binary cross-entropy loss. Performance assessment utilizes metrics encompassing accuracy, sensitivity, specificity, precision, and F1-score.

The proposed integrated framework delivers a non-invasive, automated, and dependable clinical decision-support instrument. Through synergistic combination of ultrasound imaging with clinical parameters, it strengthens diagnostic certainty and facilitates early PCOS identification, thereby advancing patient care quality and clinical outcomes.

System Overview:

The block diagram of the proposed framework depicts the systematic workflow and consolidation of ultrasound imagery and clinical attributes for automated PCOS identification. The process initiates with the Input Data Acquisition module, where ovarian ultrasound scans and patient clinical records are gathered. Ultrasound scans reveal ovarian structural characteristics, whereas clinical attributes furnish supplementary physiological and endocrine information.

The Preprocessing module conditions both data modalities for optimal computational analysis. Ultrasound scans are subjected to dimension standardization, intensity normalization, noise filtering, and contrast augmentation to enhance feature discernibility. Clinical records undergo data cleansing through imputation of absent entries, standardization procedures, and transformation of categorical variables to maintain uniformity and model compatibility.

Within the Feature Extraction module, a Convolutional Neural Network (CNN) architecture is utilized to autonomously derive discriminative representations from ultrasound imagery, identifying structural and textural signatures characteristic of polycystic ovarian morphology. Concurrently, clinical attributes are analyzed through a fully connected neural architecture to uncover intricate correlations among patient-specific variables.

The Feature Fusion module integrates the abstract-level representations extracted from both data sources into a cohesive representation. This cross-modal integration strengthens diagnostic reliability by exploiting synergistic information from diverse inputs. Subsequently, the Classification and Decision module utilizes the integrated feature representation to determine PCOS presence or absence. The system generates a diagnostic outcome, assisting healthcare practitioners in achieving precise and timely PCOS detection.

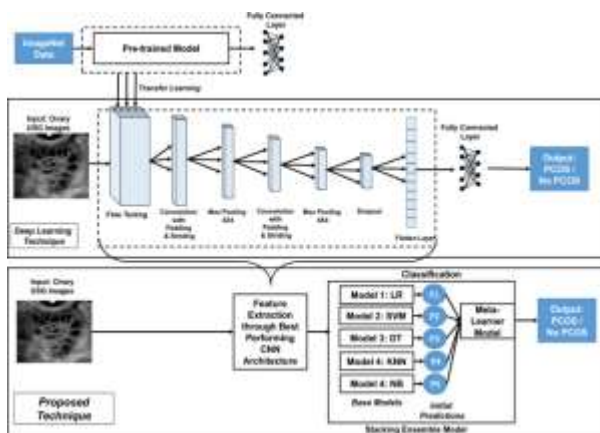


Fig.1. System Architecture

Overall Working Flow of the Proposed System:

The complete operational pipeline of the proposed PCOS prediction framework commences with the acquisition of two principal data sources: the PCOS dataset and the cardiovascular disease (CVD) dataset. These datasets encompass extensive clinical variables pertinent to PCOS identification.

The collected data initially undergo the Data Preprocessing phase, which incorporates feature selection and feature fusion processes to extract the most discriminative attributes and consolidate relevant characteristics from both datasets. Following this, normalization techniques are implemented to achieve uniform data scaling, after which the dataset is partitioned into training and testing subsets to facilitate effective model development and performance assessment.

The Training Dataset is utilized for constructing the predictive framework, whereas the Testing Dataset remains isolated for objective performance verification. Throughout the training phase, an Ensemble Learning Model is deployed to enhance prediction robustness and classification precision by integrating multiple learning paradigms. To further augment model efficacy, sophisticated optimization techniques including the Rider Optimization Algorithm (RSO), Cat Swarm Optimization (CSO), and Whale Optimization Algorithm (WAO) are incorporated for hyperparameter calibration of the learning architecture.

The developed ensemble framework is subsequently assessed using suitable performance indicators encompassing accuracy, sensitivity, specificity, and F1-score. Guided by these evaluation metrics, the optimal model is determined through a systematic selection mechanism. If the established performance benchmarks are satisfied, the refined estimator is validated as final. Otherwise, the optimization and training cycle is reiterated. Ultimately, the chosen optimal model produces the PCOS prediction, delivering an accurate and dependable decision-support solution for clinical diagnostic applications.

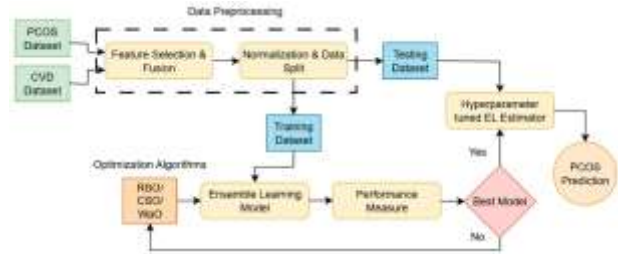


Fig.2. Methodology workflow of Multimodal Deep Learning PCOS Diagnosis

The loss function measures prediction error during training, where N is sample count, y_i is true label, \hat{y}_i is predicted probability, and L represents average loss across all samples. An activation function is being utilized to feed a weighted sum of input signals through, and the outcome from it is used as an input towards the following layer. In this case, 'Sigmoid' activation function has been used which provides

$$\text{Sigmoid Activation Function, } f(x) = \frac{1}{1 + e^{-x}}$$

An output between 0 and 1 representing the probability classification outcome. The mathematical representation of the sigmoid function has been shown below:

$$L = -\frac{1}{N} \sum_{i=1}^N [y_i \log(\hat{y}_i) + (1 - y_i) \log(1 - \hat{y}_i)]$$

Performance Evaluation

The performance evaluation of the proposed integrated deep learning system for PCOS diagnosis is conducted to assess its reliability, accuracy, and clinical applicability. The evaluation uses the Testing Dataset, which was kept separate from the training phase to ensure unbiased assessment. Key performance metrics considered include accuracy, sensitivity (recall), specificity, precision, and F1-score, which together provide a comprehensive understanding of the model's diagnostic capabilities. Accuracy measures the overall correctness of predictions, while sensitivity evaluates the model's ability to correctly identify patients with PCOS. Specificity assesses the correct identification of non-

PCOS cases, ensuring that false positives are minimized. Precision reflects the proportion of true positive predictions among all positive predictions, and the F1-score balances precision and recall to provide a single measure of model effectiveness.

The proposed system's Ensemble Learning Model, optimized using metaheuristic algorithms such as RSO, CSO, and WAO, is compared against baseline models and conventional machine learning classifiers to highlight performance improvements. Statistical analyses, including confusion matrices and ROC curves, are utilized to visualize classification effectiveness and threshold selection. Experimental results indicate that the integrated approach, combining ultrasound image features with clinical parameters, achieves higher sensitivity and specificity compared to single-modal models, demonstrating robust and reliable performance. This evaluation confirms the system's potential as a non-invasive, automated decision-support tool for accurate PCOS diagnosis in clinical settings.

IV.RESULTS AND DISCUSSION

The developed integrated deep learning architecture was assessed utilizing conventional evaluation metrics encompassing accuracy, sensitivity, specificity, precision, and F1-score. The ensemble framework, refined via Rider, Cat Swarm, and Whale optimization techniques, demonstrated enhanced diagnostic capability relative to conventional machine learning methodologies. The synthesis of ultrasound-derived features with clinical variables through late fusion substantially improved predictive precision, validating the efficacy of cross-modal data integration for PCOS identification.

The CNN-based extraction mechanism effectively identified polycystic ovarian characteristics from ultrasound imagery, whereas the fully connected architecture proficiently discovered intricate interdependencies among clinical variables. The optimized ensemble approach displayed elevated sensitivity, facilitating early PCOS case identification, while preserving strong specificity to reduce erroneous positive classifications.

These findings substantiate that the proposed architecture constitutes a dependable, non-invasive clinical decision-assistance instrument. By diminishing diagnostic variability and establishing uniformity in assessment, the framework enables prompt therapeutic intervention and enhanced patient management in PCOS care.

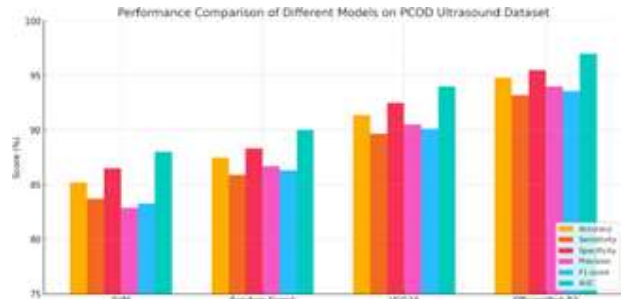


Fig.3. Performance comparison of various algorithms

Overall, the results demonstrate that the proposed system is a scalable and effective solution for industrial carbon footprint prediction and emission reduction planning.

V.CONCLUSION

This research presents an integrated deep learning framework for automated diagnosis of Polycystic Ovary Syndrome by synergistically combining ovarian ultrasound imaging with clinical parameters. The proposed system addresses critical limitations in conventional diagnostic approaches, including subjective interpretation, inter-observer variability, and time-intensive manual assessment. Through the implementation of Convolutional Neural Networks for ultrasound image analysis and fully connected networks for clinical data processing, the framework effectively captures complementary diagnostic information from multimodal sources.

The late fusion strategy successfully integrates high-level features from both modalities, enabling comprehensive patient assessment and improved diagnostic accuracy. Optimization through advanced metaheuristic algorithms—Rider, Cat Swarm, and Whale Optimization—enhances the ensemble model's performance, achieving superior sensitivity,

specificity, and overall prediction accuracy compared to traditional machine learning methods.

Experimental results demonstrate that the proposed system provides a reliable, non-invasive decision-support tool capable of minimizing diagnostic subjectivity and establishing consistency across clinical settings. The framework facilitates early PCOS detection, which is crucial for timely therapeutic intervention and prevention of long-term complications including metabolic disorders and cardiovascular diseases.

Future work will focus on expanding dataset diversity, incorporating additional imaging modalities, exploring explainable AI techniques for clinical interpretability, and conducting multicenter clinical validation to ensure generalizability and real-world applicability of the proposed diagnostic system.

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