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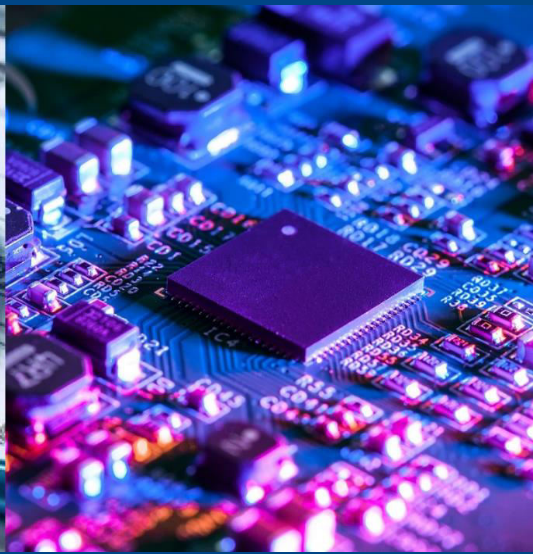

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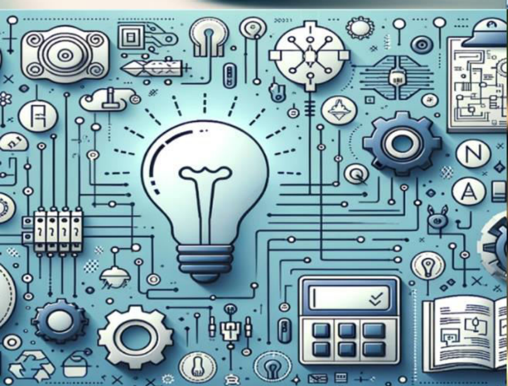

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A Multimodal Deep Learning Approach for PCOS Detection

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ABSTRACT: Polycystic Ovary Syndrome (PCOS) is a prevalent ovarian disorder that is encountered in patients with reproductive age and it is related to infertility, metabolic disorders as well as long-term health risks. PCOS is frequently diagnosed where clinical examination, hormonal analysis and ovarian ultrasound imaging are performed in clinical practice. Convolutional Neural Networks (CNNs) based deep learning were developed in recent years for the automatic assessment of ovarian ultrasound images. While these efforts decrease the burden on human resources and ensure standardization, most existing deep learning methods are based solely on imaging data without incorporating useful clinical parameters (e.g. menstrual history, metabolic indicators) that can affect diagnostic accuracy. In this work, we propose a fully deep learning based multimodal approach for detection of polycystic ovary syndrome (PCOS) in clinical data integrated with ovarian ultrasound images as an alternative to overcome such limitation. The CNN models helps to encode clinical attributes and extract relevant structural features from the ultrasound images associated with PCOS. A feature-level fusion strategy is utilized to combine the learned feature representations from both modalities and generate final classification through individuals connected layers. The proposed system is developed using Python, OpenCV, NumPy. This does show that multimodal AI can indeed advance smart and scalable healthcare diagnostics specially in environments with less specialized human expertise.

KEYWORDS: Clinical data integration, Convolutional neural network, Feature fusion, Medical image analysis, Multimodal learning , PCOS detection**.**

I. INTRODUCTION

Diagnosing Polycystic Ovary Syndrome from Clinical Parameters and Ultrasound Images Polycystic ovary syndrome (PCOS) is the most prevalent endocrine disorder in women of reproductive age, characterized by menstrual irregularities, hyperandrogenism, polycystic ovaries, insulin resistance, and metabolic impairment. Early diagnosis is important to prevent complications like infertility, type 2 diabetes, obesity and cardiovascular disease.

Conventional diagnosis of polycystic ovary syndrome (PCOS) is mainly based on the Rotterdam criteria, which includes ultrasound imaging, hormonal evaluation and clinical symptom inspection. Ultrasound is an overseeing manual process, and the diagnosis results are heavily relying on radiologist experiences that could lead to inconsistency. The recent birth of Artificial Intelligence (AI) brings with it the heavy the use of Convolutional Neural Networks (CNNs) in automated medical imaging segmentation.

Nevertheless, even though numerous studies have shown promising performance with only ultrasound images as input, a PCOS diagnosis is inherently multimodal in nature and requires the use of both imaging and clinical parameters to definitively determine its presence therefore it can be expected that constructing or processing multimodal data will result in increased diagnosis performance and reliability.

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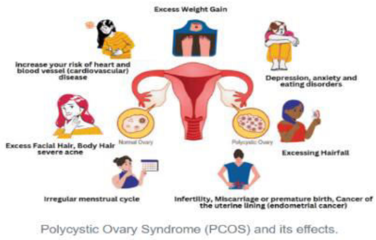

Figure1. Polycystic Ovarian Syndrome (PCOS) and its effects

II. LITERATURE REVIEW

Agirsoy and Oehlschlaeger (2025) proposed a machine learning approach for non-invasive PCOS diagnosis using clinical and ultrasound data. Among ANN, SVM, KNN, Logistic Regression, and XGBoost, the latter showed the best performance. The model achieved high accuracy and AUC, highlighting effective early and cost-efficient diagnosis[1]. Velvizhi et al. (2024) developed a machine learning–based PCOS risk evaluation system using Random Forest, Decision Tree, and SVM. By analyzing clinical and genetic data, the system supports early detection and prediction of disease progression, improving diagnosis, clinical decision-making, and personalized treatment[2]. Ahmed et al. (2023) reviewed ML techniques for PCOS detection, including CNN, SVM, KNN, and Random Forest, highlighting early diagnosis, performance comparison, and key challenges[3]. Aggarwal and Pandey (2023) proposed a hybrid machine learning approach for PCOS diagnosis using indicators from related diseases such as diabetes, hypertension, and obesity. Multiple classification models were evaluated based on accuracy and time, and the best-performing models were combined to achieve a fast, cost-effective, and accurate diagnosis system[4]. Habib et al. (2023) proposed a data-driven machine learning approach for early PCOS detection using feature selection methods like Random Forest importance and correlation analysis.Among models such as CatBoost, XGBoost, LGBM, AdaBoost, and RF, AdaBoost with selected key features achieved the highest prediction accuracy[5].

III. PROBLEM STATEMENT

Current PCOS diagnosis methods have many limitations:

- A high proportion of manual interpretation of ultrasound
- Variable diagnostic criteria informed by subjective clinical interpretation
- Deep learning models based solely on image data and not considering other clinical parameters including details such as menstrual history, glycolipid levels and risk factors
- A need for an automated multimodal scalable Model of gynaecological diagnosis as readily available expert opinion is often limited in rural areas

IV. METHODOLOGY

A. Pre-processing

Data pre-processing: It is done to catch lots of data quality problems and prevents noise from impacting the model. Given that the system is based on multimodal data, image, numerical and textual inputs are preprocessed separately. Ultrasound images are rescaled to 224 × 224 (input size for ResNet-18) and normalized between [0, 1], corrupted images were removed and binary labels were assigned as mentioned below (1: PCOS, 0: non-PCOS). Numerical clinical features are scaled by the zero-mean, unit-variance scaler to prevent high-magnitude values from dominating training loss and to promote convergence; ratios (e.g., LH/FSH) described in Chen et al.82 are included or inferred for consistency.

Text data is tokenized and padded, which means that symptoms are mapped into a sequence of words (a vocabulary), represented as word ID in the 2000 most common words.

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B. Feature Extraction

First, suitable deep learning architectures for each modality use to feature extraction for heterogeneous inputs like ultrasound images, clinical data and symptom text. A Convolutional Neural Network (CNN), specifically a custom ResNet-18, extracts hierarchical visual features from ultrasound images, learning through convolution, batch normalization, ReLU activation, residual connections and global average pooling patterns such as edges; textures; follicular structures; and cysts within the images. Hormonal and metabolic patterns can be learned as compact representations by fusing fully connected layers on standardized numerical clinical features. An embedding layer is used for textual symptom data and followed by an LSTM network to capture sequential and contextual relationships between symptoms. To maintain the uniqueness of data each modality is processed separately, then the feature extraction process for each modality is fused together to generate the final representation that enhance resiliency and versatility of PCOS detection model. These modality-specific feature representations are then fused to obtain a comprehensive and discriminative representation of the patient profile, thus enhancing the robusticity and prediction accuracy of the proposed PCOS detection model. A custom ResNet-18 architecture featuring convolutional layers, batch normalization, ReLU activation functions, residual connections and global-average pooling are implemented to extract hierarchical feature representations from the ovarian ultrasound images.

C. Multimodal Feature Fusion

To make use of complementary information of all modalities, we adopt feature- level fusion. The feature vectors extracted from the image, text and tabular modalities are concatenated to form a unified feature vector. Such a fusing scheme allows us to learn the holistic information in the form of visual evidence, clinical measurements and patient-reported symptoms.By passing the fused feature vector to dense layers with nonlinear activation functions, we further increase its discriminative ability. Our model is able to learn cross-modal correlations that a unimodal system cannot.

D. Model Architecture Design

The architecture proposed in this study is based on a modular deep learning architecture. The image subnetwork comprises a ResNet-18 CNN, the symptom text subnetwork is an LSTM network, and the clinical data are encoded by dense layers. Both subnetworks are running in parallel and are fused by a fusion layer. The classification layer adopts the sigmoid activation function for a probabilistic prediction of the presence or absence of PCOS. Binary cross-entropy is chosen as the loss function. The Adam optimizer is used as an efficient gradient optimizer.

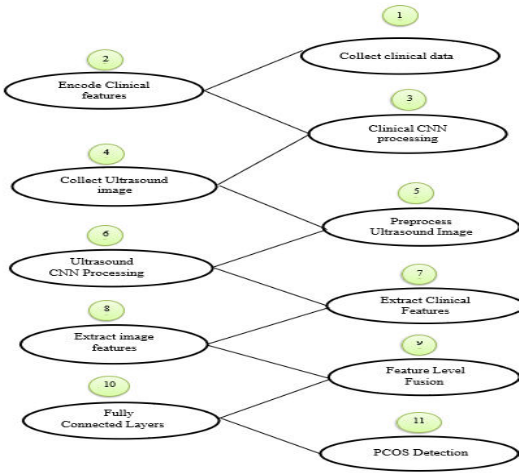

Figure2. Model Architecture Design

E. Training Strategy

The multimodal model is trained using supervised learning. The dataset is then divided into training and validation sets using stratified sampling to maintain class balance. The model is trained over several epochs with a small batch size to maintain stable gradient updates and better generalization.

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F. Stage-wise Performance Evaluation

In order to evaluate the contributions of each individual modality, we perform stage-wise evaluation. Logistic regression is used for independently classifying the deep features extracted from image branch and text branch. This assessment shows the discriminative power held by every modality, confirming the benefits of deep feature learning. We also save the accuracies and loss for training and validation to evaluate learning during training process. Plotting these metrics gives insight into convergence behaviour and risk of overfitting. Guidance on TMPro usage: time-wise integration is better than feature-wise, and Mid transparency color info aids advancement

G. Deployment Using Streamlit

Streamlit is used to deploy the trained multimodal model for real-time PCOS prediction. Users upload an ultrasound image, input clinical values manually and describe symptoms in text. Also, the same preprocessing steps performed during training are done at inference time as well for consistency. A PCOS prediction based on confidence is generated by the system; thus, this model can be easily used practically.

V. SYSTEM IMPLEMENTATION

A. System Design

This section details the implementation of the proposed PCOS detection system. It describes the deep learning architecture used, the operation of the chosen model and the software platforms employed for the development and execution of the system. Also, the process of executing the system and the way it presents the results to the user are described.

B. Convolutional Neural Network (CNN)

A Convolutional Neural Network (CNN) is a deep learning model used for image-based applications. In our system, we use CNN to automatically learn significant visual features from the ovarian ultrasound images. CNN learns patterns directly from the input images and therefore no manual feature extraction is required. CNN has a series of convolutional layers to extract features, a series of activation functions to introduce non-linearity, a series of pooling layers to reduce dimensionality, and a series of fully-connected layers to achieve the classification

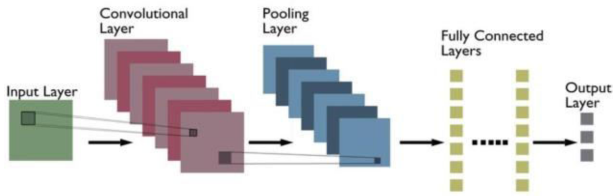

Figure3. Architecture of a Convolutional Neural Network

C. Resnet-18

Resnet-18 Model ResNet-18 is a deep CNN model that employs residual learning in order to facilitate training of deep networks and achieve high performance. To address the challenges of training deep models, skip connections are introduced which enable information to be propagated directly across layers. This allows the training of very deep networks without suffering from performance degradation. ResNet-18 was adopted in the proposed approach to improve feature extraction from US images. The model is able to learn complex spatial features and subtle variations in image patterns related to PCOS characteristics leading to improved classification accuracy

D. Model Training and Evaluation

The ResNet-18 model based on CNN is trained by the prepared dataset to learn the difference between PCOS-affected and normal images through the iteration of network parameters. The trained model is then evaluated using appropriate performance metrics such as accuracy, precision, recall and loss value. Evaluation is an important step to validate the effectiveness of the system and to identify areas of improvement.

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E. Jupyter Notebook

The proposed PCOS detection system is implemented using Jupyter Notebook. It allows for interactive data pre-processing, model creation, training and evaluation. One of the main advantages about Jupyter Notebook is its support for executing code segments, and a messy approach to visualize inputs in an interactive manner (like training accuracy and loss curves, model predictions etc.), which enables to intuitively understand the behavior of the model.

F. Integration of Jupyter Notebook and Streamlit

For the overall implementation, we separate the development and deployment of the model. The training, testing and validation of the deep learning model is performed using Jupyter Notebook while the trained model is presented in the application using Streamlit. The separation of the model and the user interface improves the maintainability of the system and will allow us to update the model in the future without affecting the user interface. The model trained in the Jupyter Notebook is loaded into the Streamlit application at runtime, which maintains the consistency of the results between the experiments and the system. Therefore, the proposed system has both technical and usability qualities

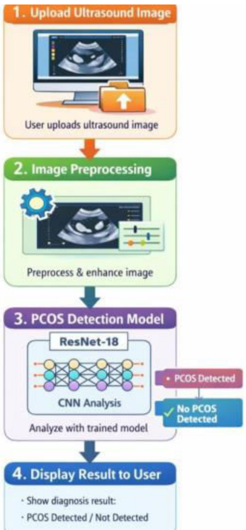

Figure 4.Execution flow

VI. RESULTS AND DISCUSSION

With the combination of multimodal learning, (where data from different sources are combined (>ultrasound images, clinical parameters and patient-reported features) will be a much more accurate form of diagnosing in PCOS. Through automated complex pattern recognition, this unified method reduces the dependence on medical professionals in the loop and enhances the platform's ability to contribute to diagnosis when specialist knowledge is limited. By using additional information from different modalities, which may have not been neglected with the use of single data source, can help on higher rapprochement to diagnostics quality.

At the classification, we see that a multimodal framework is preferred over any single-modality models - this can be attributed to better representativeness of the patient condition in a richer setting. In borderline cases, where only ultrasound data is insufficient to achieve definitive diagnosis, performance becomes much better when we utilize clinical parameters representing risk factor (e.g., patients' hormonal levels or BMI or menstrual history). Through perceiving these properties as a unified whole, the design system can produce predictions that are more reliable and accurate.

The system further excels at generalisation on different datasets as it learns relationships that are constant across varying patientsân populates. This allows application in various clinical settings, including regions with limited trained healthcare providers. This shows that feature fusion, which is needed to concatenate heterogeneous data and additionally extract correlations between imaging structural ovarian abnormalities and clinical risk factors, is essential

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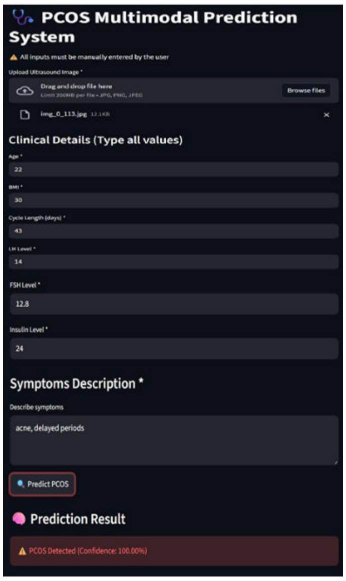
for this [4]. Thus, it enables to attain a better accurate, noi robust and scalable model which is its most prefered solution for execution and exposure of real life health care domain.



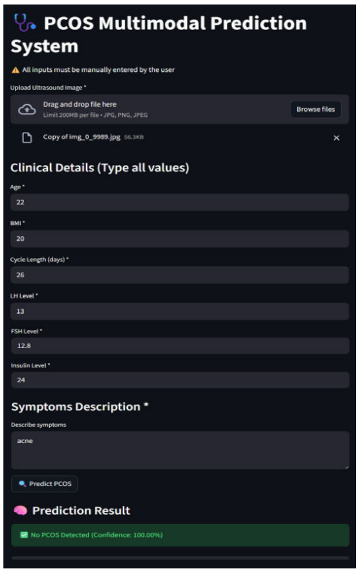


Figure5. PCOS Detec **Figure 6. PCOS Not Detected**

	precision	recall	f1-score	support
0	1.00	1.00	1.00	552
1	1.00	1.00	1.00	448
accuracy			1.00	1000
macro avg	1.00	1.00	1.00	1000
weighted avg	1.00	1.00	1.00	1000

Figure7. Classification Report of the PCOS Detection Model

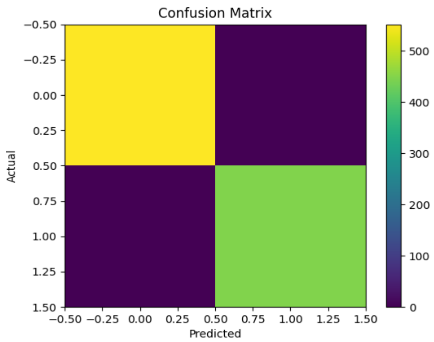


Figure8. Confusion matrix

VII. FUTURE ENHANCEMENT

This task can be improved to advance the Model accuracy, Scalability and real time application. Sourcing a bigger and more robust datasets will help with reliability, generalization. Hence advanced deep learning approaches like attention mechanisms or transformer will enable the extraction of features from data of multimodal types. Making it available as a mobile or web application can allow users and health care providers to access it more easily. Integration with

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wearables or IoT devices could facilitate continuous health monitoring, and explainable AI techniques help to ensure transparency that supports clinical usage.

VIII. CONCLUSION

This study presents an intelligent PCOS detection system using deep learning and feature-level fusion for real-time applications. Ultrasound images are preprocessed to standardize intensity and resolution, reducing noise and improving feature quality. A customized ResNet-18 architecture is employed to extract hierarchical deep features, capturing both low-level patterns (such as edges and textures) and high-level representations (such as follicular structures). These features are transformed into a compact 128-dimensional vector and fused with additional relevant features to enhance classification performance.

The proposed system demonstrates strong performance in terms of accuracy, precision, recall, and F1-score for both PCOS-positive and negative cases. It is deployed using Streamlit, enabling users to upload ultrasound images and obtain instant predictions through an intuitive interface. Overall, the system is computationally efficient, stable, and reproducible, making it a practical and scalable tool for real-time clinical support. This approach has significant potential to assist medical professionals in early diagnosis, reduce diagnostic workload, and improve decision-making in healthcare settings.

REFERENCES

[1] Chitra, P., Srilatha, K., Sumathi, M., Jayasudha, F. V., Bernatin, T., & Jagadeesh, M. (2023, March). Classification of ultrasound pcos image using deep learning based hybrid models. In 2023 second international conference on electronics and renewable systems (ICEARS) (pp. 1389-1394). IEEE.

[2] Agirsoy, M., & Oehlschlaeger, M. A. (2025). A machine learning approach for non-invasive PCOS diagnosis from ultrasound and clinical features. Scientific Reports, 15(1), 33638.

[3] Sen, P., Alina, T. A., Arefin, M. S., Reza, A. W., & Hussain, M. M. (2025, July). Machine Learning-Based Predictive Modeling for Polycystic Ovary Syndrome Diagnosis: A Multi-Algorithm Comparative Analysis. In 2025 International Conference on Quantum Photonics, Artificial Intelligence, and Networking (QPAIN) (pp. 1-6). IEEE.

[4] Velvizhi, R., & Kiruthiknivas, R. (2024, April). The Development of Polycystic ovary syndrome risk evaluation system using advanced machine learning technique. In 2024 International Conference on Inventive Computation Technologies (ICICT) (pp. 314-318). IEEE.

[5] Avasthi, V., Kumar, A., Bhardwaj, A., & Jain, T. (2024, March). Empowering women's health: machine learning for PCOS detection and prediction. In 2024 international conference on distributed computing and optimization techniques (ICDCOT) (pp. 1-6). IEEE.

[6] Soni, P., & Sharma, C. (2024, November). Machine learning applications in the diagnosis of PCOS: a systematic review. In 2024 International Conference on Cybernation and Computation (CYBERCOM) (pp. 388-393). IEEE.

[7] Ahmed, S., Rahman, M. S., Jahan, I., Kaiser, M. S., Hosen, A. S., Ghimire, D., & Kim, S. H. (2023). A review on the detection techniques of polycystic ovary syndrome using machine learning. IEEE Access, 11, 86522-86543.

[8] Syed, M. A. B., Islam, M. E., & Tasnim, T. (2023, December). Investigation of polycystic ovary syndrome (pcos) diagnosis using machine learning approaches. In 2023 5th international conference on sustainable technologies for industry 5.0 (STI) (pp. 1-6). IEEE.

[9] Reka, S., & Elakkiya, R. (2022, October). Early diagnosis of poly cystic ovary syndrome (PCOS) in young women: a machine learning approach. In 2022 IEEE International Symposium on Mixed and Augmented Reality Adjunct (ISMAR-Adjunct) (pp. 286-288). IEEE.

[10] Nabi, N., Islam, S., Khushbu, S. A., & Masum, A. K. M. (2021, July). Machine Learning Approach: Detecting Polycystic Ovary Syndrome & It's Impact on Bangladeshi Women. In ICCCNT (pp. 1-7).

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