Project: Early Detection of Polycystic Ovary Syndrome

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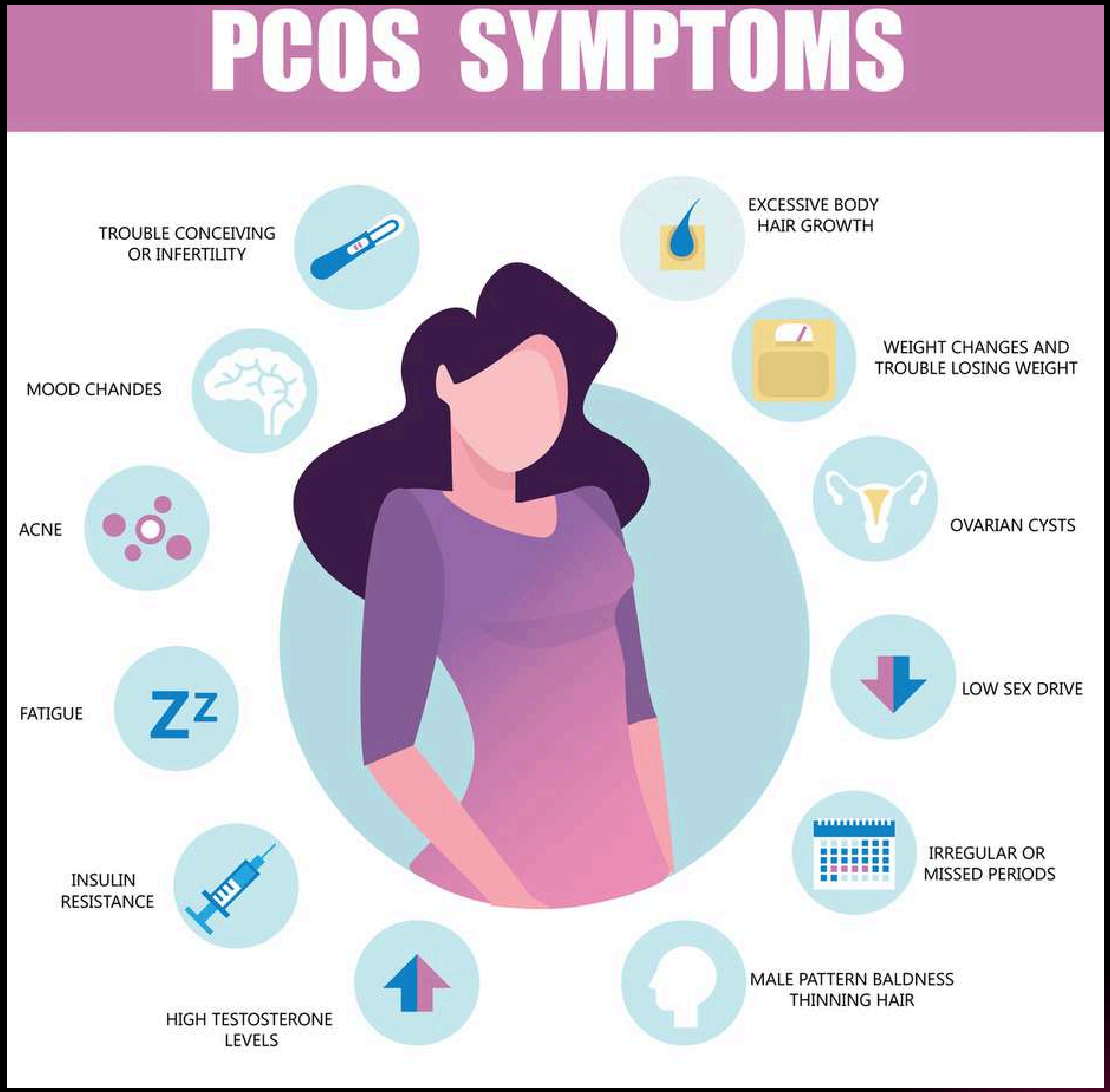
Problem Statement

PCOS (Polycystic Ovary Syndrome) is a common health problem in women that affects their hormones, metabolism, and overall well-being. Despite its prevalence, PCOS is often diagnosed late due to its complex symptoms, such as irregular menstruation, excessive androgen levels, and ovarian cysts. This delay in diagnosis can lead to complications like infertility, diabetes, cardiovascular diseases, and mental health issues.

Solution:

We are developing a machine learning model to detect PCOS early using image-based data. Our dataset consists of images categorized as infected (PCOS-affected) and non-infected (healthy) ovaries. By training the model to recognize patterns in these images, we aim to improve early detection, making diagnosis faster and more accurate, ultimately helping women receive timely treatment.



POTENTIAL APPLICATIONS

- **Faster PCOS Detection:** The model can quickly analyze medical images like ultrasound scans to spot signs of PCOS early.
- **Helping Doctors with Diagnosis:** Doctors can use the AI tool to make PCOS detection more accurate and efficient.

POTENTIAL IMAPCT

- Detecting PCOS early can help women get the right treatment sooner and avoid bigger health problems.
- Women can track their health and make informed lifestyle choices to manage PCOS.

LITERATURE REVIEW

Polycystic Ovary Syndrome or PCOS represents one of the most prevalent endocrinological disorders affecting women of reproductive age worldwide, with significant implications for fertility, metabolic health, and long-term well-being.

Research from recent years indicates that artificial intelligence and machine learning methods have shown a lot of promise in improving the accuracy, efficiency, and accessibility of PCOS diagnosis, addressing longstanding challenges in traditional detection methods.

Barrera FJ, Brown EDL, Rojo A, Obeso J, Plata H, Lincango EP, Terry N, Rodríguez-Gutiérrez R, Hall JE, Shekhar S, 2023. Application of Machine Learning and Artificial Intelligence in the Diagnosis and Classification of Polycystic Ovarian Syndrome: A Systematic Review. Frontiers in Endocrinology.

Main Research Papers for Reference

Authors	Technique Used	Objective of the Study	Year
A. Denny, A. Raj, A. Ashok, C. M. Ram and R. George	"i-HOPE: Detection And Prediction System For Polycystic Ovary Syndrome (PCOS) Using Machine Learning Techniques	PCOS detection using machine learning techniques	2019
Silva IS, Ferreira CN, Costa LBX, Sóter MO, Carvalho LML, de C Albuquerque J, Sales MF, Candido AL, Reis FM, Veloso AA, Gomes KB	Polycystic ovary syndrome: clinical and laboratory variables related to new phenotypes using machine-learning models	Identification of PCOS	2022
Kumar, S., Sharma, R., & Singh, S.	BorutaShap feature selection, Random Forest classifier	PCOS prediction and patient clustering using clinical/biochemical data	2021
Singh, S., Kumar, S., & Sharma, R.	Deep learning (VGGNet16), XGBoost ensemble	PCOS prediction using ultrasound images	2022
Tiwari, R., Singh, S., & Sharma, K.	Integrated transfer learning-based CNN (ITL-CNN)	Automated classification of PCOS from ultrasound images	2022
Sharma, P., Verma, A., & Singh, R.	Explainable ML framework, local/global explanations	Explainable detection of PCOS	2023
Patel, R., Gupta, N., & Mehta, S.	Mutual information, web-based ML model	Early detection of PCOS via accessible web platform	2024
Doi, K.	Computer-aided diagnosis in medical imaging: Historical review, current status and future potential	Computerized Medical Imaging and Graphics	2007
Barrera FJ, Brown EDL, Rojo A, Obeso J, Plata H, Lincango EP, Terry N, Rodríguez-Gutiérrez R, Hall JE, Shekhar S	Application of Machine Learning and Artificial Intelligence in the Diagnosis and Classification of Polycystic Ovarian Syndrome: A Systematic Review	PCOS detection	2023

Evolution of PCOS Detection
From Traditional to AI-Driven Methods

Traditional diagnosis relied on clinical expertise, lab tests, and manual ultrasound interpretation, but faced challenges:

- High inter-observer variability
- Time-consuming and subjective processes
- Limited early detection before symptoms appear

The introduction of computational methods in 2007 marked a turning point, enabling algorithmic detection of ovarian morphology in ultrasound images and paving the way for machine learning applications.

Early computational approaches (2007–2015) used basic machine learning algorithms (e.g., SVM, decision trees) and established proof-of-concept for automated diagnosis.

M. J. Lawrence, M. G. Eramian, R. A. Pierson and E. Neufeld, "Computer Assisted Detection of Polycystic Ovary Morphology in Ultrasound Images," Fourth Canadian Conference on Computer and Robot Vision (CRV '07), Montreal, QC, Canada, 2007, pp. 105-112

Gap: Need for Early Detection

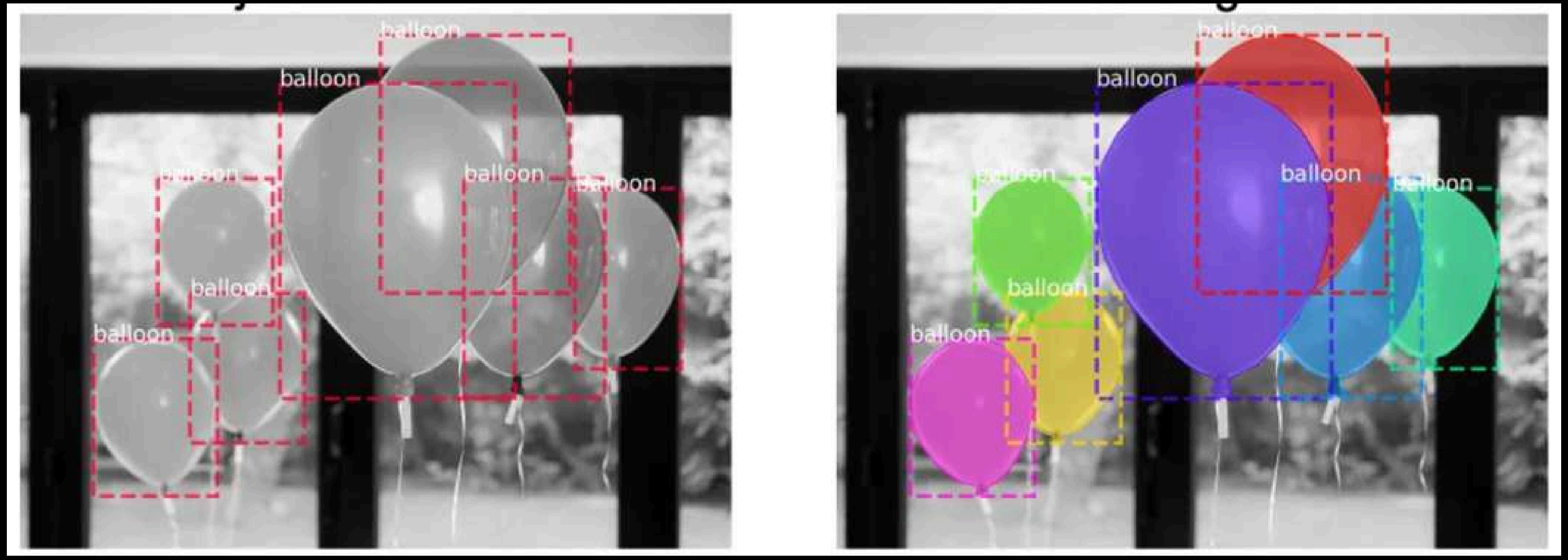
Many previous approaches focus on classifying images or detecting regions of interest without achieving precise, pixel-level segmentation of ovarian follicles and cysts. This limits the ability to accurately quantify and characterize relevant structures essential for early diagnosis

Despite progress, current research has key gaps:
Most image-based models focus on classification, not precise segmentation of ovarian structures.
Early-stage or pre-symptomatic PCOS detection remains underexplored.
There is limited integration of real-time feedback and adaptability across diverse populations and imaging equipment.

There is a demand for automated, robust, and accurate systems that can detect, segment, and classify PCOS directly from ultrasound images, reducing manual workload and improving reproducibility

Focus of Research

Mask-RCNN offers a promising solution:
Enabling pixel-level segmentation and classification of individual follicles and ovarian features in ultrasound images,
and the potential to detect subtle morphological changes before full symptom development, supporting truly early intervention.



Classification VS Segmentation

Project significance:
Developing a fast, accurate Mask-RCNN model could fill a critical gap, enabling timely diagnosis and improved outcomes for women with PCOS.
Early detection supports fertility preservation, better metabolic health, and improved psychological well-being.

Gopalakrishnan, C., & Iyapparaja, M. (2022). ITL-CNN: Integrated Transfer Learning-Based Convolution Neural Network for Ultrasound PCOS Image Classification. International Journal of Pattern Recognition and Artificial Intelligence, 36(16), 2240002.

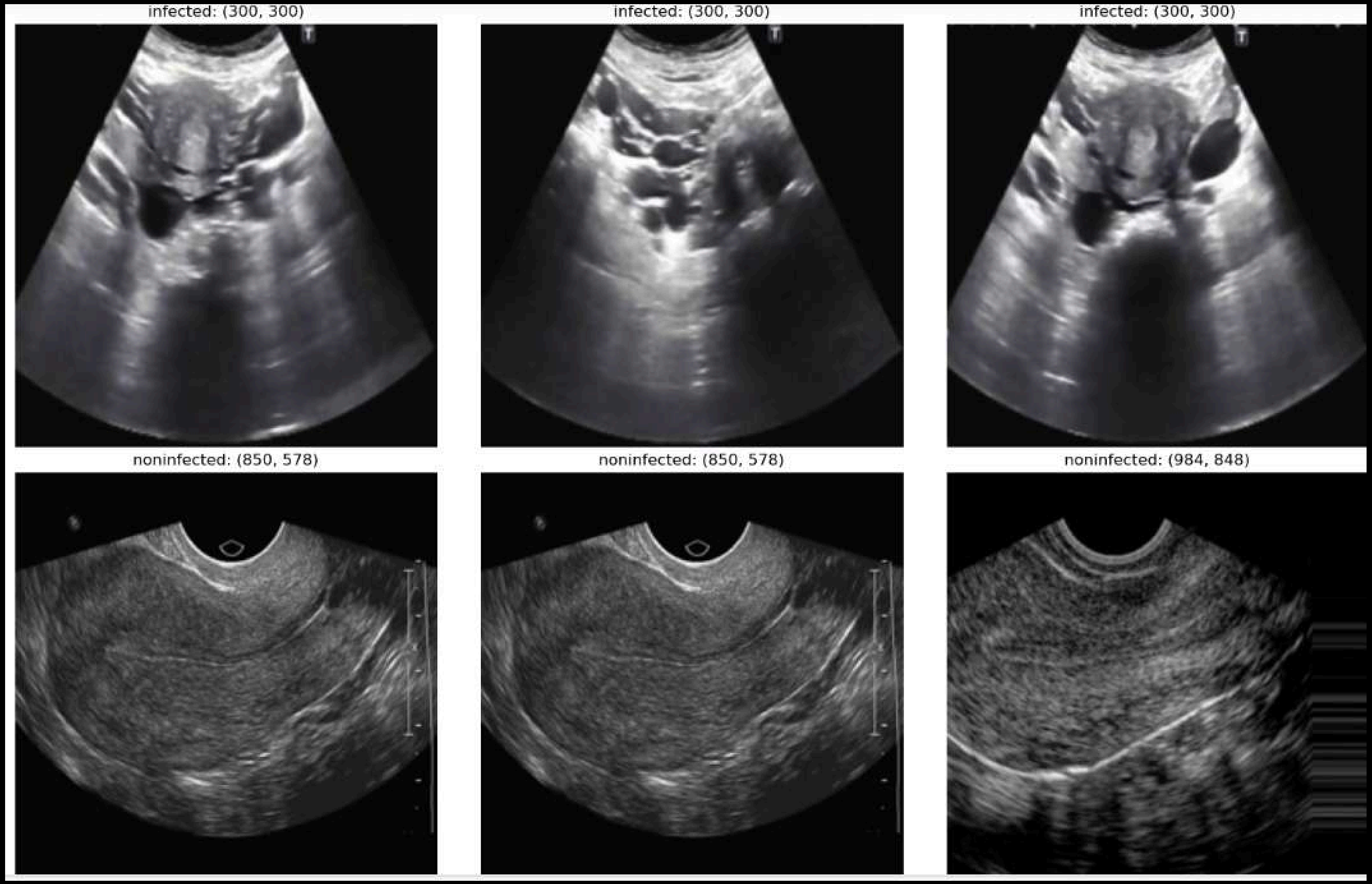
Dataset and Feature Preprocessing

About the Dataset:

- The dataset comprises of 3859 ultrasound images of ovaries.
- During our literature review, we identified a paper with noteworthy findings and high accuracy for PCOS detection.
- We contacted the authors of the paper and obtained a large, high-quality dataset with clear ultrasound images suitable for detection tasks.
- Although the authors did not explicitly mention the source of their dataset, the paper was published in the 2024 Asia Pacific Conference on Innovation in Technology (APCIT).
- Given the reputed conference and the fact that the authors are professors and students from VIT, we assumed the data is credible.
- The authors also indicated that there were no ethical concerns involved in data collection.

Data Preprocessing

Data Sample:



1. Handling Missing Features-

We haven't explicitly handled missing features in the dataset yet since there were no missing values. However, if we were to encounter missing values in the images (e.g., corrupted files or unreadable formats), we would consider interpolation methods like mean pixel value replacement or nearest neighbor interpolation to fill in gaps.

In [24]:

```python
from PIL import Image

# Check for corrupted images
for category in categories:
    category_dir = os.path.join(data_dir, category)
    for image_file in os.listdir(category_dir):
        img_path = os.path.join(category_dir, image_file)
        try:
            with Image.open(img_path) as img:
                img.verify()  # Verify if the image can be opened
                print("no corrupted image")
        except (IOError, SyntaxError) as e:
            print(f"Corrupted image found: {img_path}")
```

```
no corrupted image
no corrupted image
no corrupted image
no corrupted image
no corrupted image
no corrupted image
no corrupted image
no corrupted image
no corrupted image
no corrupted image
no corrupted image
no corrupted image
no corrupted image
no corrupted image
no corrupted image
no corrupted image
no corrupted image
no corrupted image
no corrupted image
```

In [*]:

```python
import numpy as np
import cv2

# Check for blank or black images
for category in categories:
    category_dir = os.path.join(data_dir, category)
    for image_file in os.listdir(category_dir):
        img_path = os.path.join(category_dir, image_file)
        img = cv2.imread(img_path, cv2.IMREAD_GRAYSCALE)
        if img is None:
            print(f"Unreadable image: {img_path}")
            continue

        #
        mean_pixel_value = np.mean(img)


        if mean_pixel_value < 5:
            print(f"Blank/Black image found: {img_path}, Mean pixel value: {mean_pixel_value}")
        else:
            print("no blank image found")
```

```
no blank image found
no blank image found
no blank image found
no blank image found
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no blank image found
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no blank image found
no blank image found
no blank image found
```
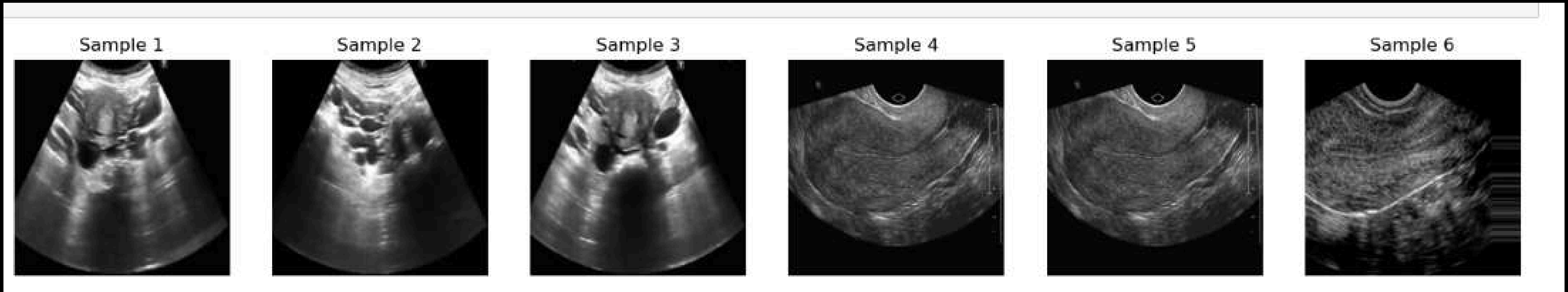

2.Resizing:

All input images are resized to a standard resolution of 256 × 256 pixels.

3.Data Augmentation (Training Only)

A random horizontal flip is applied with a probability of 0.5 to improve model generalization and robustness.

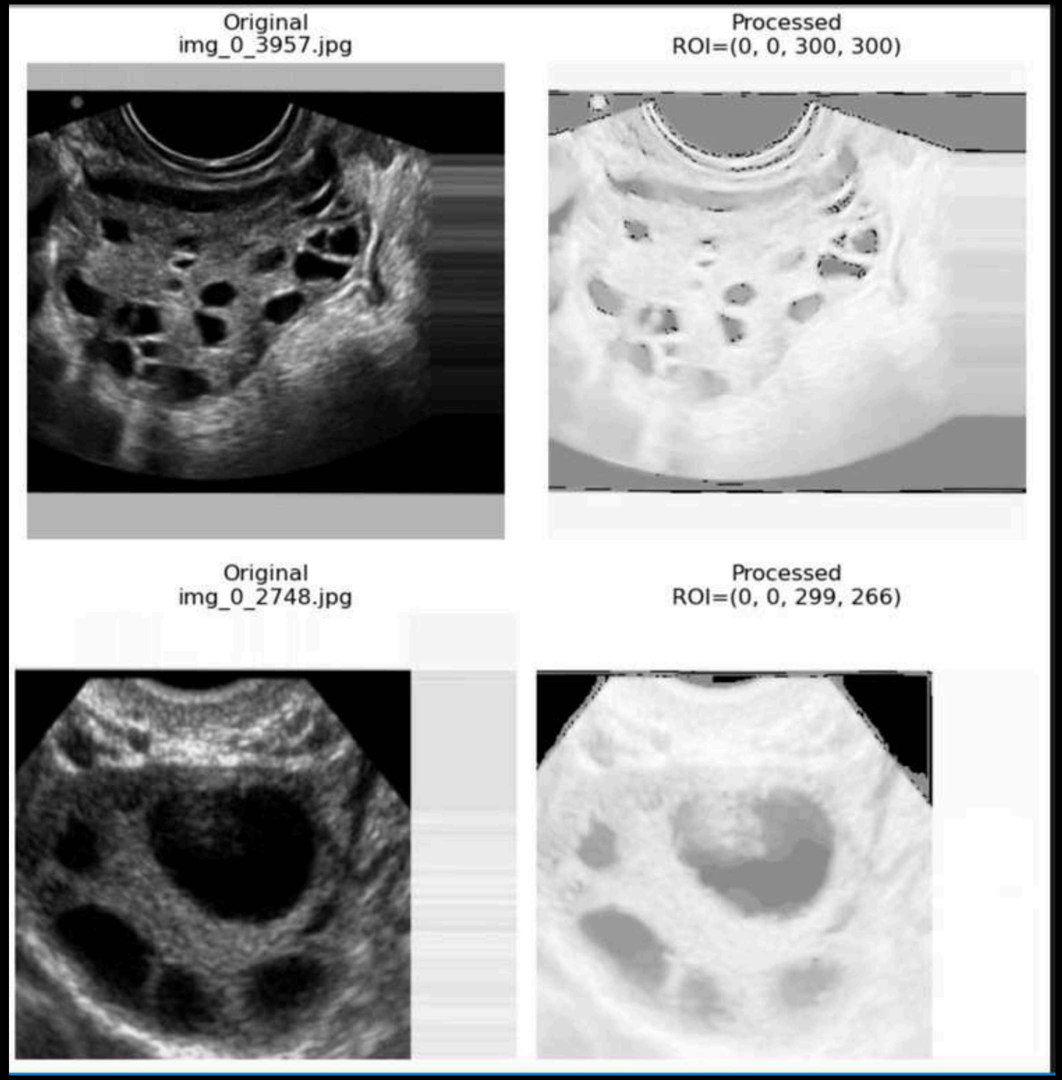


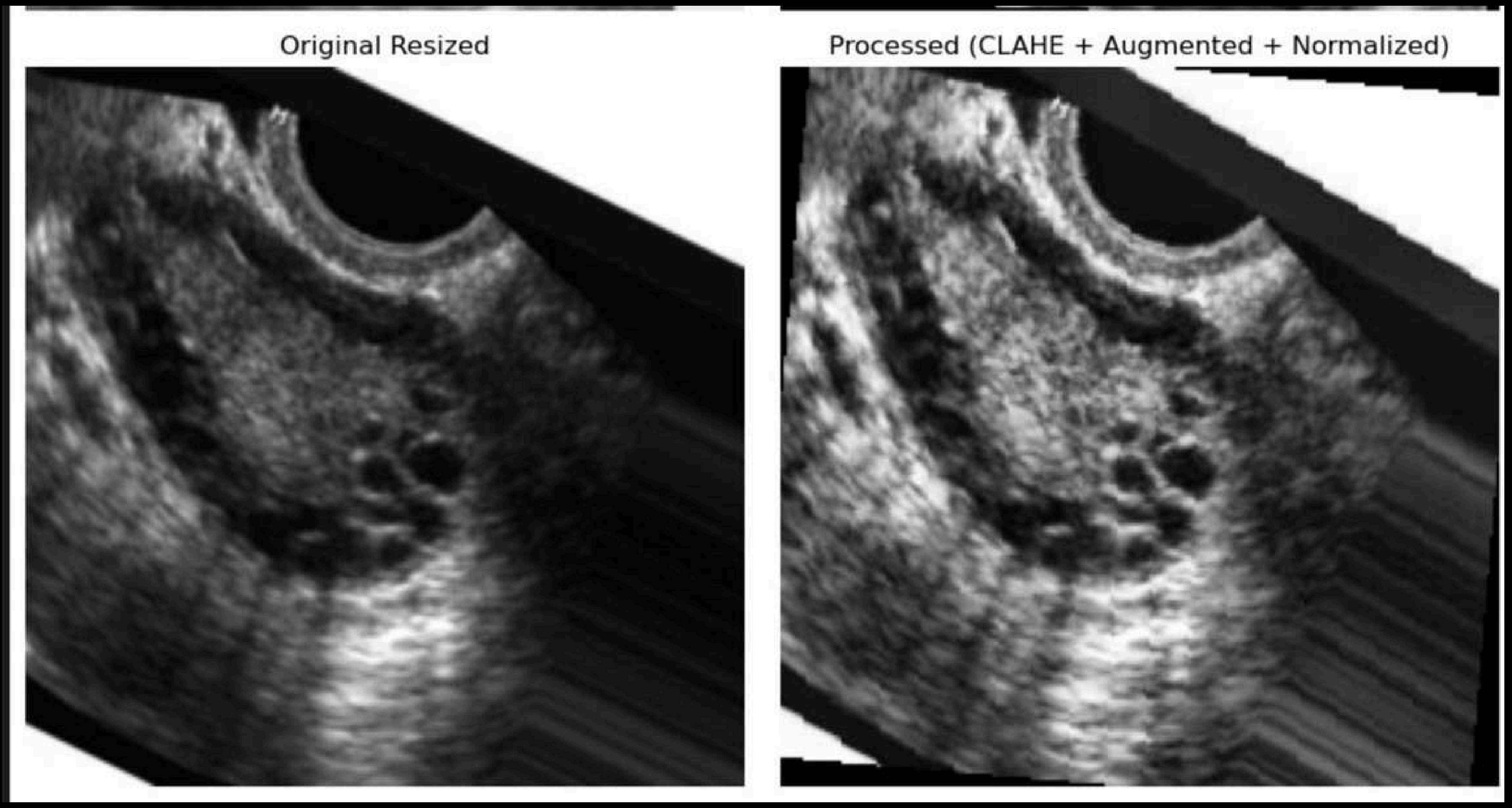
4.Tensor Conversion:

Images are converted from PIL format or NumPy arrays into PyTorch tensors, enabling compatibility with deep learning models.

5.Normalization

The normalization scales pixel values to [0,1], which helps improve model performance.

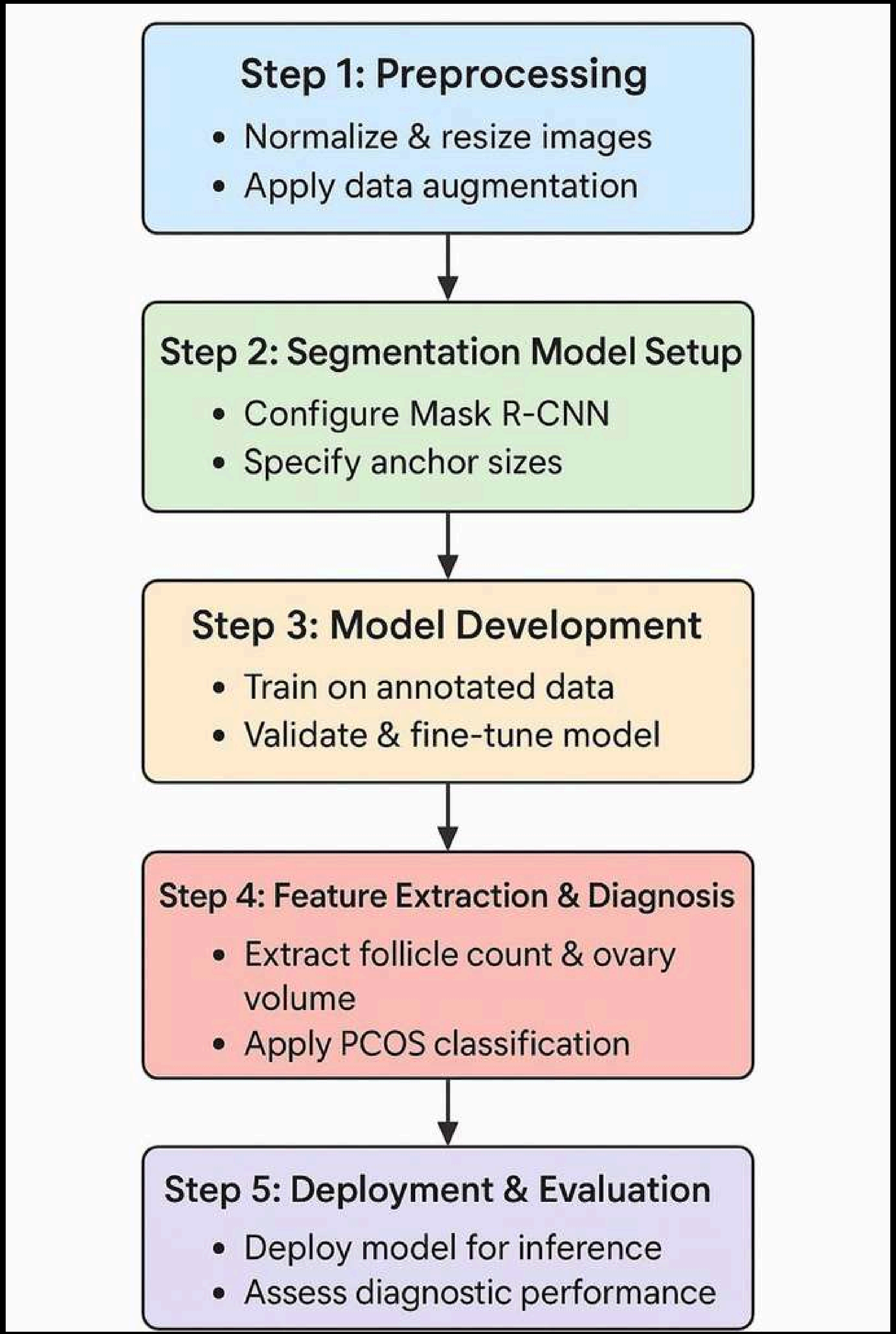




METHODOLOGY

Models Used:

- Binary Classification using CNN (6-layer architecture)
- Segmentation using Mask R-CNN



CNN

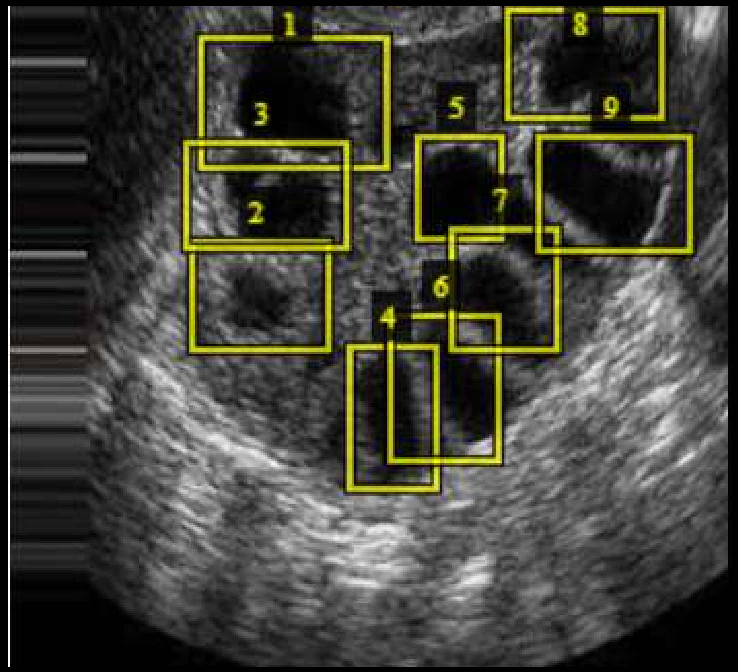
We developed a custom Convolutional Neural Network with 6 layers to classify ultrasound images into two categories: PCOS-positive and PCOS-negative.

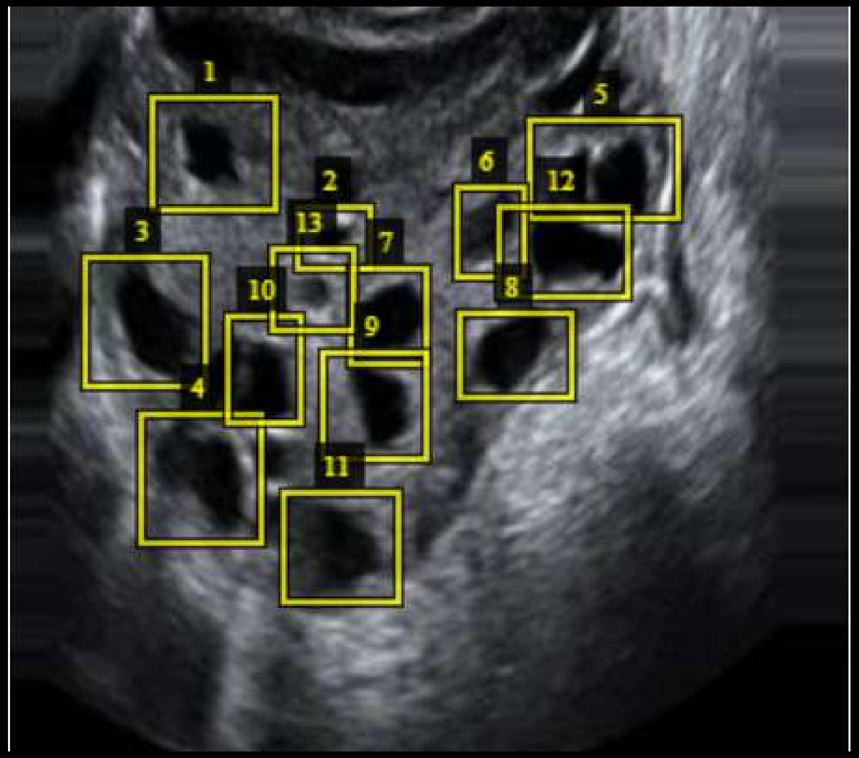
CNNs are well-suited for image classification as they automatically learn spatial hierarchies of features through convolutional layers, enabling detection of relevant patterns such as the presence and arrangement of follicles.

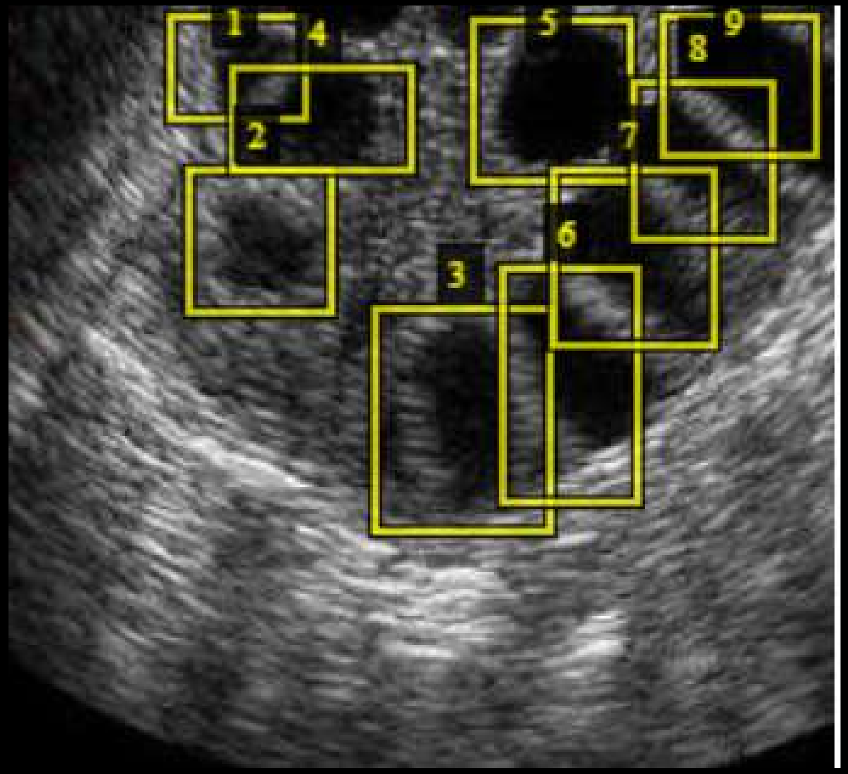
Mask-RCNN

To localize and segment individual follicles within the ovary region, we employed Mask R-CNN, a state-of-the-art instance segmentation model.

Mask R-CNN not only detects objects (follicles) but also generates pixel-level masks, which is critical for medical imaging tasks where precise boundaries are essential.







CHALLENGES FACED

Unlabeled Dataset:

One of the major challenges was the lack of labeled data, especially for segmentation.

We had no prior knowledge of what constitutes a follicle, which made it difficult to create accurate training labels.

Solution: We consulted a professional gynecologist (Dr. Bedi) to understand ultrasound features and manually annotate key regions, helping us build a reliable ground truth for model training.

RESULT

Our 6-layer CNN model achieved perfect classification metrics on the evaluation dataset:

```
Overall Accuracy    : 100.00%
Sensitivity (TPR)   : 100.00%
Specificity (TNR)   : 100.00%
Precision (PPV)     : 100.00%
F1 Score            : 100.00%
```

These results indicate that the model correctly identifies all PCOS-positive and PCOS-negative cases, with no false positives or false negatives on the test set. The high F1 Score confirms a strong balance between precision and recall, showing that the model is robust and reliable.

Model’s evaluation metrics

```
loading annotations into memory...
Done (t=0.01s)
creating index...
index created!
loading annotations into memory...
Done (t=0.00s)
creating index...
index created!
loading annotations into memory...
Done (t=0.00s)
creating index...
index created!
Epoch 1/10  loss=0.7621
Epoch 2/10  loss=0.5829
Epoch 3/10  loss=0.5607
Epoch 4/10  loss=0.5546
Epoch 5/10  loss=0.5186
Epoch 6/10  loss=0.5077
Epoch 7/10  loss=0.5003
Epoch 8/10  loss=0.5056
Epoch 9/10  loss=0.4932
Epoch 10/10  loss=0.4761
```

```
Average Precision  (AP) @[ IoU=0.50:0.95 | area=   all | maxDets=100 ] = 0.613
Average Precision  (AP) @[ IoU=0.50      | area=   all | maxDets=100 ] = 0.822
Average Precision  (AP) @[ IoU=0.75      | area=   all | maxDets=100 ] = 0.678
Average Precision  (AP) @[ IoU=0.50:0.95 | area= small | maxDets=100 ] = 0.471
Average Precision  (AP) @[ IoU=0.50:0.95 | area=medium | maxDets=100 ] = 0.587
Average Precision  (AP) @[ IoU=0.50:0.95 | area= large | maxDets=100 ] = 0.692
Average Recall     (AR) @[ IoU=0.50:0.95 | area=   all | maxDets=  1 ] = 0.505
Average Recall     (AR) @[ IoU=0.50:0.95 | area=   all | maxDets= 10 ] = 0.651
Average Recall     (AR) @[ IoU=0.50:0.95 | area=   all | maxDets=100 ] = 0.712
Average Recall     (AR) @[ IoU=0.50:0.95 | area= small | maxDets=100 ] = 0.604
Average Recall     (AR) @[ IoU=0.50:0.95 | area=medium | maxDets=100 ] = 0.693
Average Recall     (AR) @[ IoU=0.50:0.95 | area= large | maxDets=100 ] = 0.736
```

These results indicate that the model accurately detects objects across all sizes, with no major misdetections at standard IoU thresholds. The high AP@0.50 (0.822) shows excellent precision, while the strong mAP@[0.50:0.95] (0.613) confirms consistent performance under stricter conditions. The high recall values demonstrate that the model rarely misses objects, and the steadily decreasing loss shows effective learning during training.

Deployability at Plaksha

Current Status:
The solution cannot be deployed at Plaksha at the moment, as the campus does not currently have ultrasound imaging infrastructure.

Future Possibility:
If ultrasound machines are made available in a healthcare or research setup at Plaksha, the model can be integrated into a diagnostic support system to assist with automated PCOS detection and follicle segmentation.

Scalability Challenges

Limited and Unlabeled Data: Requires expert annotations and more diverse training samples for broader applicability.

Clinical Integration: Needs collaboration with healthcare professionals for real-world validation.

Infrastructure Requirements: Requires computational resources for deployment in a clinical environment.

Thank You