

# Improved Identification of Polycystic Ovary Syndrome by Ultrasound Imaging Employing Multi-Stage Image Processing and Deep Learning-Driven Segmentation with Hybrid Classification Methods

V. Lakshmi<sup>1</sup>, Dr. B. Pushpa<sup>2</sup>

<sup>1</sup>PhD Research Scholar, Department of Computer and Information Science, Annamalai Nagar, Annamalai University, India.

lakshmivaithianathan9764@gmail.com

<sup>2</sup>Assistant Professor / Programmer, Department of Computer and Information Science, Annamalai Nagar, Annamalai University, India.

pushpasidhu@gmail.com

**Abstract:** Polycystic Ovary Syndrome (PCOS) is a widespread hormone illness impacting women of adulthood, usually defined by the emergence of many follicles within the ovaries and hormone dysregulation. Timely and precise identification by ultrasound imaging is essential to successful assessment & therapy. This research introduces a computerized method for the diagnosis & categorization of PCOS utilizing images and ML methodologies. The proposed framework starts with the preparation of ovary ultrasound images utilizing noise removal techniques, including Speckle Reducing Anisotropic Diffusion (SRAD), and contrast enhancement by Contrast Limited Adaptive Histogram Equalization (CLAHE). The improved pictures undergo U-Net segmentation technique to figure out the area of interest (ROI) and detect follicular features. Following that, mobileNetV2 technique is used for feature extraction. MobileNetV2 recovers organizational characteristics at many levels, encompassing low-level boundary details, mid-level texture patterns, and high-level semantic illustrations of ovary architecture. Classification is ultimately performed using machine learning models, such Support Vector Machine (SVM) and Convolutional Neural Network (CNN) to differentiate between PCOS and normal instances. Experimental findings indicate that the suggested design enhances diagnostic precision.

**Keywords –** Polycystic Ovary Syndrome (PCOS), Ultrasound images, Speckle Reducing Anisotropic Diffusion (SRAD), Contrast Limited Adaptive Histogram Equalization (CLAHE), Support Vector Machine (SVM), Convolutional Neural Network (CNN).

## I. INTRODUCTION

Polycystic ovarian syndrome (PCOS) is a prevalent hormonal disorder impacting a substantial population of women worldwide. A precise evaluation along with rapid intervention to PCOS are important for favorable results. Ultrasound (USG) has emerged as an effective modality for the identification of PCOS within the past few years [1]. Nonetheless, the precision and resilience of existing remedies, reliant on machine and deep learning models, are constrained, prompting the formulation of innovative ways to enhance detection outcomes. Nonetheless, AI is rapidly transforming healthcare by identifying mental health conditions such as Alzheimer's, arthritis, and PCOS through the analysis of diverse data, using diagnostic imaging and digital health records [2]. The present study was driven by the pressing necessity to rectify the deficiencies present in currently employed PCOS diagnosis approaches. In conventional approaches, accurate and consistent diagnosis is challenging caused by the nuanced variations and intrinsic intricacy of ultrasound images. An incorrect diagnostic may result in a gap in treatments for PCOS individuals, thereby exacerbating their condition. The predominant present approaches utilize initial

1



artificial intelligence frameworks and conventional machine learning models [3]. The intricate structures and nuanced features within USG images hinder aforementioned models from effectively diagnosing PCOS, even though algorithms exhibit potential in several clinical contexts. This is generally evident that algorithms exhibiting enhanced discriminatory capabilities, resilience to picture variations, and robust extension must be developed. These nuanced features of PCOS in ultrasound images are generally challenging for modern methods to process, resulting in worse accuracy as well as dependability. Such constraints originate in difficulties pertaining to distinguishing varying picture quality, diverse individual anatomies, especially the importance for systems capable of detecting minute abnormalities indicative of PCOS [4]. A prior research [5] employed ultrasound scans to detect individuals with PCOS at an initial stage. Inability to become pregnant is a significant medical consequence of PCOS. Conventional diagnostic approaches are time-consuming; subsequently, computerized identification utilizing deep learning, particularly Convolutional Neural Networks (CNNs), was initially proposed as a remedy. This study proposes a CNN-based approach for categorizing ultrasound ovary pictures either PCOS & non-PCOS classifications through follicular segmentation. The CNN determines PCOS follicle through an exactness with around 83%, potentially aiding throughout the early identification of PCOS. An investigation examines pertinent research and delineates prospective advancements for such an approach.

Machine learning [6], transfer learning, or various deep learning methodologies are among AI technologies. Health images are easily divided to find pertinent regions utilizing methods such as edge detection, cropping, k-means clustering, and the watershed technique. categorization, employing multiple classifiers, provides a crucial stage in the diagnosis approach. Identification methodologies encompass image analysis, neural network algorithms, and pattern recognition. The integration between multiple AI methodologies enhances both the effectiveness and precision of PCOS identification, resulting in improved clinical results and timely treatment. The reliability of the resulting models for PCOS diagnosis using ultrasound pictures was set after a comparative analysis. A bespoke ResNet model surpassed the remaining frameworks, achieving a score of 96.7% compared to 58% for VGG16, ResNet50, and CNN. The findings indicate this customized ResNet system surpasses VGG16 and ResNet50 in the particular job of predicting PCOS given ultrasound pictures. A prior thorough study investigates the correlation across food choices and PCOS, underscoring the importance of adequate nutrients in the control of PCOS [7]. A considerable proportion of women suffer by PCOS, that is linked to several medical conditions, including pregnancy. The research uses Deep Learning algorithms to categorize images of meals and ascertain nutritional content. Diverse meal picture collections can be used for evaluation employing already developed Convolutional Neural Networks (CNNs). The primary objective is to create a nutritional management system that utilizes meal pictures to monitor eating habits and provide food suggestions for individuals with PCOS. The research involved offers a thorough analysis of picture categorization and advice techniques that may assist those who practice dieting in efficiently controlling PCOS. The primary goal of this preceding initiative intends to provide an in-depth system addressing women's hormonal wellness, known as FemTech (female technology) [8]. Fig. 1 depicts the effects of PCOS in women ovary. Fig. 2 shows the difference between PCOS ovary form the normal ovary.



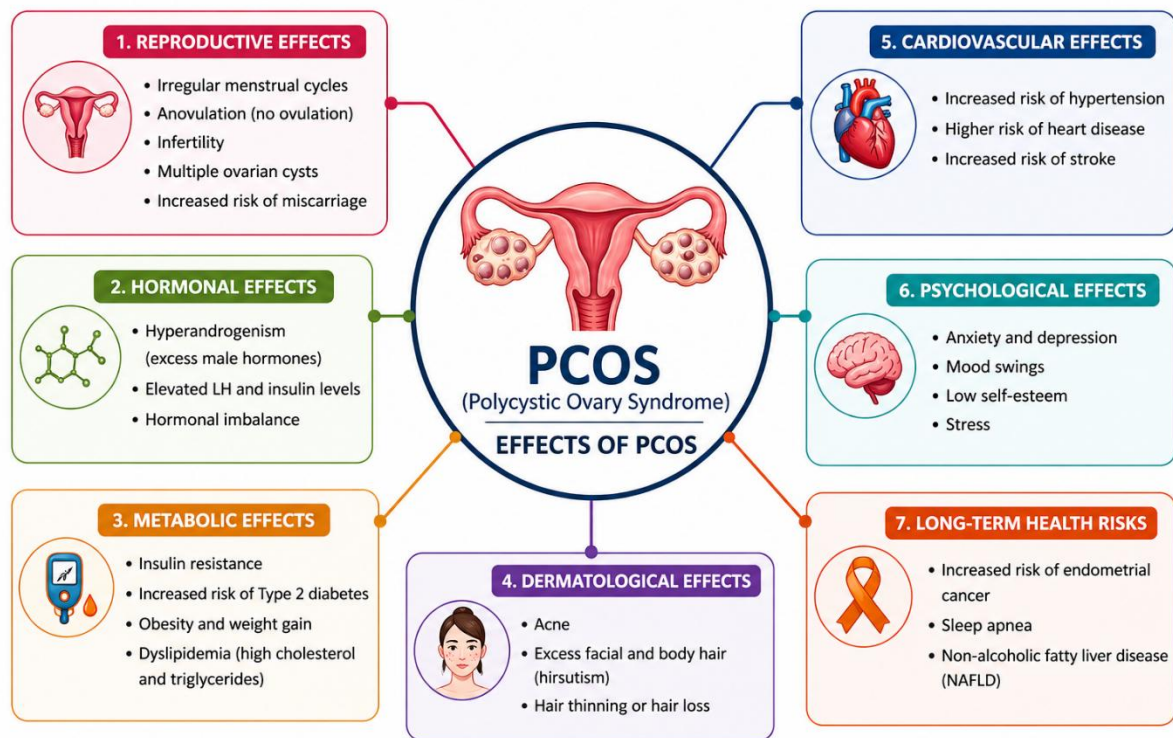


Fig. 1 Effects of Polycystic Ovary Syndrome (PCOS)

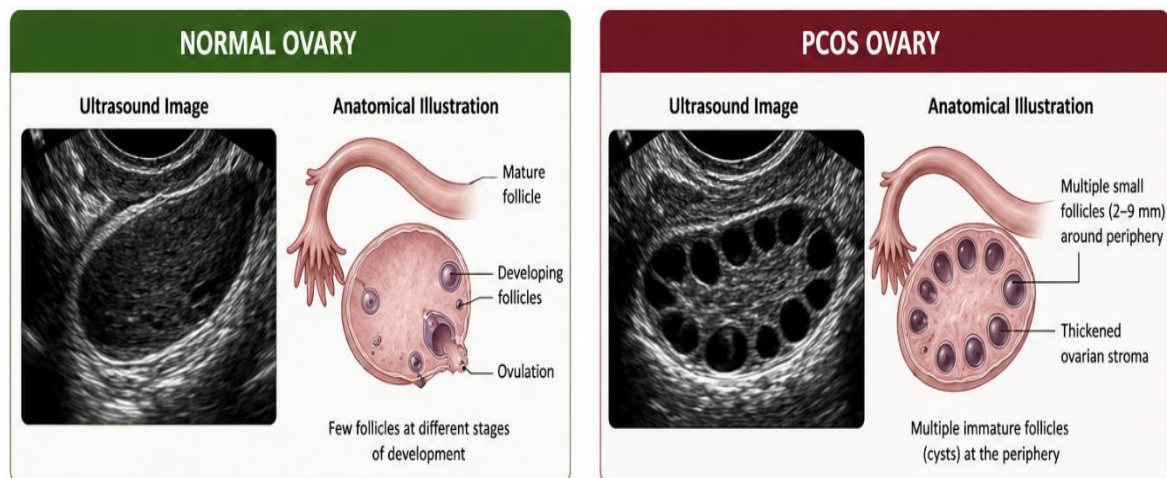


Fig. 2 Difference between the PCOS ovary from Normal Ovary

## II. RELATED WORKS

MonAmie is a portal that offers a range of offerings, such period tracking, PCOD identification, product discovery, health advice, and access to learning tools. A further component of research is to contrast each machine learning algorithm employed in the end result. The fundamental goals of MonAmie is to improve women's general wellness and to raise knowledge about menstrual. A thorough screening approach has been proposed for the timely identification of PCOS [9]. The framework employs randomized under sampling and SMOTE to provide an equitable data set for training its supervised learning algorithms. XGBoost achieves the highest possible performance of 96% in the detection of PCOS. This prior study sought to predict PCOD in female patients via

machine learning [10]. The acquisition has 541 cases including 45 attributes pertaining to diseases. The framework had a peak accuracy of 91.7% in PCOD forecasting via Gradient Boosting, accompanied by an F1 score of 92%.

Prior research has examined the volume of electronic medical information produced on internet medical conversations, encompassing blogging posts, comments, and discussions. This paper presents a novel approach called DEODORANT (Detection and Prevention of Polycystic Ovarian Syndrome Utilizing Association Rule Hypergraph and Dominating Set Property) [11], using PCOS as an instance model. The methodology entails the current extraction of raw data across multiple places following preparation with the Natural Language Toolkit (NLTK). Association's laws are generated by the Apriori method, thereafter shown as hypergraphs and processed into graphical line graphs for the purpose of grouping creation. Spectral grouping is employed to partition the line graph into groupings of hypergraphs. Subsequently, signs and reasons are emphasized by the utilization of the dominant set characteristic. The trial findings illustrate the correlation between consequences & actual information, providing important information for timely diagnosis and proper treatment, while enabling companies and healthcare practitioners to monitor diseases.

The prior design had three phases: YOLO learning, identification and harvesting, and visualization [12], [13]. YOLO effectively identifies follicles areas and extracted pertinent characteristics if used alongside morphological. Physicians utilize technology for visual representation to aid in the investigation of PCOS. YOLO's F1-score of 87.33% surpassed the prior highest outcome of 50.83% achieved by traditional structural procedures. The incorporation of structure facilitates the automated identification of the Region of Interest for ovary follicles, achieving a normal Intersection over Union value of 94.63%, in accordance with professional comments. That improves digital shading, material shading, shape augmentation, pattern refinement, and other imaging approaches, hence enhancing assessment and evaluation the PCOS and boosting the precision of health care treatment. An ultrasound frequently experiences propagation errors that impede diagnostic reliability. Novel methods utilizing a correction for at and intensity-based normalizing have demonstrated efficacy in mitigating shadowed impacts and enhancing picture uniformity. These algorithms utilize dynamic adjustment methods tested on both virtual and in reality, information sets, markedly improving brightness measurement and extraction of features that are essential for usage in computerized testing systems like PCOS diagnosis. Approaches over airway tree segmentation have shown considerable progress in improving picture recovery for medical use [14]. The suggested Interpolation-Split method employs approximated information and visualization to enhance the quality of data; this is essential for superior segmentation efficacy. This technique attains enhanced diced matching scores through the integration of ensemble learning, simultaneously decreasing GPU usage. In our PCOS detection investigation, strategies for clarity enhancement, such as FIS and augmentation, immediately increase the algorithm's predicted accuracy, underscoring the essential importance of picture quality.

A previous work [15] suggests a computerized approach to enhance deep learning in computer-assisted lung disease detection utilizing chest X-ray pictures. It utilizes a process of evolution to construct and reduce convolutional neural networks (CNNs) for visual classification. This enables the precise identification of chest abnormalities, including COVID-19. The approach utilizes transfer learning to fine-tune an established CNN on a large dataset for COVID-19 detection, possibly minimizing data requirements and boosting performance relative to other systems. Research performed on cutting-edge designs validates the technique. The previously described system employed machine learning techniques for precise identification and supervision of PCOS. The method facilitated individualized therapies, ongoing treatment tracking, and enhanced healthcare results using timely identification and customized therapies by merging predictions with e-health records [16].

In predicting HGB-anemia and nutrient deficiencies (iron deficiency, B12 deficiency, and folate deficiency anemia) as well as individuals lacking a condition, the CNN achieved an accuracy of 98.50%, while Genetic Algorithm (GA)-driven mixed models utilizing Stacked Autoencoder (SAE) attained an accuracy of 97.02%. The parameters known as "hyper utilized" included size of batch, losses, stimulation, learning speed, maximum epochs, training epochs, velocity, and L2 normalization. The reliability of the RF model was 96.07%. The Multiple-stage Ensemble model (MSEN), via an improved weighted voting-based strategy for COPD





identification, attained an exactness of 98.20% through an evolutionary method to enhance variables. The amounts of every classifier and the two ensemble models generated have been optimized by the grid search method. LightGBM, coupled using repeated characteristic removal, was employed for characteristic selections; the Isolation Forest was utilized to eliminate irregularities, and the KNN approach was implemented to impute omitted data. A combination of approaches named ResNet 50V2, which integrates a residual CNN with a GA, was created to forecast acute lymphoblastic leukemia. The reliability ratio was 98.46%. Genetic Algorithms were employed to identify the optimal hyperparameters that have the most precise rate. In the context of GA hyperparameter optimizing, the efficacy of the model has been assessed against Random Search and Bayesian optimization methodologies. The hyperparameters allowing for dropout, momentum, and learning rate were utilized. A prior work offers a balanced a classifier with for categorization into of skin cancers utilizing seven deep learning models [17]. The amounts assigned for every framework are determined by its correctness. The combination attained 93.36% success on the ISIC collection for melanoma and nevus categorization, surpassing previous state-of-the-art approaches.

A recently published study incorporates ML methods to forecast PCOS and implements explainable artificial intelligence (XAI) [18] approaches to discern the principal elements affecting the condition. Machine learning methods, attained a reliability of 97%. XAI approaches (LIME and SHAP) identified glucose levels and egg counts as the paramount elements influencing PCOS, providing information for enhanced treatment and identification. A most recent investigation establishes an innovative ML structure for diagnosing PCOS via demographics and medical characteristics. The model attained a reliability of 97.42%, illustrating its efficacy in a prompt recognition of PCOS [19]. The GWO-based choosing characteristics method markedly enhances results, rendering the methodology suitable for multidimensional information and many pertinent disorders.

### III. PROPOSED METHODOLOGY

The demonstrated diagnostics model for Polycystic Ovary Syndrome (PCOS) adheres to a systematic five-stage analytical workflow intended for highly accurate ultrasound evaluation. During the preliminary preprocessing stage, unprocessed ultrasound images undergo Speckle Reducing Anisotropic Diffusion (SRAD) for noise attenuation, targeted artifact elimination methods, and Contrast Limited Adaptive Histogram Equalization (CLAHE) to improve morphological clarity. The segmentation step employs a U-Net architectural to delineate the Region of Interest (ROI) and identify follicular characteristics. MobileNetV2 functions as a powerful feature extractor, gathering multi-scale information encompassing low-level borders, mid-level textures, and high-level semantic structures. The system utilizes an ensemble classification method using Support Vector Machines (SVM) and Convolutional Neural Networks (CNN) to distinguish among normal ovaries and those affected by PCOS, resulting in a categorized diagnostic result. Fig 3. Shows the overall workflow for the proposed system.

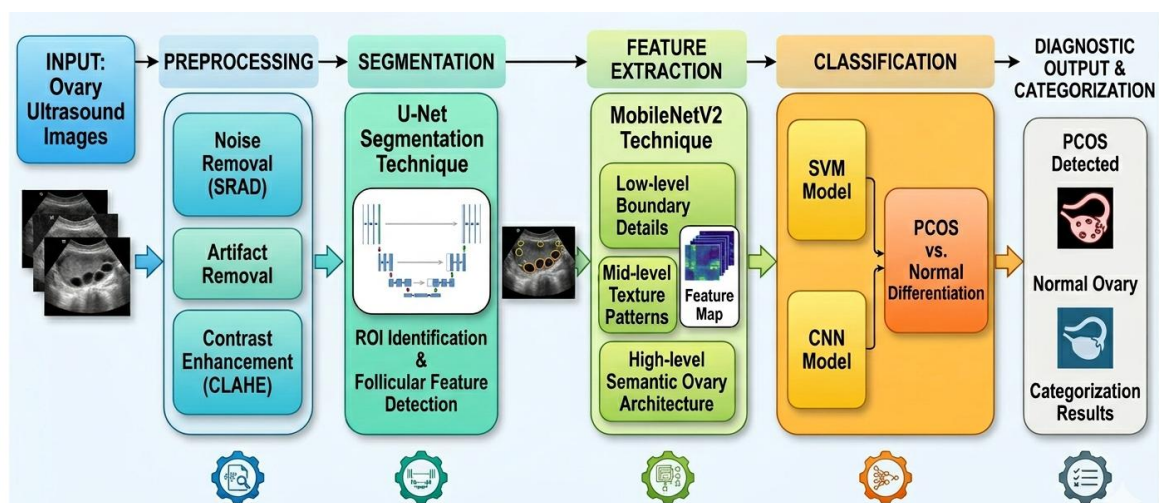


Fig 3. Overall workflow architecture diagram for the proposed system

### 3.1 Dataset Description

This research utilized data set including 1986 ultrasound pictures, classified into PCOS and normal categories. Of the whole dataset, 1588 photos are designated for training, including 675 PCOS specimens and 913 normal specimens. The rest of the 398 photos are allocated for testing, consisting of 169 PCOS patients and 229 normal cases. The dataset comprises 844 photos classified as PCOS-positive and 1142 as PCOS-negative, reflecting a significantly skewed distribution. Table 1 shows the representation of dataset description. Dataset [20] gathered from Kaggle: <https://www.kaggle.com/datasets/bharatsh001/pcos-cleaned-and-splitted>. Fig 4. Shows the sample dataset images.

Table 1. Dataset for PCOS and Normal cases

| Ultrasound Images | PCOS | Normal | Total |
|-------------------|------|--------|-------|
| Training Data     | 675  | 913    | 1588  |
| Testing Data      | 169  | 229    | 398   |
| Total             | 844  | 1142   | 1986  |

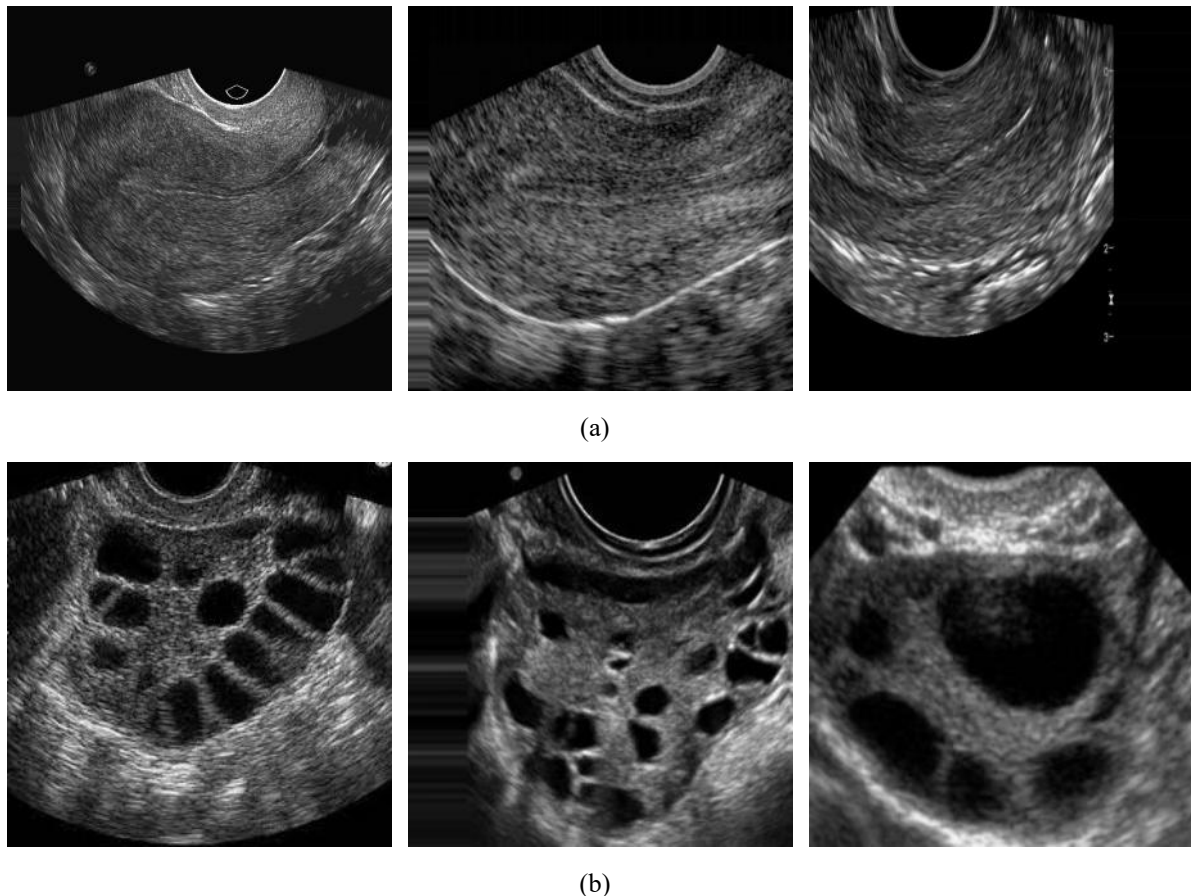


Fig. 4 Sample Dataset (a) Normal ovary (b) PCOS affected ovary

### 3.2 Preprocessing

#### 3.2.1 Noise Removal

Speckle Reducing Anisotropic Diffusion (SRAD) is an efficient preprocessing method utilized frequently in ultrasound analyzing images for enhancing the resolution of ovaries scanning used during Polycystic Ovary Syndrome (PCOS) diagnosis. Ultrasound pictures are intrinsically impacted by speckle noise, that is additive naturally and decreases image contrast, rendering it not possible to precisely distinguish follicle components. The SRAD approach tackles this restriction by utilizing an altered anisotropic diffusion technique which specifically refines homogenous areas yet retains considerable border knowledge. Despite typical screening approaches, SRAD employs a diffusion parameter that changes determined by localized strength fluctuations and speckled patterns, therefore efficiently reducing distortion avoiding distorting key structural bounds. This trait is especially advantageous in PCOS diagnosis, where accurate localization of ovaries is required for further segments and characteristic extraction. By boosting picture quality and solidity, SRAD considerably enhances the efficacy and exactness of computationally assisted medical systems using ultrasound imaging. Fig 5 depicts the processed SRAD image

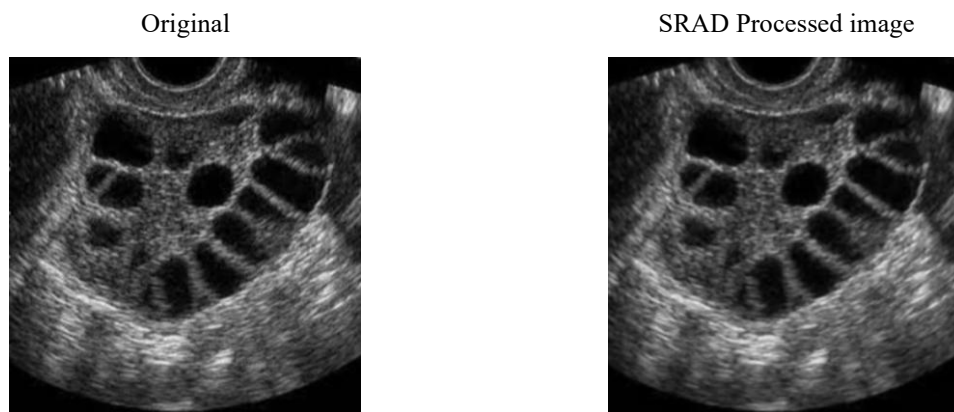


Fig 5. Output for the Speckle Reducing Anisotropic Diffusion (SRAD)

#### 3.2.2 Contrast Enhancement

Contrast Limited Adaptive Histogram Equalization (CLAHE) is a prevalent preprocessing method in ultrasound analyzing pictures that improves the standard of ovaries scanning utilized in the identification of Polycystic Ovary Syndrome (PCOS). Ultrasound pictures sometimes exhibit little brightness and uneven lighting, obscuring follicle features and impeding accurate identification. The CLAHE technique mitigates these constraints by partitioning the picture into tiny graphical areas tiles and executing histogram equalization individually for every section.

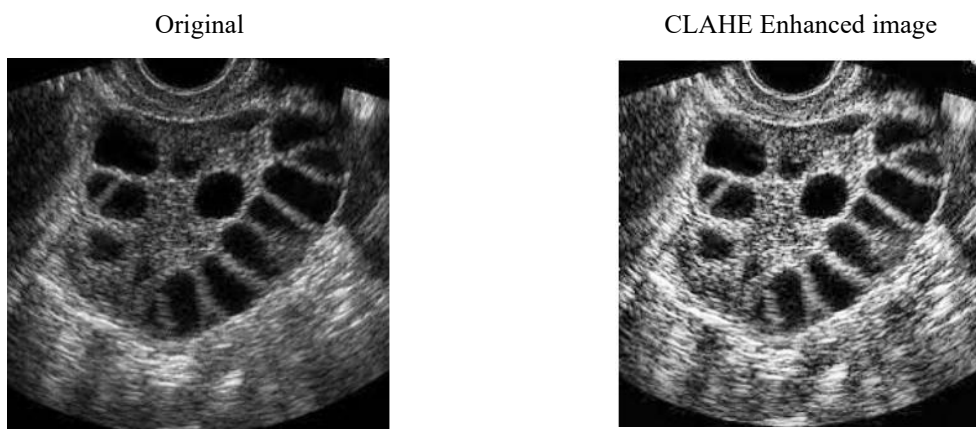


Fig 6. Output for the Contrast Enhancement (CLAHE)

CLAHE employs contrast restriction strategy to avert loudness amplifying by truncating the histogram at a particular level prior to redistributing. This dynamic method improves localized distinction yet preserves crucial structure characteristics, especially the borders of ovaries. Consequently, CLAHE markedly enhances the visual clarity and accessibility of ultrasound pictures, hence enabling more precise categorization and obtaining features. Thus, it improves the efficacy and dependability of automated tests for the identification of PCOS. Fig 6 shows the CLAHE processed outcome.

### 3.2.3 Artifact Removal

The removal of black borders is a specialized approach for eliminating ultrasonic artifacts while preprocessing, aimed at eradicating insignificant portions bordering the real scanning location in ovary ultrasound pictures for the identification of PCOS. The dark boundaries often result through the constraints of the detectors connection or instrument and have any pertinent structural data. Their appearance might adversely impact images analyzed by adding extraneous pixilation, diminishing the efficient area of interest (ROI), and distorting categorization or characteristic extraction methods. Fig 7 shows the black border removal of the preprocessed image

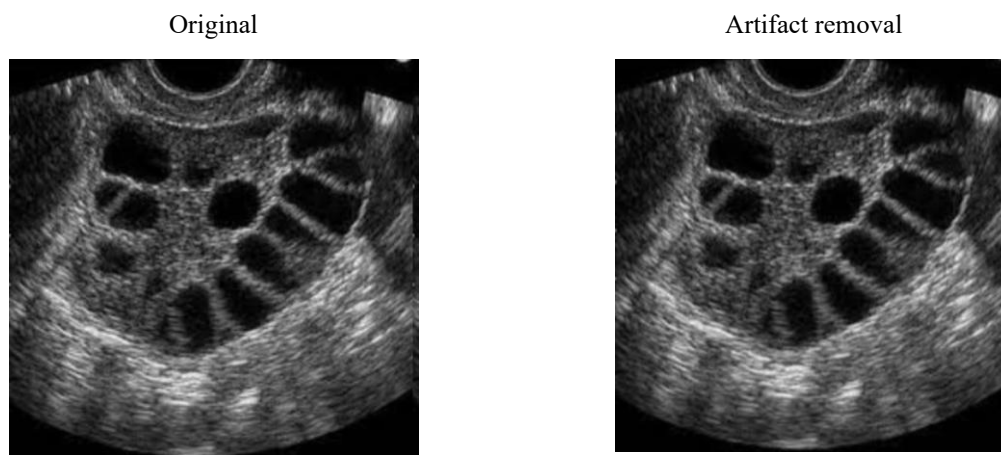


Fig 7. Output for the Artifact Removal

The Black Border Removal approach resolves this problem by detecting and eliminating the black background areas by strength threshold or edge-finding methods. A certain level is often employed to identify near-zero intensity pixels at the border, next by contouring or box boundary retrieval to delineate the significant ultrasonic area. The picture is subsequently trimmed to preserve just the approved scanning region. This procedure optimizes computing effectiveness, sharpens emphasis on essential follicular patterns, and guarantees excellent results in following stages, including separation and categorization. Thus, the elimination of black borders is a crucial preprocessing step in the development of precise and resilient PCOS systems for identification utilizing ultrasound picture collections.

### 3.3 Segmentation

#### U-Net

U-Net-based segmentation for Region of Interest (ROI) capture is a reliable deep learning method utilized in diagnostic visualization to precisely delineate ovulation areas for the identification of Polycystic Ovary Syndrome (PCOS). The U-Net model executes pixel-wise categorization with a balanced encoder-decoder architecture, whereby an encoder extracts the highest-level contextually relevant data and the decoder decodes spatial information for accurate positioning. Skip connectivity among matching stages facilitate the retention of detailed border data, proving crucial for precisely distinguishing ovaries in ultrasound scans marked by speckle noise and poor contrast. A system produces segmented filter than differentiates the region of interest via the nearby context, so can then be used to extract the ROI via filtering or bounds-box methods. This computerized separation approach removes extraneous areas and documents, hence improving the emphasis on therapeutically important





components. Thus, U-Net-based ROI collection enhances the exactness, effectiveness, and efficacy of next steps, including feature extraction and categorizing, in computer-driven PCOS detectors utilizing ultrasound imaging collections. Fig 8 depicts the U-Net architecture for the proposed system.

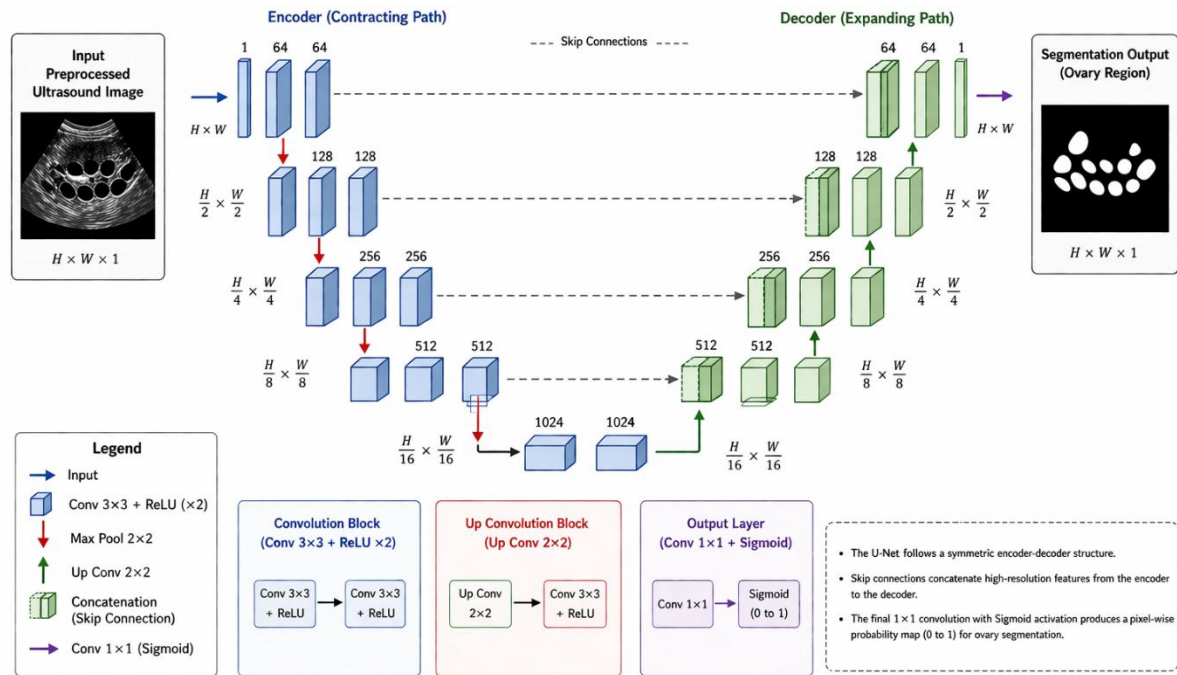


Fig. 8 U-Net architecture for proposed system

$$S = \sigma(D(E(X), \{E_i(X)\})) \quad (1)$$

Where

$X$ =input ultrasound image

$E(.)$ =encoder function (downsampling + feature extraction)

$D(.)$ =decoder function (upsampling + reconstruction)

$E_i(X)$ =feature map from encoder

$\sigma(.)$ =sigmoid activation

$S$ = segmentation mask

### 3.4 Feature Extraction

#### MobileNetV2

MobileNetV2 has proven especially successful for multilayer feature extraction in ultrasound-associated PCOS diagnosis, as it acquires and maintains picture knowledge throughout various tiers of conceptualization. The MobileNetV2 design accomplishes this by means of layered flipped remainder blocks, depth-wisely detachable convergence, and regulated data transfer via logistic constraints. The earliest convolutions at the low-level capture border and edge information, including cyst contours, strength variation, and delicate changes among ovaries and the backdrop. These attributes are crucial in ultrasound imaging, because borders frequently exhibit weakness owing to speckle noise and low contrast. Depth wise scalability transformations provide effective filtering spatially while maintaining intricate architecture. At the mid-level, layers that are commence the encoding of textural variations & localized logical frameworks, including the range, clustered, and inner characteristics of follicular. In instances of PCOS, eggs frequently manifest as several small cells positioned proximally, and these

locations are represented via the augmented feature space in reversed block residuals. The extension step enables the system to investigate intricate interactions among images and pathways, enhancing its capacity to depict diverse patterns. At a high level, the more complex parts of the system acquire conceptual characterizations of ovarian anatomy, encompassing general form, dimensionality, and aberrant structural characteristics linked to PCOS. They consolidate data obtained from preceding phases to create a comprehensive knowledge of the picture. The uniform bottlenecks have significance for retaining important data while avoiding superfluous unpredictability, hence preventing distortion of sensitive clinical aspects.

Furthermore, skip (residual) connections facilitate the preservation regarding data consistency between levels, enabling low-level and mid-level elements to enhance high-level comprehension. Using multilayer feature acquisition is reinforced by the global average pooling (GAP) layer, that consolidates geographic knowledge through a concise and distinctive graph of features. MobileNetV2 offers a thorough depiction of ovary imaging pictures by retrieving and combining organizational factors at a variety of levels, from intricate border boundaries to complicated conceptual frameworks. Both broad attribute extraction capacity markedly improves the correctness and resilience of subsequent model-based classification in PCOS detectors. Fig 9 finds the MobileNetV2 architecture.

$$F = GAP \left( W_p * DWConv(ReLU6(W_e * X)) \right) \quad (2)$$

Where

$X$ =input

$W_e$ =Expansion (1X1 convolution weights)

$ReLU6(.)$ =activation function

$DWConv(.)$ =depth-wise convolution

$W_p$ =projection

$GAP(.)$ =global average pooling

$*$ =convolution operation

$F$ =final feature vector

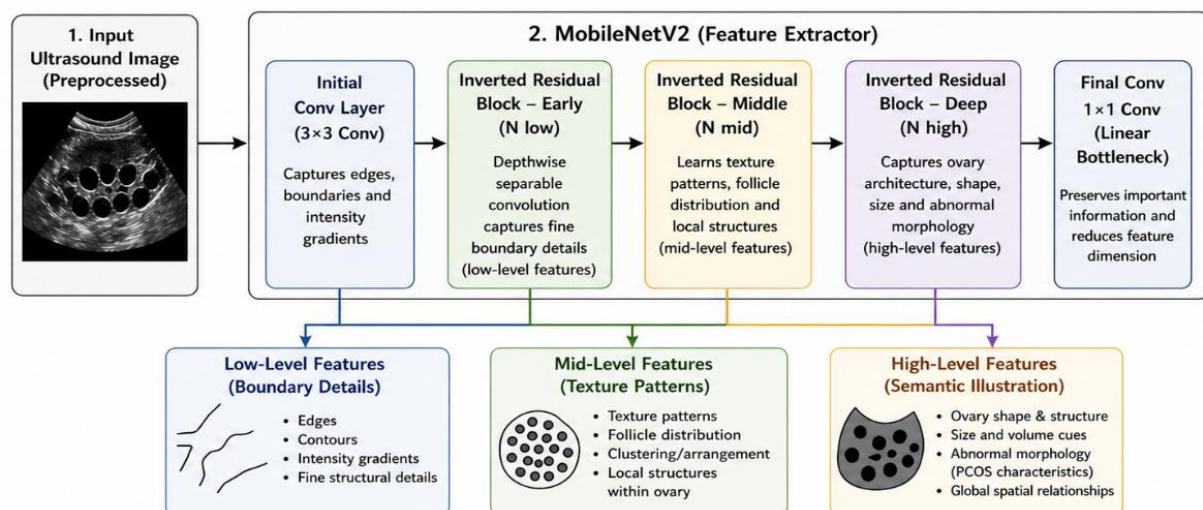


Fig 9. MobileNetV2 feature extraction

### 3.5 Classification

#### 3.5.1 Support Vector Machine (SVM)

Support Vector Machine (SVM) categorization offers a statistically robust and efficient approach for detecting PCOS from medical ultrasound images by converting intricate characteristic representations into a distinct deciding limit among categories. The Support Vector Machine aims to determine an ideal separation hyperplane that optimizes margins among PCOS and non-PCOS information matrices, hence enhancing generalization efficacy.

In actual PCOS workflows, ultrasound pictures undergo preprocessing and segmentation to delineate the ovary area, followed by the extraction and standardization of shallow as well as artificial information, including textural definitions, follicular concentration characteristics, and strength characteristics. Feature vectors frequently display relationships that are not linear due to discrepancies in graphical quality, human body morphology, and illness presentation; consequently, SVM utilizes kernel functions (typically the Radial Basis Function) to subconsciously map information into a more complex field, thereby improving independence. The method of instruction entails addressing a convex optimization problem that reconciles margins maximizing with classified mistake via a regularized metric, hence assuring resilience in the presence of small and complex medical information.

A limited selection for instruction specimens, referred to as supported vectors, determines the selection boundaries, rendering the system memory-friendly rather than susceptible to extraneous input. Moreover, SVM has a reduced susceptibility to mis fitting relative to several other classification algorithms, especially when suitable hyper parameter settings are meticulously optimized by cross-validating. When deduction, a trained model assesses additional attribute vectors by calculating how close they are to the learnt hyperplane, facilitating precise categorization into PCOS or non-PCOS categories. The use of SVM as a conclusive deciding layer capitalizes on its proficiency in managing highly dimensional, irregular data, therefore markedly enhancing the diagnostic precision, stability, and therapeutic relevance of ultrasound-based PCOS detectors. Fig 10 shows the SVM architecture.

$$f(x) = \sum_{i=1}^n \alpha_i y_i K(x_i, x) + b \quad (3)$$

If  $f(x) > 0$ , the input image is classified as PCOS; otherwise Normal

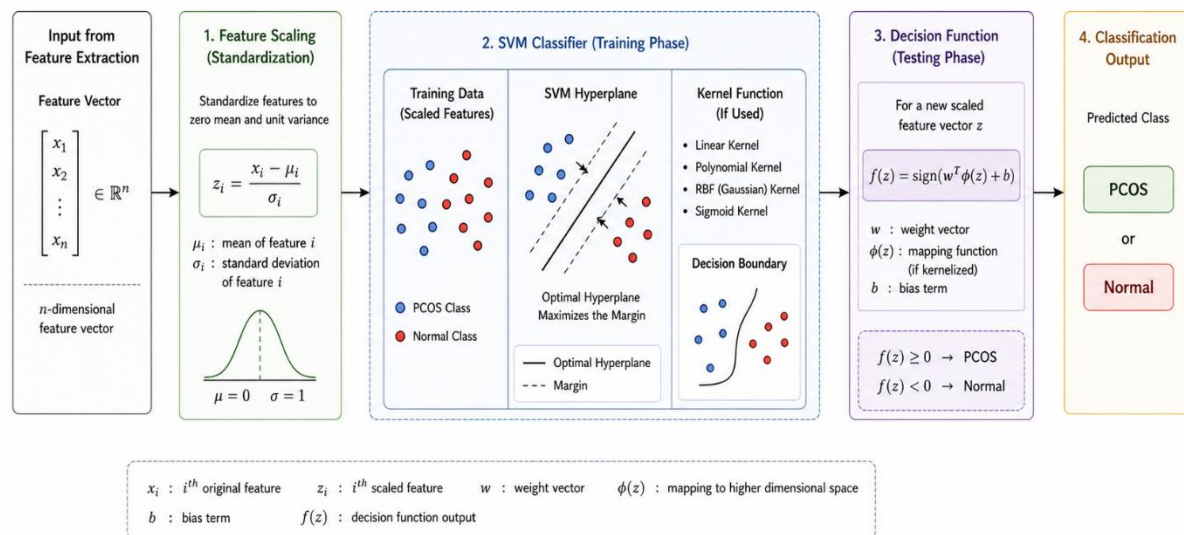


Fig 10. SVM architecture diagram for proposed system

### 3.5.2 Convolutional Neural Network (CNN)

The classification employing Convolutional Neural Networks (CNNs) offers an extensive foundation for identifying Polycystic Ovary Syndrome (PCOS) from ultrasound images by autonomously acquiring multilevel and distinguishing illustrations of ovary features. The CNN analyzes pictures via successive steps of convergence, irregular processing, and abstracting, allowing it to represent the intricate imagery linked to PCOS. In a standard PCOS pipeline, ultrasound images undergo preprocessing, including speckle minimizing noise by SRAD, contrast improvement through CLAHE, and artifact elimination, followed by optional segmentation to delineate the ovary (ROI). The transformed picture is subsequently input via CNN. The preliminary convolutional phases utilize diminutive learned filters (e.g.,  $3 \times 3$  kernels) throughout the picture to obtain fundamental properties such as borders, curves, and follicular margins. Such characteristics are essential as ultrasound pictures frequently exhibit faint borders and interference, and first layer contribute to the stabilization of such renderings.

As input progresses farther through the system, successive layers of convolution extract mid-range properties, such as texturing structure, follicular structure, and regional spatially configurations. In PCOS, cysts generally manifest as several tiny cysts positioned proximally, and convolutional neural networks (CNNs) acquire the ability to identify such frequent occurrences via layered filtering and the extension of receptor fields. Activation functions such as Sigmoid provide irregularity, enabling a system to represent intricate interactions among parameters.

Increased deep facilitates advanced feature extraction, enabling the system to encode meaningful visualizations, including total ovary dimensions, shape changes, and aberrant morphological characteristics suggestive of PCOS. At this moment in time, the CNN synthesizes data provided by the complete picture, so establishing a comprehensive assessment to determine if ovaries displays characteristics of PCOS. Pooling layers, such as maximum pooling, are interspersed across convolutional layers to diminish dimensionality, mitigate exaggeration, and ensure translating exactness. This guarantees that the system can identify appropriate trends irrespective of their exact spot within the picture. Subsequent to feature extraction, the resultant map representations are converted form a single-dimensional vector and transmitted via completely linked (dense) matrices, which function as classifiers. Such layers acquire intricate fusions of collected information and associate them with classes of outcomes. The last layer employs an activation function, like Softmax for multi-class classification or Sigmoid for binary categorization, to provide probabilities ratings that indicate either the input photograph is associated with PCOS or non-PCOS. A system is instructed by backpropagation, minimizing the discrepancy among anticipated and observed labelling (loss) with techniques for optimization such as Adam or stochastic gradient descent (SGD). While instruction, CNNs autonomously modify filters values to highlight medically pertinent variables such as cyst density, configuration, and ovary surface.

#### i) Convolution Operation:

$$X_j^l = f \left( \sum_{i \in M_j} X_j^{(l-1)} * K_{ij}^{(l)} + b_j^{(l)} \right) \quad (4)$$

Where

$X_j^l$ =output feature map

$X_j^{(l-1)}$ =input feature map

$K_{ij}^{(l)}$ =convolutional kernel

$*$ =convolutional operation

$b_j^{(l)}$ =bias

$f(.)$  =activation function





ii) **Pooling Operation (max pooling):**

$$P^{(l)} = \max_{(i,j) \in R} X^{(l)}(i,j) \quad (5)$$

Where

R=pooling region (e.g. 2X2 window)

iii) **Fully Connected Layer:**

$$z = Wx + b \quad (6)$$

$$a = f(z) \quad (7)$$

Where

W= weight matrix

x=input vector

b=bias

iv) **Activation Function (Sigmoid):**

$$\sigma(x) = \frac{1}{1+e^{-x}} \quad (8)$$

Where

$\sigma(x)$ =predicted probability

$e^{-x}$ =non-linear transformation

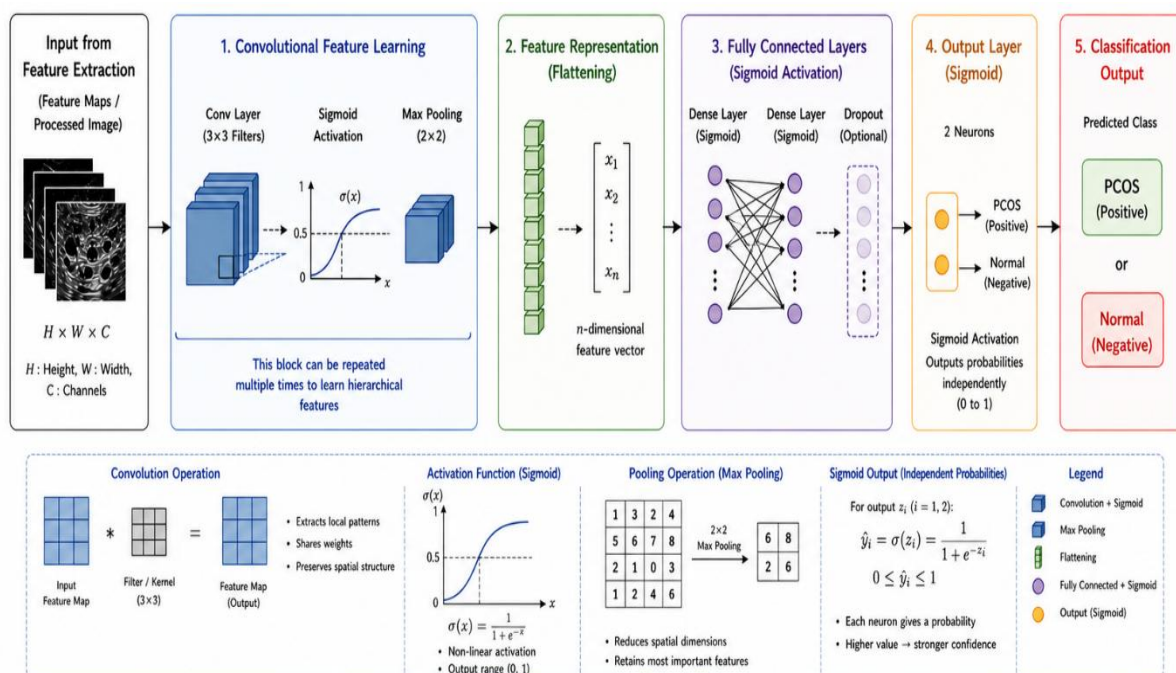


Fig 11. CNN architecture diagram for proposed system

#### IV. RESULT AND ANALYSIS

The efficacy of the developed Polycystic Ovary Syndrome (PCOS) identification method was assessed utilizing ultrasound images comprising both PCOS and non-PCOS patients. The preprocessing methods, such as speckle

noise reduction (SRAD), contrast enhancement (CLAHE), and artifact elimination, markedly enhanced visual quality and component visualization. Feature extraction using deep learning models, while classification was done by both Support Vector Machine and Convolutional Neural Network methodologies. ROC curve for SVM and CNN classifiers showed in Fig 12. Confusion matrix for proposed system showed in Fig 13 and Fig 14 shows that the performance analysis of SVM and CNN.

$$\text{i) Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \quad (9)$$

$$\text{ii) Sensitivity} = \frac{TP}{TP+FN} \quad (10)$$

$$\text{iii) Specificity} = \frac{TN}{TN+FP} \quad (11)$$

$$\text{iv) Precision} = \frac{TP}{TP+FP} \quad (12)$$

$$\text{v) F1 - Score} = \frac{2 \times TP}{2 \times TP + FP + TN} \quad (13)$$

Table 2. Statistical analysis for SVM and CNN classifiers

| Models | Accuracy | Sensitivity | Specificity | Precision | F1-score |
|--------|----------|-------------|-------------|-----------|----------|
| SVM    | 90%      | 88.8%       | 90.8%       | 87.7%     | 88.2%    |
| CNN    | 95%      | 94.7%       | 94.8%       | 93.0%     | 93.8%    |

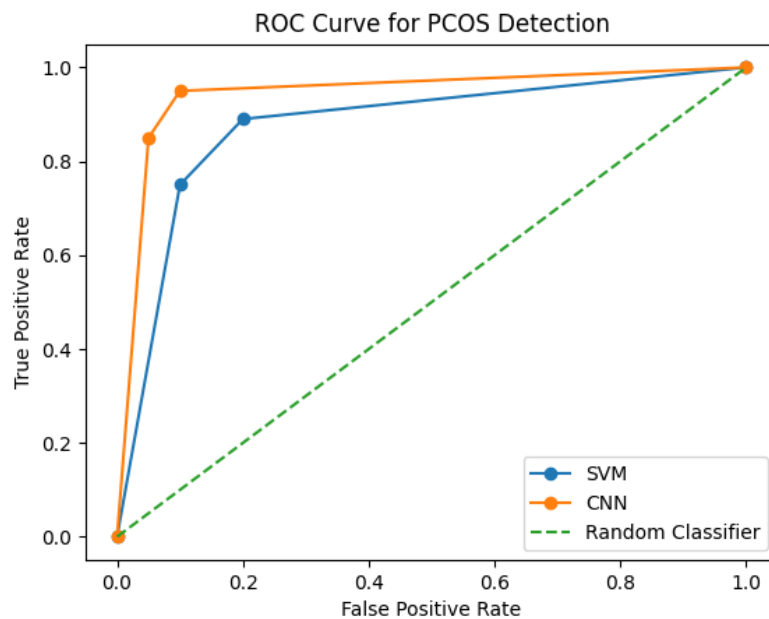


Fig. 12 ROC curve for SVM and CNN classifiers

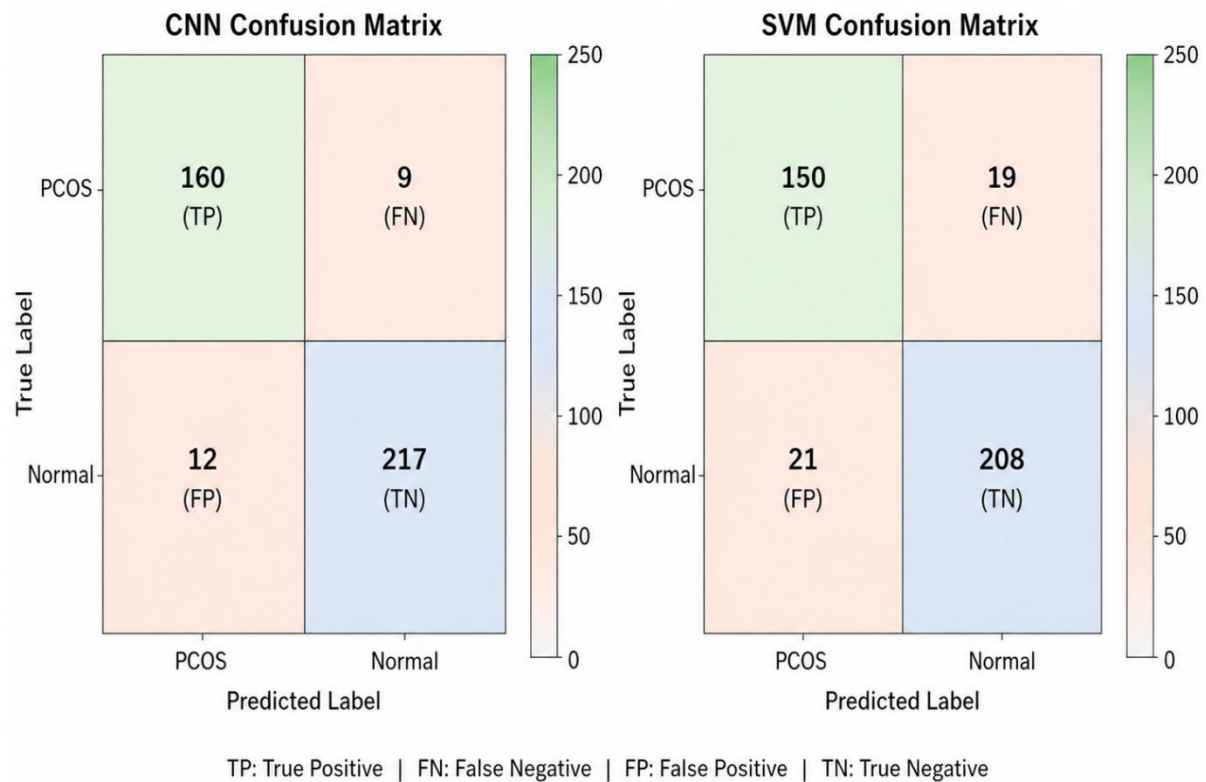


Fig. 13 Confusion matrix for proposed system

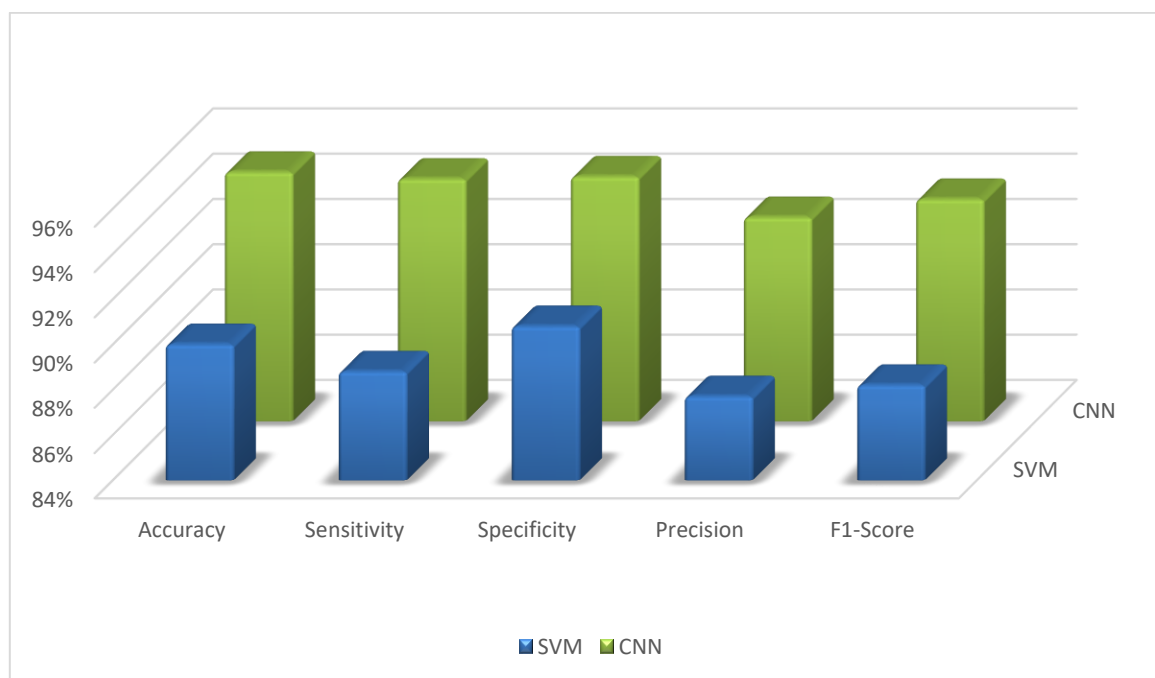


Fig. 14 Performance analysis for SVM and CNN

## V. CONCLUSION

This paper introduces a strong structure for the computerized recognition of Polycystic Ovary Syndrome (PCOS) utilizing ultrasound images through the integration of preprocessing, feature extraction, and classification

methodologies. The increase of the quality of images was attained by noise reduction, contrast augmentation, and artifact removal, which substantially enhanced visualization of ovary structures. The classification efficacy of both Support Vector Machine and Convolutional Neural Network models was assessed, revealing that CNN attains enhanced accuracy, sensitivity, and overall resilience owing to its capacity to learn structured representations of features from the data. Conversely, SVM demonstrated competing efficacy with reduced computing difficulty while integrated with efficient feature extraction techniques. Experimental findings validate that deep learning-based methodologies substantially improve clinical accuracy in the identification of PCOS relative to conventional techniques. Consequently, the suggested system provides a dependable and effective alternative for computationally aided assessment, with substantial promise for practical implementation and upcoming advances in health visual processing.

## REFERENCES

- [1] M. Di Lorenzo, N. Cacciapuoti, M. S. Lonardo, G. Nasti, C. Gautiero, A. Belfiore, B. Guida, and M. Chiurazzi, "Pathophysiology and nutritional approaches in polycystic ovary syndrome (PCOS): A comprehensive review," *Current Nutrition Rep.*, vol. 12, no. 3, pp. 527–544, May 2023.
- [2] K. Modi, I. Singh, and Y. Kumar, "A comprehensive analysis of artificial intelligence techniques for the prediction and prognosis of lifestyle diseases," *Arch. Comput. Methods Eng.*, vol. 30, pp. 1–24, Nov. 2023.
- [3] A. Ahmetašević, L. Alicelebić, B. Bajrić, E. Bečić, A. Smajović, and A. Deumić, "Using artificial neural network in diagnosis of polycystic ovary syndrome," in *Proc. 11th Medit. Conf. Embedded Comput. (MECO)*, Jun. 2022, pp. 1–4.
- [4] S. Ahmed, M. S. Rahman, I. Jahan, M. S. Kaiser, A. S. M. S. Hosen, D. Ghimire, and S.-H. Kim, "A review on the detection techniques of polycystic ovary syndrome using machine learning," *IEEE Access*, vol. 11, pp. 86522–86543, 2023.
- [5] P. H. Panicker, K. Shah, and S. Karamchandani, "CNN based image descriptor for polycystic ovarian morphology from transvaginal ultrasound," in *Proc. Int. Conf. Commun. Syst., Comput. IT Appl. (CSCITA)*, Mar. 2023, pp. 148–152.
- [6] S. Arora, Vedpal, and N. Chauhan, "Polycystic ovary syndrome (PCOS) diagnostic methods in machine learning: A systematic literature review," *Multimedia Tools Appl.*, vol. 2024, pp. 1–37, Jun. 2024.
- [7] S. Srivastav, K. Guleria, and S. Sharma, "A transfer learning-based fine tuned VGG16 model for PCOS classification," in *Proc. 2nd Int. Conf. Intell. Data Commun. Technol. Internet Things (IDCIoT)*, Jan. 2024, pp. 1074–1079.
- [8] N. Jeswani, N. Jain, A. Sharma, and S. Roychowdhury, "Comprehensive FemTech solution for feminine health," in *Proc. Int. Conf. Signal Process., Comput., Electron., Power Telecommun. (IconSCEPT)*, May 2023, pp. 1–6.
- [9] K. P. Harish, M. N. Dhivyanchali, K. N. Devi, N. Krishnamoorthy, R. D. Sree, and R. Dharanidharan, "Smart diagnostic system for early detection and prediction of polycystic ovary syndrome," in *Proc. Int. Conf. Comput. Commun. Informat. (ICCCI)*, Jan. 2023, pp. 1–6.
- [10] M. J. Lakshmi, D. S. Spandana, H. Raj, G. Niharika, A. Kodipalli, S. Kamal, and T. Rao, "Prediction of PCOS and PCOD in women using ML algorithms," in *Proc. Int. Conf. Inf. Commun. Technol. Intell. Syst. Singapore: Springer*, Apr. 2023, pp. 97–115.
- [11] S. Pradeepa, K. Geetha, K. Kannan, and K. R. Manjula, "DEODOR ANT: A novel approach for early detection and prevention of polycystic ovary syndrome using association rule in hypergraph with the dominating set property," *J. Ambient Intell. Humanized Comput.*, vol. 14, no. 5, pp. 5421–5437, May 2023.
- [12] C. J. Wang, C. S. He, R. X. Yan, and Y. C. Liu, "Application of MP-YOLO for segmentation and visualization of ovarian ultrasound imaging," in *Proc. 5th Eurasia Conf. Biomed. Eng., Healthcare Sustainability (ECBIOS)*, Jun. 2023, pp. 130–132.
- [13] K. Mahajan and P. Mane, "Follicle detection of polycystic ovarian syndrome (Pcos) using Yolo," in *Proc. 9th Int. Conf. Adv. Comput. Commun. Syst. (ICACCS)*, vol. 1, Mar. 2023, pp. 1550–1553.





- 
- [14] W. K. Cheung, A. Pakzad, N. Mogulkoc, S. H. Needleman, B. Rangelov, E. Gudmundsson, A. Zhao, M. Abbas, D. McLaverty, D. Asimakopoulos, R. Chapman, R. Savas, S. M. Janes, Y. Hu, D. C. Alexander, J. R. Hurst, and J. Jacob, "Interpolation-split: A data-centric deep learning approach with big interpolated data to boost airway segmentation performance," *J. Big Data*. vol. 11, no. 1, p. 104, Aug. 2024, doi: 10.1186/s40537-024 00974-x.
- [15] H.Louati, A.Louati, E. Kariri, and S. Bechikh, "Optimizing deep learning for computer-aided diagnosis of lung diseases: An automated method combining evolutionary algorithm and transfer learning," in *Proc. Int. Conf. Comput. Collective Intell.*, Cham, Switzerland. Springer, Sep. 2023, pp. 83–95.
- [16] R. Velvizhi and R. Kiruthiknivas, "The development of polycystic ovary syndrome risk evaluation system using advanced machine learning tech nique," in *Proc. Int. Conf. Inventive Comput. Technol. (ICICT)*, Apr. 2024, pp. 314–318.
- [17] H. Meswal, D. Kumar, A. Gupta, and S. Roy, "A weighted ensemble transfer learning approach for melanoma classification from skin lesion images," *Multimedia Tools Appl.*, vol. 83, no. 11, pp. 33615–33637, Sep. 2023.
- [18] P. Jain, R. K. Mishra, A. Deep, and N. K. Jain, "Xplainable AI for deep learning model on PCOD analysis," in *XAI Based Intelligent Systems for Society 5.0*. Amsterdam, The Netherlands: Elsevier, 2024, pp. 131–152.
- [19] P. Moral, D. Mustafi, and S. K. Sahana, "PODBoost: An explainable AI model for polycystic ovarian syndrome detection using grey wolf based feature selection approach," *Neural Comput. Appl.*, vol. 36, no. 30, pp. 18627–18644, Oct. 2024.
- [20] <https://www.kaggle.com/datasets/bharatsh001/pcos-cleaned-and-splitted>.

