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Unveiling PCOS Diagnosis with AI: A Comparative Approach using Machine Learning and Deep Learning

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Abstract: Polycystic Ovary Syndrome is a prevalent hormonal disorder among women of reproductive age, often resulting in irregular menstrual cycles, infertility, metabolic complications, and an increased risk of type 2 diabetes and Endometrial Cancer. In the realm of Computer-Aided Diagnosis, Machine Learning (ML) and Artificial Intelligence (AI) have become increasingly popular for tasks such as classification, prediction, and clustering, surpassing traditional methods in managing complex healthcare data. Numerous algorithms for machine learning, including Random Forest, Naive Bayes, Decision Trees, Multi-layer Perceptron's, and Support Vector Machines, have been employed to categorize PCOS patients. Models for deep learning, including convolutional neural networks. Deep learning models, such as Convolutional Neural Networks, UNet, and Transformers, have advanced the field further. These models are used for image analysis and segmentation, and they achieve accuracy levels comparable to those of human experts. Explainable AI approaches are covered, along with segmentation and classification methods, for comprehending, interpreting, and assessing model predictions. Future directions and limitations in this field of study are still being investigated. This all inclusive approach leverages the benefits of numerous machine learning models to produce, improve, and analyze data, which eventually results in more accurate diagnostic instruments and dependable clinical practice outcomes.

Keywords: Machine *Learning, Polycystic Ovary Syndrome, Segmentation, Transformers, Explainable AI*

1. Introduction

PCOS, also known as Polycystic Ovarian Syndrome, is a common hormonal disease that affects fertile women. It can lead to infertility, irregular menstrual cycles, metabolic issues, and an increased risk of type 2 diabetes and endometrial cancer (EC). Numerous meta-analyses indicate that EC will occur in three to four times as often women with PCOS. This highlights the significance of regular monitoring and preventive measures regarding female PCOS patients, as there's a clear correlation between PCOS with a higher chance of EC [1]. Additionally, some studies have indicated that PCOS can negatively affect the prognosis of EC, underscoring the requirement for additional research to comprehend the connection between these conditions and to develop effective treatment plans. According to Alsibai et al., [2] polycystic ovaries are characterized by having 12 follicles or more, each measuring 2 - 9 mm in diameter in the ovary. This condition is known as multifollicularity. Priya et al., [3] explored the multifactorial nature of PCOS, which is caused by genetic and non-genetic factors. The genetic variations rs3842570, rs3792267, rs2975760, and rs5030952 of the CAPN10 (Calpain-10) connected to the insulin resistance are investigated as potential risk factors for PCOS. These genetic variations can influence androgen production and lead to hypercholesterolemia, making them plausible causes of the various phenotype observed in women with PCOS. Candidate genetic variables for PCOS susceptibility include variations in the gene related to inflammatory or metabolic pathways. [4]. Research has been done to determine the correlation between metabolic gene variants, highlighting multiple potential genes linked to PCOS in improving our understanding of genetic correlations [2]. Additionally, extensive genetic tests are utilized to look into the genetic foundations of PCOS. [5] [6]. Diagnosis of PCOS typically involves the existence of two or more of the subsequent features: (i) oligo or anovulation, (ii) clinical and biochemical hyperandrogenism, or (iii) polycystic ovaries. The latter is particularly important for diagnosing PCOS; it might be identified using ultrasonography Early detection of PCOS is crucial for managing symptoms thus reducing the probability of long-term health complications.

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Ultrasound is the one that most commonly utilized imaging technique for examining ovarian pathology patients, offering several advantages over other imaging methods like Computed Tomography (CT) and Magnetic Resonance Imaging (MRI) [7]. In Artificial Intelligence (AI). Machine Learning and Computer-Aided Diagnosis techniques have become increasingly popular for classification, Prediction, and clustering tasks, surpassing traditional biostatistical methods for analysing and integrating vast amounts of complex healthcare data.

Naeem et al. [8] utilized different classification focused machine learning algorithms, including Random Forest (RF), Naive Bayes (NB), Decision Tree (DT), Multi-layer Perceptron (MLP) and Support Vector Machine (SVM). Each of these algorithms employs distinct learning approaches for prediction and classification. For example, DT algorithms use inductive gaining knowledge of pre- diction class labels, while NB relies on probability-based predictions. MLP is an artificial neural network that learns patterns through multiple layers, and RF constructs several trees during the learning process to improve prediction accuracy. Additionally, ensemble techniques like bagging and voting are often combined with these machine learning strategies to enhance the performance of the model. Deep learning has made significant progress, enabling researchers to use various structures like Transformers, Neural Networks that are Convolutional and Recurrent. Deep Neural Networks and Deep Belief Networks, to analyse unstructured data from medical records. These advancements in Deep learning facilitate integration with other cutting-edge technologies, such as Explainable AI and Natural Language Processing (NLP), achieving results comparable to human experts in image analysis, detection, and recognition of significant features. This integration further enhances diagnostic accuracy and provides a more comprehensive view of a patient's condition [9] [10]. Convolutional Neural Networks (CNNs) are a popular type of Deep Learning model used for segmentation and classification tasks. CNN architectures like VGG-16, ResNet, MobileNet, AlexNet, and GoogLeNet have produced outstanding outcomes in binary or multi class classification [11] [12]. Furthermore, variants of U-Net including UNet: U-Net++, Attention U-Net, MobileUNet, Dense- UNet, R2U-Net, and UNet 3+, [13] are frequently used for dividing medical images.

Recently, Conventional CNNs have been increasingly replaced by Transformers, particularly the Vision Transformer (ViT), because of their capacity to capture local and global visual dependencies. This is crucial for healthcare applications as it enhances interpretability and pertaining to small sample sizes. In addition to classification and segmentation techniques, Explainable AI (XAI) is employed to understand, interpret, and analyse a model's predictions. Two well-known algorithms, and Gradient Class Activation Mapping (GradCAM) and Local Interpretable Model-agnostic Explanations (LIME), NeuroXAI, are used for interpretation and image analysis. LIME is extensively employed to interpret predictions made by black-box machine learning models, identifying significant data elements for patients[16]. GradCAM is particularly useful for image classification tasks, as it visualizes class activation maps matching to several layers, making it feasibleto comprehend model predictions more clearly. Jan et al., [17] describe a strategy that combinesa traditional Convolutional Neural Network with the GradCAM saliency method to explain predictions. Grad-CAM can decipher any number of layers of a target CNN without any modifications to the network architectures, increasing flexibility for diagnosis [18].

1.1 Diseases affecting PCOS

i Infertility

ii Type 2 Diabetes

iii Cardiac Arrest

iv Endometrial Carcinoma

1.2 Infertility

One of the most prevalent causes of infertility is PCOS, which is linked to a higher chance of miscarriage. whether the pregnancy is spontaneous or assisted. Additionally, PCOS can lead to Ovarian Hyperstimulation Syndrome (OHSS) in assisted pregnancies. Research suggests that a high per- centage of spontaneous abortions occur in the first trimester in 25–73 % of women with polycystic ovaries. Among women with frequent miscarriages, defects in Luteinizing Hormone (LH) secretion have been recognized in 81 cases. High testosterone levels have also have additionally been seen in females with recurrent miscarriages, regardless of whether they have PCOS. Insulin Resistance (IR) and amount of Obesity are often linked to infertility caused by disrupted folliculogenesis in PCOS [19].

1.3 Type 2 Diabetes

Zhang et al.,[5] reported that 90-95 % of adult diabetics worldwide suffer from Type 2 Diabetes Mellitus (T2DM), a complex disease characterized by high blood glucose levels. Global prevalence is predicted to increase to 642 million by 2040. leading to significant economic costs. Common symptoms include hyperosmolar hyperglycemia, which, in addition to potentially lethal frequent urination (polyuria), excessive thirst (polydipsia), and increased hunger (polyphagia). Additionally, individuals with type 2 diabetes have higher chance to experiencing major side effects like cardiovascular disease, stroke, and diabetic retinopathy, which can be life-threatening. More than half of womenover the age of 40 with PCOS are at an increased risk of developing Type 2 Diabetes.

1.4 Cardiac Arrest

It's interesting to note that obesity and other aspects of Metabolic Syndrome (MS) act as mediating elements with in the connection between the consequences of cardiovascular disease (CVD) andPCOS[20].

1.5 Endometrial Carcinoma

Endometrial carcinoma (EC), the sixth most prevalent cancer among females, is becoming more common in both incidence and death rates. According to estimates, this disease's prevalence will increase by 50–100 % by 2030. [21] [22]. Endometrial Cancer and excessive estrogen stimulation of the endometrium are often associated. The endometrial glandular epithelium may eventually undergo a malignant change due to this stimulation, causing mitotic activity. The consequences of this hormone-sensitive illness on the endometrium and its dependence on estrogen are well-known[23]. Obesity, miscarriage, PCOS, type 2 diabetes, insulin resistance, and estrogen exposure therapy are a few of the danger indicators for EC that have been discovered. When determining a person's risk of acquiring EC, these characteristics ought to be taken into account, as they have been connected to an increased likelihood of the condition. [1] **(referring Fig. 1).**

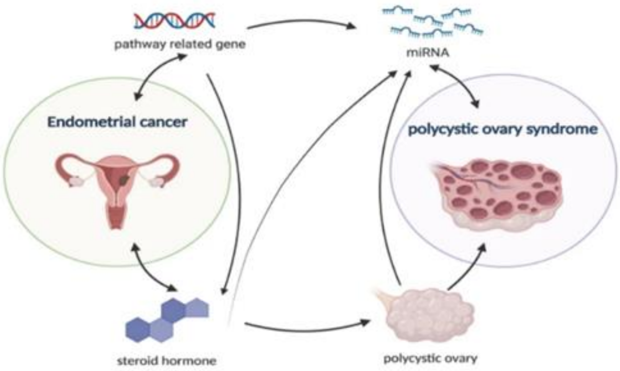

Fig 1. Endometrial Carcinoma and PCOS

1.2 Procedure for choosing papers

This study analyzed 110 articles that were published between 2020 and 2024,, emphasizing the use of machine learning (ML) and deep learning (DL), and machine learning (ML), and Explainable AI (XAI) for PCOS detection. A chronological overview of the selected articles, showing that 2023 had the highest publications, with 29 papers. Journal and conference papers on ML, XAI,DL applications in PCOS detection were sourced from well-known databases such as Google Scholar, IEEE Xplore, and ScienceDirect. After removing duplicates, 95 articles remained. Of these, 75 full-length Articles eligibility were evaluated, but 35 were rejected for various reasons, such as being published before 2020 or lacking full-text availability. Ultimately, 67 papers were incorporated into the synthesis of data, focusing on those incorporating computer assisted PCOS detection techniques. **(referring Fig. 2, Fig 3).**

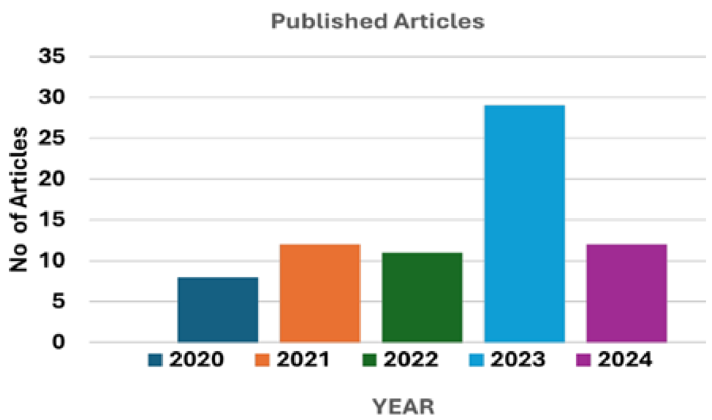

Fig 2. Procedure for Selecting Papers

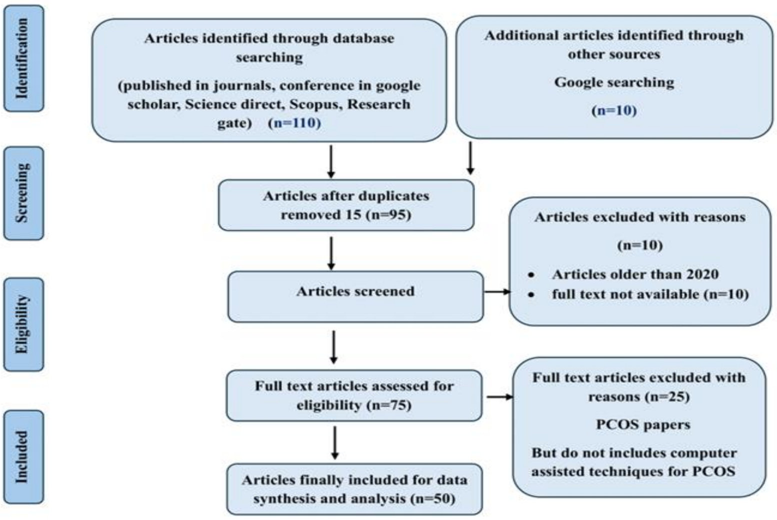

Fig 3. No. of Paper published between 2020 to 2024

2. Work Flow Architecture for PCOS Detection

The workflow architecture for PCOS Detection using clinical and ultrasound-sound images of ovaries. Various techniques of Machine learning (ML) and Deep Learning (DL) are applied by various researchers to classify PCOS and non-PCOS data. Further, XAI methods are employed to interpret the features selected by ML and DL techniques Furthermore to this, various segmentation and clustering techniques are deployed to identify infected ovary follicles and thereby decrease the computational time required for PCOS detection. The detailed explanations are discussed below: **(referring Fig. 4).**

Hospital at the University of Khobar, Saudi Arabia. Among these files are 391 images, comprising 264 of normal ovaries from patients without PCOS and 127 PCOS positive data. Dana et al., [25] used the Polycystic Ovary Syndrome dataset from Kaggle. images were obtained from Telkom University’s public website. Alamoudi et al. [7] utilized 1250 patient files from King Fahad It provides a diverse set of physical and clinical parameters for diagnosing PCOS. Mohammad et al.,[2] utilized two public online datasets to train and test the DenseNet201 architecture to extract the significant features from PCOS images.

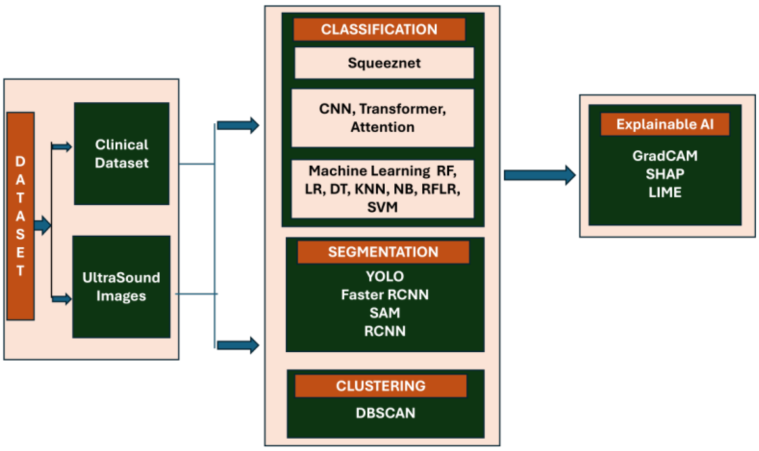

Fig 4. Work Flow Architecture for PCOS Detection

2.1 Datasets

Multiple clinical and ultrasound datasets are utilized by researchers to develop and evaluate DLand ML models for detecting and diagnosing Polycystic Ovary Syndrome (PCOS). Debasmita et al., [11] utilized the Annotated 3D Ovarian Ultrasound Image (USOVA3D) Dataset, which includes 3419 2D ultrasound images of the ovary with dimensions of 315 x 312. Pradeep et al., [24] used the MultiModality Ovarian Tumor Ultrasound (MMOTU) dataset of ovarian ultrasound images collected from Beijing Shijitan Hospital, Capital Medical University. The MMOTU image dataset contains 1469 2D ultrasound images (OTU 2D) and 170 Contrast-enhanced ultrasound images (OTU CEUS) from 294 patients. Gulhan et al., [24] used the Dataset, which included 54 ultrasound images from 14 PCOS patients and 40 controls. The

Yuanyuan et al., [26] researched Endometrial samples from September 2019 to September 2020, the Reproductive Center of the Second Hospital of Lanzhou University saw 33 PCOS patients and seven healthy controls. **(referring Table 1).**

2.1.1 Highlights of the papers which used Clinical Data

Various studies have explored feature selection techniques and machine learning algorithms to enhance classification effectiveness in identifying PCOS. The highlight of the studies: Hela Elmannai et al., [28] proposed an embedded approach that combines tree-based feature selection with Enhancing the Recursive Feature Elimination (RFE) training data's learning accuracy. They discovered that more outstanding evaluation metrics were obtained when machine learning models were stacked using RFE instead of stacking with tree-based feature selection. Md. et al., [26] said that Mutual Information is the ideal filtering technique for feature selection. The Kerala dataset shows the greatest results when this method is used. Ejay et al.,[44] used Synthetic Minority Oversampling (SMOTE) to balance the clinical dataset. They demonstrated that support Vector Machine (SVM) performance was superior, mainly when significant overlapping was observed in the PCA plot. Sakib et al., [50] integrated two sampling strategies, SMOTE and Edited Nearest Neighbors (ENN), to boost the minority class's sample size and establish a outlier removal rule. According to Guhdur et al., [51], the blend of SMOTE, PCA, and K-Nearest Neighbor gives the best possible categorization performance. Ipek et al., [52] found the important factors in determining the presence or absence of PCOS are the follicles numbers in the left and right ovaries. **(referring Table 2).**

2.1.2 Highlights of the papers which used Ultrasound Images

The study by Sayma et al., [49] achieved the best-performing results utilizing the Convolutional Neural Network (CNN) model "VGGNet16," which has already been trained as a feature extractor. After the features are extracted, a stacking ensemble model using "XGBoost" as the meta-learner for image classification is applied to the features. attaining an impressive accuracy of 99.89 % . Pradeep et al., [24] highlighted the efficiency of U-Net and residual U-Net with attention mechanisms for semantic segmentation in the study of medical image. The author proposed an attention-based residual UNet (AResUNet) that uses the Adam optimizer with 0.0001 learning rate. The networks were trained for 100 epochs with data augmentations to mitigate over fitting. These methods enhance gradient flow and parameter efficiency, making them popular choices in this domain.

Asma et al., [54] examined the result of various probe and follicle conditions on ultrasonography images. They discovered combining Otsu's thresholding and the Chan-Vese method significantly improved ultrasonic image segmentation. Saha et al. [11] introduced MU-net, a novel 2D segmentation network that integrates MobileNetV2 and U-Net. Despite challenges low contrast in images, MU-net achieved a remarkable accuracy of 98.4 % on the USOVA3D Training Set 1. **(referring Table 3).**

2.1.3 Highlights of the papers which used both Clinical data and Ultrasound Images (Fusion model)

The following study emphasizes the integration of clinical data and ultrasound images for improved diagnostic performance: Ashwini et al., [36] found that Random Forest, especially when coupled with hyper parameter optimization, outperformed other ensemble models. Bayesian optimization—Bayesian tuning significantly enhanced the execution of Random Forest than the other hyper parameter tuning methods such as grid search CV and randomized search CV.

Zhang et al., [30] reported that the Stacking classification model, incorporating Principal Component Analysis (PCA), achieved higher accuracy with follicular fluid samples than plasma samples. In a comparative evaluation of methods for transfer learning on multimodal data, Alamoudi et al., [7] found that MobileNet outperformed other transfer learning models, achieving 82.46 % accuracy. **(referring Table 4).**

2.2 Feature selection Techniques

Alamoudi et al., [7] employed traditional feature extraction techniques, including modified furious flies and classifiers like Artificial Neural Networks (ANN) and Naive Bayes (NB), using a limited sample size of 68. They also used PCA and chi-square segmentation techniques. According to Nasim et al., [32], the Gaussian Naive Bayes (GNB) outperformed other machine learning models with 100 % accuracy and reduced computational time of 0.002 sec using the proposed Chi Squared PCOS (CSPCOS) feature selection techniques.

Maheswari et al., [55] applied furious flies to identify features through three stages: ROI selection, follicle selection, and follicle identification, with classification, achieved an accuracy of 98.63 % using NB and ANN. Harsha et al. [56] evaluated eight ML techniques and three Correlation feature selection, Recursive feature elimination, and Select-K-Best are feature selection strategies. Features from Correlation Feature Selection had the highest accuracy, at 92 %. Bharti et al, [34] used univariate analysis to find the best features for predicting PCOS. Harshita et al. [31] compared Harris Hawks and Salp Swarm Optimization with Mutual Information. Kaushik et al. [57] utilized correlation-based feature selection as the initial strategy. Simple linear algorithms such as Logistic Regression (LR) and Linear Discriminant Analysis (LDA) are compared with nonlinear methods, including KNN, CART, Random Forest Classifier (RFC), NB, and SVM. The RF model achieved 89 % accuracy after data optimization. **(referring Table 5, Fig.5, Fig.5.1).**

2.3 PCOS Detection using Machine Learning Models

Subha et al., [53] developed a dependable and effective diagnostic model for detecting PCOS that selects features using Swarm Intelligence (SI) and Machine Learning (ML) for classification. RF combined with Particle Swarm Optimization produced the best results. Mohamad et al., [33] for feature selection the Mutual Information model was applied. Random Forest and AdaBoost models achieved 94 % accuracy. Tiwari et al., [39] diagnosed PCOS based on a clinical dataset using noninvasive screening parameters where the Random Forest method achieved 93 % accuracy [60] Preeti Chauhan Create an application utilizing machine learning KNN, NB, DT, SVM, LR, and the Decision Tree Classifier to predict PCOS early. This model was most accurate as revealed in the confusion matrix. **(referring Table 6, Fig.6).**

Table 1.1. Dataset of Clinical and Ultra Sound Images	
[7]	King Fahad Hospital at the University of Khobar, Saudi Arabia, collected 391 images, including 264 normal ovaries and 127 PCOS data. **https://www.kaggle.com/datasets/ahmedsharaf97/kingfahd-hospital-sql (Open Source)**
[36]	https://service.tib.eu/ldmservice/dataset/sdm-genomicdataset/resource/d65a3ddc-ff78-4a5e-8863-cbecdc76d803 (Open Source)

Table 2. Highlight of papers which used clinical data to detect PCOS

Author	***Algorithm /Feature used***	***Key Findings***
Hela El-mannai [28]	Embedded approach (tree-based and RFE) feature selection technique, Recursive Feature Elimination (RFE) with Stacking ML	ML models Stacked with meta-learner improves performance, Bayesian optimization enhances ML model effectiveness, SMOTE and ENN address class imbalance
Ejay [44]	SMOTE for balancing clinical Dataset, SVM performance	SVM's performance was best as strong overlapping was seen in PCA's plot
Pijush Datta [16]	SMOTE with five ML algorithms (LR, RF, SVM, DT, KNN), SMOTE-based Logistic Regression	Logistic regression based on SMOTE was executed best among all SMOTE based algorithms after PCA
Guhdur [51]	SMOTE for classification performance improvement	K-Nearest Neighbor performed the best among classifiers with SMOTE
Subha [53]	Swarm Intelligence (SI) approaches like Particle Swarm Optimization and Flashing Firefly	ML models with PSO-based feature selection achieve the maximum output with minimum feature size, avoiding redundancy in feature subsets.
Ipek [52]	Follicle (No) L. and Follicle (No) R. variables	Follicle No L. and Follicle No R. are the most effective variables in determining the presence or absence of PCOS

Angela [35]	CatBoost a gradient boosting decision tree classifier	Noninvasive model accuracy: 81-82.5 % ; Invasive model accuracy: 87.5-90 %

Table 3. Highlight of **papers which used ultrasound images to detect PCOS**		
Author	***Algorithm /Feature used***	***Key Findings***
Sayma [49]	VGGNet16 pre-trained model and stacking ensemble model with XG-Boost	Achieved 99.89 % accuracy using VGGNet16 for feature extraction and XGBoost for classification, increase in accuracy and decreased in training time.
Pradeep [24]	U-Net or residual UNet with attention mechanism	Improved gradient flow and parameter efficiency in semantic segmentation for medical image analysis
Asma [34]	Otsu's thresholding combined with Chan–Vese method	Improved ultrasonic image segmentation despite changes in probe and follicle conditions
Saha [12]	MUNet, combining U-Net and MobileNetV2	achieved 98.4 % accuracy on USOVA3D Training Set 1 in spite of problems with low contrast.

Table 4. Highlight of papers which used Fusion Model to detect PCOS		
Author	***Algorithm /Feature used***	***Key Findings***
Ashwini [36]	Random Forest with hyper parameter optimization	Bayesian tuning significantly enhances Random Forest's performance
Zhang [30]	Stacking classification model with Principal Component Analysis	Higher accuracy using follicular fluid than plasma samples
Alamouli [7]	VGG16, InceptionNet, DenseNet, MobileNet	MobileNet outperformed on multimodal data (clinical data + US images)

Table 5. Feature Selection		
Author	Algorithm	Key findings
Nasim et al. [32]	GNB, Chi-Squared PCOS (CSPCOS), PCOS Exploratory Data Analysis (PEDA)	Gaussian Naive Bayes (GNB) outperformed with CS-PCOS feature selection techniques.
Maheswari et al. [55]	Naive Bayesian classifier, ANN, Furious Flies,	ANN and Naive Bayesian classifier achieved 98.63 accuracy.
Harsh et al. [56]	Accuracy of 92 % was obtained using the Select-K-Best, Correlation Feature Selection, RFE, and Bernoulli	Bernoulli classifier using Correlation Feature Selection.
Bharati et al. [34]	Univariate analysis	Univariate analysis applied to find the best features predicting PCOS.

Varada et al. [31]	Salp Swarm Optimization, Mutual Information	Harris Hawks Optimization, and Salp Hawks Optimization were compared, and the top 14 features were chosen to predict PCOS.
Sulekha et al. [57]	Correlation based feature selection	used correlation-based feature selection as the primary feature selection method.
Denny et al. [58]	LR, LDA, KNN, CART, RFC, NB, SVM	Random Forest Classifier model achieved 89 % after data optimization.
Pinar et al. [59]	CKSAAP (Composition of k-Spaced Amino Acid Pairs)	Utilized CKSAAP technique for feature extraction.

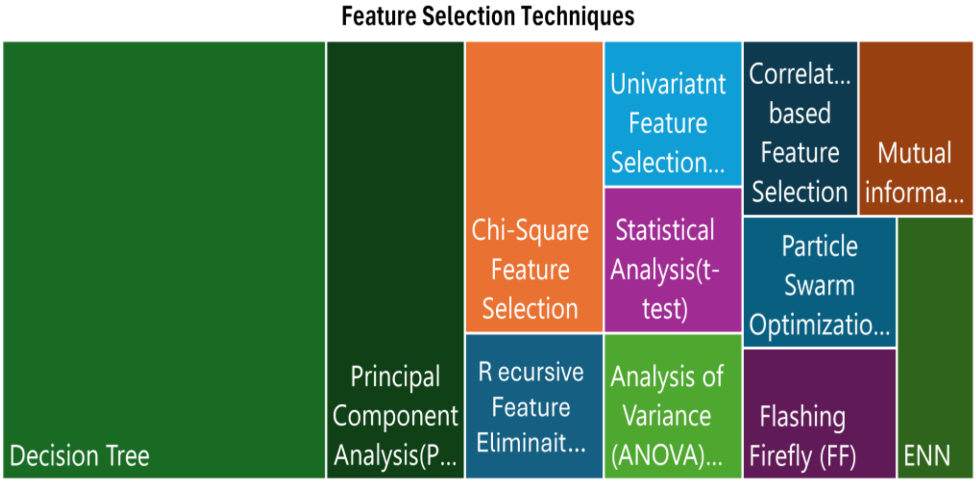

Fig. 5. Feature Selection Technique

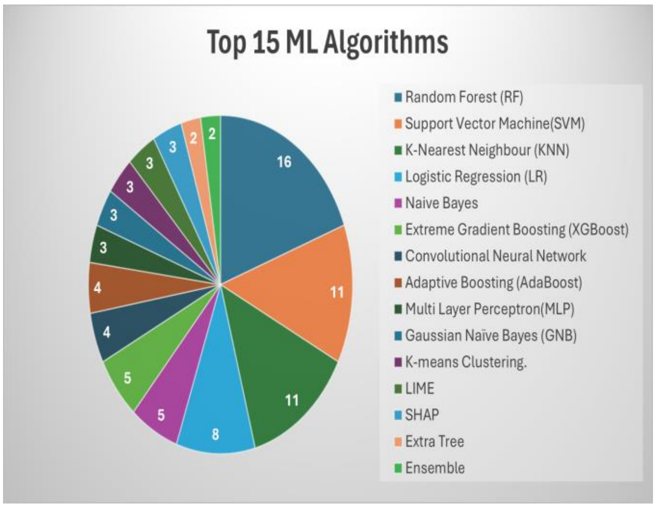

Fig. 6. Machine Learning Algorithm used in different papers

Table 5.1. Feature Selection Techniques

Algorithm	***Reviewed Papers***
Recursive Feature Elimination RFE	[53]
Chi-Square Feature Selection	[53] [50]
Decision Tree	[8] [16] [28] [51] [33] [60] [61]
Univariaint Feature Selection method	[34]
Statistical Analysis(t-test)	[53]
Analysis of Variance (ANOVA) Test	[50]

Correlation-based Feature Selection	[53]
Mutual information	[33]
Principal Component Analysis(PCA)	[44] [35] [30]
Particle Swarm Optimization (PSO)	[53]
Flashing Firefly (FF)	[53]
SMOTE WITH Edited Nearest Neighbour (ENN)	[50]

Table 6. Machine Learning Algorithm used in different Papers

Algorithm	***Abbreviation***	***Reviewed Papers***
Random Forest	RF	[8] [16] [52] [34] [62] [36] [33] [28] [53] [30] [29] [39] [31] [56] [57] [50]
Multi Layer Perceptron	MLP	[63] [41] [50]
K-Nearest Neighbour	KNN	[16] [28] [51] [57] [60] [30] [25] [62] [56] [61] [50]
Support Vector Machine	SVM	[8] [16] [28] [57] [29] [44] [60] [62] [56] [61] [50]
Naive Bayes	NB	[8] [28] [60] [61] [50]
Gaussian Naive Bayes	GNB	[62] [32] [57]
K fold Cross validation	KF	[35]
Logistic Regression	LR	[16] [28] [33] [60] [51] [56] [34] [57]
Linear Discriminant	LDA	[25]
Multi Variant Regression	MVR	[26]
Random Forest Linear Regression	RFLR	[34]
Gradient Boosting	GB	[8]
Extra Tree	ET	[29] [41]
Ensemble	EN	[8] [49]
Adaptive Boosting	AdaBoost	[28] [33] [41] [50]
Categorical Boosting	CATBoost	[35]
Extreme Gradient Boosting	XGBoost	[28] [50] [30] [29] [50]

Table 7. Deep Learning Algorithm used in different Papers for Classification, Segmentation and Clustering

Classification	
Algorithm	***Reviewed Papers***
Convolutional Neural Network (CNN)	[8] [63] [49] [27]
Recurrent Neural Network RNN	[63]
Long Short-Term Memory Networks LSTMs	[63]
Deep Neural Network DNN	[62]
VGG16	[7] [12] [45]
MobileNet	[10] [36] [7]
SqueezeNet	[64] [27]
ResNet	[10]
DarkNet	[64]
AlexNet	[64]
InceptionNet	[7] [10] [65]
DenseNet201	[7] [2]
DenseNet	[10]
Transformer	[13]

Table 7. Deep Learning Algorithm used in different Papers for Classification, Segmentation and Clustering

Algorithm	***Reviewed Papers***
UNet	[66] [36] [11] [7] [67]
ResUNet	[68]
Attention Residual UNet AResUNet	[69] [24]
Refine UNet	[70]
Channel Attention Residual UNet CAR-UNet	[68] [71]
Yolo	[72] [73] [13] [74]
Clustering	
K-means Clustering	[35] [27] [59]
Hierarchical Clustering.	[59]
Density-Based Spatial Clustering of Applications with Noise DBSCAN	[59]

2.6 PCOS Detection using Deep Learning (DL) Models

Perihan et al., [27] evaluated several techniques for follicle detection, including CNN architecture. . Wiener filter with Adaptive Thresholding, Gaussian Filtering, Discrete Wavelet Transform, k-means Clustering. Among these methods, the Wiener filter with Adaptive Thresholding achieved 97.63 % accuracy. Meanwhile, Saha et al., [11] developed a segmentation approach that combines MobileNetV2 and UNET (MUNET) and an impressive accuracy of 98.4 % was achieved in detecting ovarian follicles. Additionally, Pradeep et al., [24] focused on PCOS detection and found that adaptive bilateral filter-based image preprocessing with Attention Residual UNET (AResUNet) yielded exceptional results on both 2D and multimodal images. (referring Table 7, Fig.7).

2.7 Advanced Techniques

Transfer learning has advanced deep learning by enabling pre-trained models with modest quantities of extra training data for new tasks. The well-known transfer learning models and techniques are: (referring Table 8, Table 9).

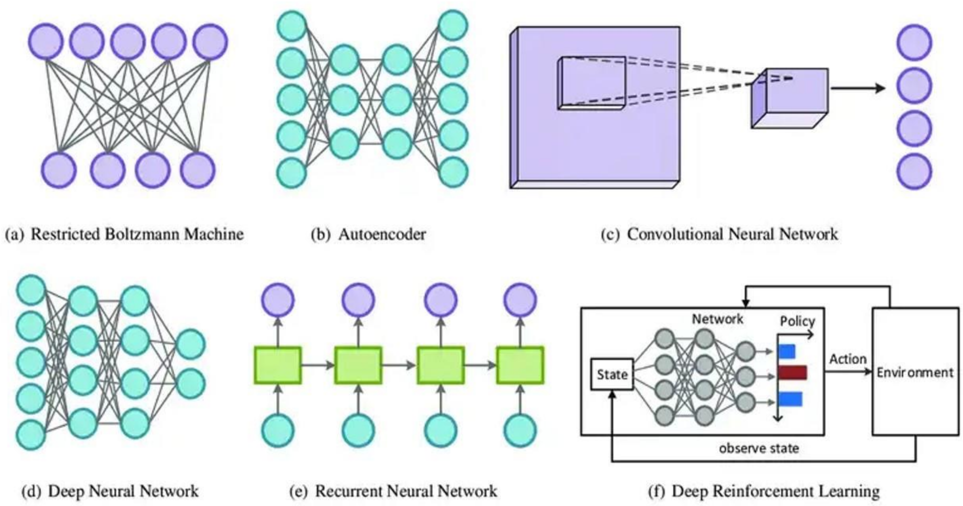

Fig. 7. Deep Learning Models

Table 8. Deep Learning Algorithm		
Deep learning Techniques	***Advantages***	***Disadvantages***
Generative Adversarial Networks (GANs)	Generate high-quality, realistic images. (super-resolution). Enhances data augmentation and synthetic data generation—training instability (mode collapse, oscillation).	Requires careful balancing of generator and discriminator. Evaluation and assessment of generated images can be subjective and challenging.
Autoencoders	Unsupervised feature learning for image denoising and compression. Efficient in learning compact representations of images.	Difficulty in choosing optimal architecture and hyperparameters. Limited in handling complex variations in image data.
Variational Autoencoders (VAEs)	Probabilistic models for generating diverse and realistic images. Continuous latent space enables interpolation and sampling. It can learn disentangled representations.	Complex loss function (reconstruction + KL divergence). It is challenging to balance reconstruction quality and latent space regularization.
Capsule Net-works	Capture hierarchical relationships between parts of objects in images. More robust to affine transformations and distortions. Potential for better generalization on small datasets.	Limited implementations and practical applications compared to CNNs. Higher computational cost in terms of training time.

Table 8.1: Transfer Learning Models		
Model Name	Advantages	Disadvantages
VGG (VGG16, VGG19) [45] [12]	Simple and straightforward architecture. Good performance on image classification tasks. Pre-trained on large datasets like ImageNet.	Huge model size, resulting in high computational and memory requirements.

ResNet (ResNet50, ResNet101) [10]	Residual connections help train deep networks effectively. Excellent performance on a wide range of image classification tasks. High computational and memory requirements.	Complex architecture, making it harder to implement and tune.
Inception (InceptionV3) [10]	Efficient regarding computational resources. High accuracy on image classification tasks. Pre- trained on large datasets like ImageNet.	Complex architecture, making it harder to implement and tune. Large model size.
MobileNet (MobileNetV1, MobileNetV2) [10]	Lightweight and efficient, designed for mobile and embedded devices. Good trade-off between accuracy and model size. Pre-trained on large datasets.	Lower accuracy compared to larger models like ResNet and Inception. Limited versatility for very complex tasks.
DenseNet (DenseNet121, DenseNet169) [10]	Efficient regarding parameter usage due to dense connections. Excellent performance on image classification tasks. Pre-trained on large datasets.	High computational and memory requirements. It can be challenging to implement and tune.

Table 9. XAI Algorithm used in different Papers

Algorithm	***Advantages***	***Disadvantages***
SHAP (Shapley Additive Explanations) [63] [35] [31]	Provides consistent and accurate feature importance, applicable to any model.	Computationally expensive, especially for large models or datasets.
LIME (Local Interpretable Model-agnostic Explanations) [63] [52] [31]	Offers local fidelity by providing explanations for individual predictions.	May produce unstable explanations, dependent on the sampled data for perturbation.
Grad-CAM (Gradient weighted Class Activation Mapping) [63]	Generates visual explanations by highlighting essential regions in the input image.	Primarily applicable to CNNs, less effective for transformer-based models.
Integrated Gradients	Provides a comprehensive attribution method by integrating gradients along the input path.	Can be computationally intensive and requires a baseline input for comparison.
Attention Mechanisms [36] [24] [69] [71] [68] [63]	Naturally, provide Interpretability by showing which parts of the input the model focuses on.	Interpretability may be limited by the Complexity and opacity of attention distributions.

2.8 PCOS Detection using Explainable AI

Ipek et al., [52] found that among various features such as Follicle-stimulating hormone (FSH), Thyroid Stimulating Hormone (TSHm), Follicle L, and Follicle R, the two variables follicle L and follicle R were the most influential for PCOS detection. Priyanka et al., [62] performed Exploratory Data Analysis (EDA) on the tabular Dataset to evaluate essential features and applied ML algorithms, including Random Forest (RF), k- Nearest Neighbors (kNN), Support Vector Machines (SVM) with linear and RBF kernel, Gaussian Naive Bayes (GNB), and Dense

Neural Network (DNN) classifier. This method obtained an accuracy of 97 % after feature extraction. Varada et al., [31] employed Explainable AI techniques such as SHAP, LIME, ELI5, Qlattice and feature importance with Random Forest to make model predictions more interpretable. **(referring Table 9).**

2.9 Segmentation

In the field of PCOS research, precise analysis and diagnosis depend on efficient image segmentation. In the paper ”U-Net: Convolutional Networks for Biomedical Image Segmentation” [75], a well-known deep learning model, the U-Net architecture is among the innovative techniques employed in recent investigations. This architecture is well know for its U-shaped structure, which includes an encoder decoder method that is intended to improve segmentation performance in situations where there is a shortage of labeled data. U-Net’s architecture strives for efficiency, accuracy, and performance optimization while lowering the intricacy of Fully Convolutional Networks (FCNs).

U-Net’s exceptional skills in semantic segmentation, which is necessary for dividing images into meaningful segments, have led to its utilization in recent articles [66] [36] [11] [7] [67]. U-Net, with its expanding (decoder) and contracting (encoder) routes, captures both local and global features, making it an excellent choice for a variety of biomedical applications, despite its inherent complexity [24]. U-Net’s ability to integrate precise data from multiple layers makes it a powerful tool in PCOS research. It produces precise and comprehensive segmentation findings, which are essential for additional analysis and diagnosis. **(referring Table 7, Fig.8).**

The You Only Look Once (YOLO) model has attracted a lot of interest among the researchers [45] [72] [67] [73] [13]. With the ability to analyze an entire image in a single run, YOLO offers significant speed advantages over typical CNN algorithms, making it especially useful for real-time applications. Due to its effectiveness, YOLO is a great option in situations when quick processing is essential [67]. Researchers can improve object identification and classification by using YOLO, which strengthens the segmentation capabilities of models such as U-Net increases the overall efficacy of examination of medical image in PCOS research.

Another important model in object detection is Faster R-CNN, which builds on the advances made by U-Net and YOLO. Designed as a unified, end-to-end deep convolutional network, Faster RCNN streamlines and simplifies object detection. It incorporates a Region Proposal Network (RPN), which makes it superior to its predecessor, Fast R-CNN. Fully convolutional network, RPN improves the model’s object detection performance by producing region proposals that vary in aspect ratios and scales. Mask R-CNN adds a second branch to Faster R-CNN’s repertoire, predicting segmentation masks for every object it detects. This shows more accurate instance segmentation. In contrast to more traditional techniques such as Selective Search, this innovation provides increased accuracy and capability for the precise detection and delineation of items inside an image. These intricate models provide a comprehensive approach to object detection and segmentation that improves on previously discussed techniques and advances the analysis of medical image. **(referring Table 10, Fig 10).**

3. Performance Metrics

Performance metrics are crucial to assessing the model’s effectiveness in diagnosing PCOS and analysis utilizing Machine Learning (ML) and deep learning (DL) approaches. Metrics like Pixel accuracy, Dice Similarity Coefficient (DSC), and Intersection over Union (IoU) are frequently employed for segmentation tasks, which are essential in defining characteristics like ovarian cysts or follicles.

A gauge of the model’s performance recognizes and segments pertinent structures is decided by the images, which quantifies the overlap between anticipated and actual segmentation masks. To evaluate how well the model performs in precisely detecting and defining these structures, DSC also known as the F1 score—reconciles and precision are balanced. Pixel accuracy provides a clear indicator of segmentation performance by counting the percentage of pixels in the overall image that are correctly identified.

Conversely though the classification models are assessed using classification metrics such as accuracy, precision, recall and the F1 score. Accuracy indicates how accurate the forecasts produced by the model show respect for the truth label. Recall gauges the model’s capacity to recognize all pertinent cases, whereas precision shows the percentage of genuine positives among all positive predictions. When dealing with imbalanced datasets, which are typical in PCOS research, the F1 score offers a fair assessment of recall and precision. Researchers can efficiently assess and compare the efficacy of ML and DL models in precisely diagnosing PCOS-related features. **(referring Table 11).**

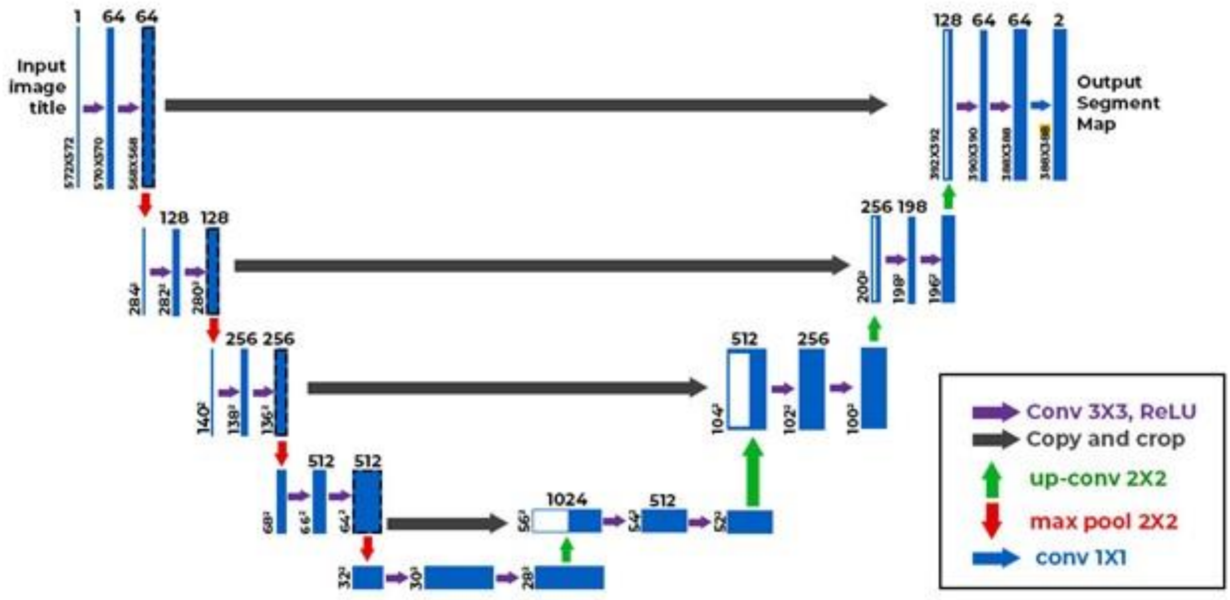

Fig 8. UNet's Architecture [36]

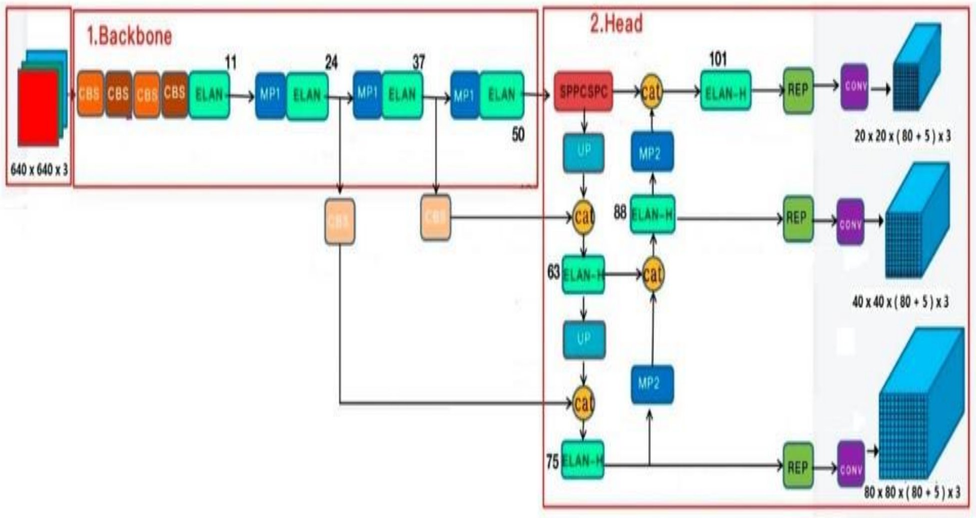

Fig 9. Yolo v7's overall framework network process.[74]

Table 10: Segmentation Techniques		
Model	***Advantages***	***Disadvantages***
Vision Transformer (ViT)	Provides global context and long-range dependencies, suitable for detailed segmentation tasks.	Requires large datasets and significant computational resources for training.
DETR(Detection Transformer)	Combines transformers with CNNs for robust end-to-end segmenting and detecting object.	May struggle with small object detection and require extensive training data.

Swin Transformer	Efficiently captures local and global content and performs well in high-resolution image segmentation.	Complex architecture may require a lot of processing power.
Segmenter	Effectively models long-range dependencies; specifically tailored for semantic segmentation.	May require substantial computational resources and training data.
CNN-Transformer (Hybrid Model)	Make use of CNNs' and transformers' strengths for improved segmentation accuracy.	Increased Complexity in model design and training process.
Self-supervised Learning with Transformers	Learns useful representations from unlabeled data, reducing the requirement for annotated datasets.	Pre-training can be computationally costly, and the caliber of the pretext tasks determines how well people execute.
Attention U-Net	Enhances focus on relevant regions, improving accuracy in medical images segmentation.	Can be more complex and computationally demanding than standard U-Net models.
Grad-CAM for Transformers	Provides visual explanations, enhancing model interpretability for clinical applications.	It might not be as intuitive as Grad-CAM for traditional CNNs and requires adaptation for transformer models.

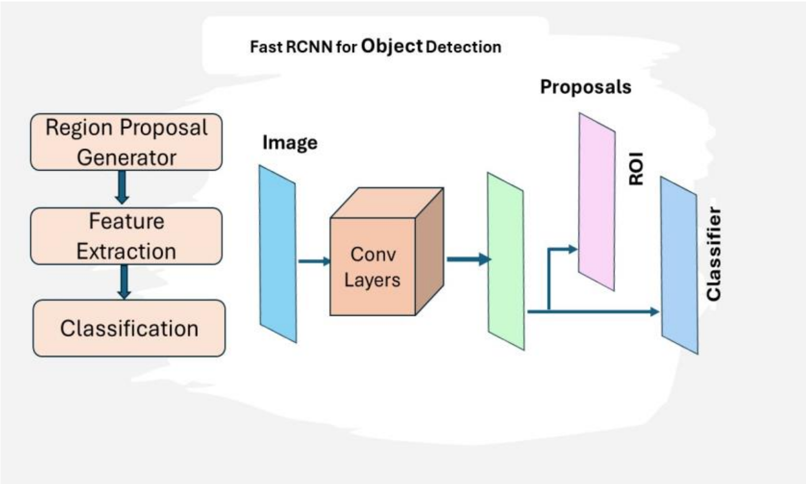

Fig 10. Fast RCNN Segmentation

Table 11. Performance Metrics
Performance Metrics - Segmentation

Metric used	***Description***
$DiceCoefficient = \frac{2TP}{2(TP+FP+FN)}$	Measures overlap, sensitive to segmentation accuracy
$JaccardIndex(IoU) = \frac{(overlap)}{(Union)}$	Quantifies overlap, interpretable, and widely used.
Hausdorff Distance H(A,B) H(A,B) = max(h(A,B),h(B,A))	Captures maximum discrepancy between segmentation, useful in boundary evaluation.
Performance Metrics - Classification	
$Sensitivity(TPR) = \frac{TP}{TP+FN}$	Measures of genuine positivity are essential for detecting anomalies.
$Specficity(TNR) = \frac{TN}{TB+FP}$	Measures true negative (TN) rate, crucial for avoiding false positives (FP).
$Accuracy = \frac{TP+TN}{TP+TN+FP+FN}$	Overall correctness measure, easy to interpret.
$Precision = \frac{TP}{TP+FP}$	Measures positive predictive value, which is essential in classification tasks.
$Recall = \frac{TP}{TP+FN}$	Measures true positive (TP)rate, crucial for detecting all positive instances.
ROC Curve AUC $TPR = \frac{TP}{TP+FN} FPR = \frac{FP}{FP+TN}$	visualizes classifier performance across thresholds, robust to class imbalance.
Mean Absolute Error (MSE) $MSE = \frac{1}{n}\sum_{i=1}^{n} abs(y_i - \hat{y}_i)^2$ [45]	Measures the average absolute difference between pixel intensities.
Root Mean Squared Error (RMSE) $RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}$ [45]	Measures square root of average squared difference, sensitive to significant errors.

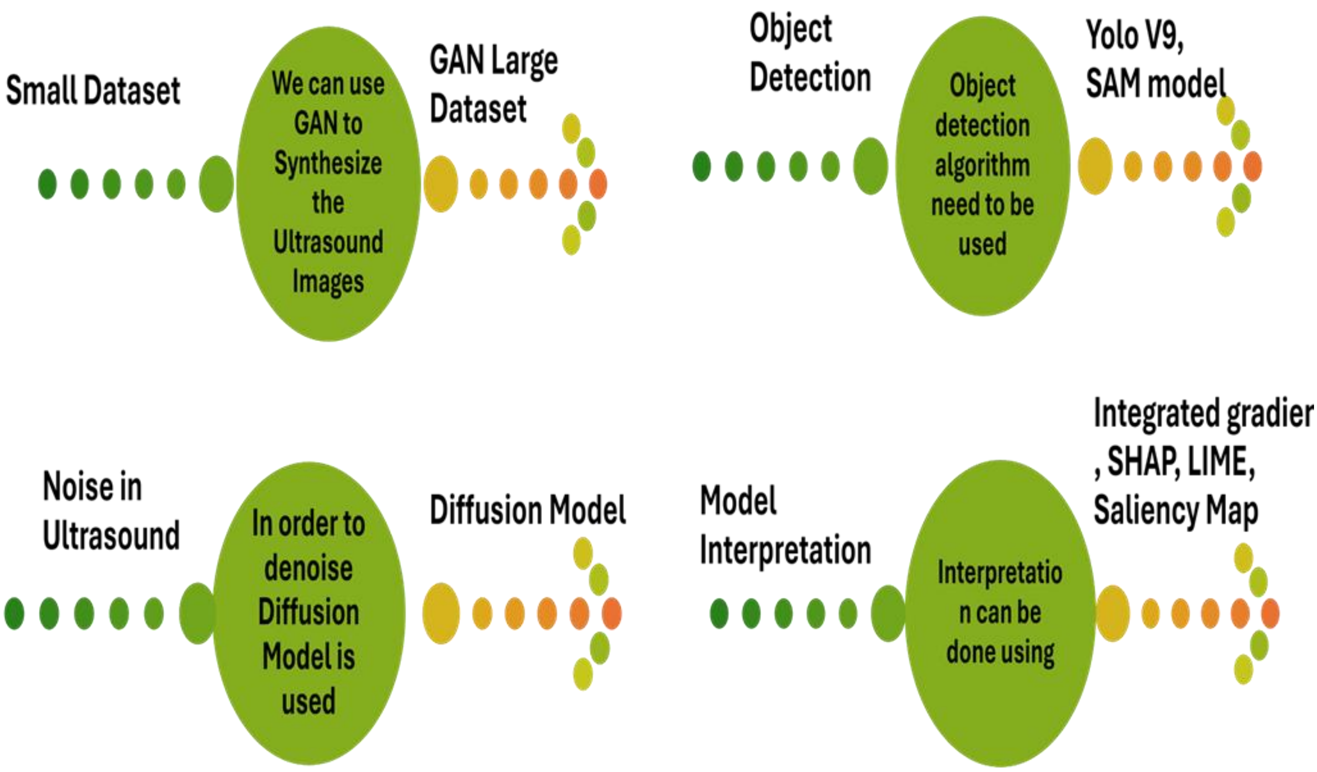

Fig 11. Challenges encountered in earlier literature and potential solutions

4. Future Scope

To improve ultrasound image quality and interpretability, a sophisticated multi-step approach can be implemented using cutting-edge machine learning techniques. Here's how the process unfolds:

Image Synthesis with GANs: Synthetic ultrasound images are generated by Generative Adversarial Networks (GANs). GANs work by having two networks—a generator and a discriminator—compete with each other, leading to the production of realistic images that resemble those found in clinical settings.

Denoising with Diffusion Models: Once the synthetic images are generated, diffusion models are employed to reduce noise. Diffusion models, which are a class of probabilistic generative model, gently reduce noise from images through a series of transformations, resulting in more transparent and more precise visuals.

Resolution Enhancement with SRGAN: The following action involves increasing the resolution of the denoised images using Super-Resolution Generative Adversarial Networks (SRGAN). SRGANs are designed explicitly to upscale images while preserving fine details, making the ultrasound images sharper and more detailed, which is crucial for accurate medical diagnoses. Interpretation with Explainable AI: Ultimately, Explainable AI (XAI) techniques are used to comprehend the improved photos. XAI techniques make certain that the rationale behind the models' interpretations of the ultrasound pictures is transparent and comprehensible by offering insights into the decision-making procedure of the models. In medical settings, interpretability can help physicians make well informed judgments based on insights given by AI, therefore this stage is crucial. This comprehensive approach leverages the advantages of several machine learning models to generate, refine, enhance, and interpret ultrasound images, ultimately leading to better diagnostic tools and more reliable outcomes in clinical practice.

1. Comprehensive and Diverse Datasets Gather extensive datasets: ultrasound images and diverse imaging modalities have a few images. Therefore, advanced data-augmentation techniques increase the dataset size and integrate clinical and genetic data for comprehensive analysis.
2. Incorporate attention mechanisms and Transformer techniques in U-Net for efficient Segmentation.
3. Explore alternative XAI techniques beyond Grad-CAM to increase the openness and reliability of AI models.
4. Improve Computer-Aided Diagnosis for PCOS detection and management.

5. Summary of Research Papers

A literature review of 67 relevant articles was done to identify PCOS in females using computer assisted methods. The studies tried to evaluate and compile evidence on this carefully, and they came to several important conclusions:

Publication Trends: It is evident from the titles and keywords chosen to focus on PCOS diagnostic methods. Research domain is found in both journal and conference publications. Year-wise statistics show an increasing trend in research interest, indicating a growing global focus on autonomous PCOS prediction using Machine Learning (ML), Deep Learning, Explainable AI, and Segmentation approaches.

Research Objectives: While the primary goal across all publications is PCOS detection using computer-assisted methods, each study has unique research objectives. These objectives often involve identifying the most critical features for PCOS detection. A considerable amount of research endeavors to isolate cysts from ovarian ultrasound pictures and categorize them as either non-PCOS or PCOS.

Data Utilized: The article's analysis indicates two main dataset used for PCOS detection: clinical test dataset features and patient's ovarian ultrasound images. Most studies utilize datasets collected from various hospitals or open-source repositories.

Technologies Employed: Various advanced technologies are employed, including machine learning (e.g., RM, SVM, KNN, DT), deep learning (e.g., CNN, ANN, DNN), segmentation and processing of images (e.g., UNET, YOLO), feature selection techniques (e.g., PCA, PSO, ANOVA, FF), and explainable AI (e.g., Shap, GradCAM). Some papers define patients as having PCOS or not by using machine learning approaches with digital image processing techniques for follicle segmentation. However, only five articles have utilized explainable AI in this domain.

Performance Variations: Despite employing similar classifiers, different studies report varying performance results because of many implementation methods and data preprocessing techniques. For example, 18 papers used the same Kerala dataset to identify PCOS detection but have achieved different performance outcomes.

In summary, this literature review highlights the increasing interest in using advanced computer assisted and hybrid methods for detecting PCOS. The diversity in research objectives, datasets, and technologies leads to evolution in this field.

6. Conclusions

This Research provides a thorough assessment of the several methods used to identify PCOS, concentrating on machine learning (ML), deep learning, explainable AI, and segmentation strategies. The study outlines the various techniques employed by the researchers, examining their characteristics, effectiveness, analytical strategies, and outcomes. Additionally, it briefly discusses the datasets utilized by these algorithms. The research identifies shortcomings in existing methods and potential challenges in this domain that exist. Despite substantial efforts to create effective PCOS detection models, specific issues remain unresolved. To improve the quality and interpretability of these images, a multi-step process using advanced machine learning techniques will be employed. This process begins with the generating images using generative adversarial networks (GANs) and then denoised through diffusion models, which remove noise through iterative transformations. Next, the image's resolution is improved using Super-Resolution GANs (SRGAN), ensuring sharper and more detailed visuals. Explainable AI (XAI) approaches are ultimately used to interpret the images. These approaches provide transparency and aid physicians in making well informed decisions. This technique improves the accuracy and reliability of medical imaging diagnoses by utilizing a range of machine learning models.

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