Minimax Theory and its Applications

Volume 11 (2026), No. 3s, 814 to 829

Enhanced Feature Extraction-Based Hybrid Deep Learning Model for Polycystic Ovary Syndrome Detection

Savitha A Shenoy[1], Dr. R.Roopa Chandrika[2]

[1]Research Scholar Department of Computer Science & Engineering Karpagam Academy of Higher Education,
Email: savithashenoy2003@gmail.com
[2]Professor Department of Cyber Security Karpagam Academy of Higher Education,
Email: roopamurugan@gmail.com

Abstract
Polycystic ovary Syndrome (PCOS) has been recognized as one of the greatest health complications affecting majority of women around the world. Early identification and management of PCOS are crucial to minimize the risk of long-term morbidity. Proper and early diagnosis can assist the healthcare systems in reducing the problems and complications of the disease. The conventional methods of diagnosis, including blood examination and ultrasounds, are time-consuming and expensive. Although there have been previous methods with efforts to counter these shortcomings, they are still limited by poor feature learning ability and extreme overfitting. To overcome these challenges, this study introduces an Enhanced Feature Extraction Module Enclosed Hybrid Deep Learning (EFEM-HDL) model. The proposed methodology addresses class imbalance and overfitting through Generative Adversarial Networks (GAN) for synthetic data generation, employs a Feature Interaction Channel Attention-enclosed Variational Autoencoder (FICA-VAE) for feature extraction, and utilizes a Cross Attention-based Convolutional Neural Network (CA-CNN) for classification. Experimental findings show that the EFEM-HDL model greatly improves diagnostic performance with an accuracy rate of 99.1%, hence presenting a strong solution to early PCOS detection.

*Keywords:*Polycystic Ovary Syndrome, GAN, Channel attention, spatial attention, Variation Autoencoder, Cross Attention, CNN.

1. Introduction

Polycystic ovary syndrome (PCOS) is a significant disease in women dealing with reproductive age and afflicts 5 to 10% of women, leading to the endocrine disorder and infertility [1]. The high amount of unusual and outgrowth follicles during the ovulation stage is the major intention for infertility, and it is defined as inability of the ovary to produce eggs by the ovary [2]. The World Health Organization (WHO) states that polycystic ovarian syndrome, which affects eight to thirteen percent of all women of reproductive age it is the most frequent hormonal scenario among women the 12-55 women's [3]. PCOS is an analysis of thyroid, pituitary, adrenal-related disease and endocrinopathies. They identified PCOS based on the Rotterdam criteria, indicating the presence of two of three criteria, including the polycystic ovary morphology (PCOM) evident in biochemical hyperandrogenism [4]

PCOSgenerates several health problems and increasesthe number of mortality and disease, in addition treatment process for the chronic is very high. Most of the anovulatory women's such as 90%, are affected by this PCOS [5]. The PCOSdisease is a reason to generate, high blood pressure, diabetes, anxiety, sleep apnea, depression, heart disease, endometrial thickness, endometrial cancer, and eating disorders. The environmental factors, genetic factors also reason toPCOSin women. Weight loss and treatment difficulty can be decreased by diagnosingPCOSat an earlier stage [6]. Most women are not aware of these types of diseases and it not diagnosed. According to the report, 70% of women do not take proper treatment for PCOS. Also, 8% of African Americans, 31.3% of Asia, 4.8% of white Americans, and 8% of Spain women are affected by PCOS [7]. The structure of the ovary is shown in Figure 1.

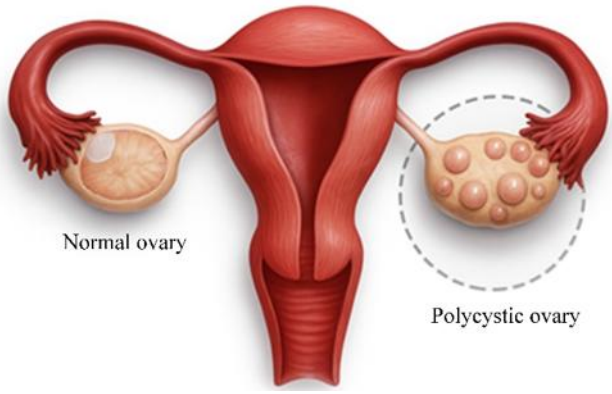


Figure 1: PCOS and Normal ovary illustration

The early diagnosis of PCOS is necessary because choriocarcinoma increases the medical burden by its long-term complications, as well as it increases the economic burden also such as the annual PCOS economic burden is calculated as 8 billion United States Dollars (USD) [8]. In the medical field, several number of process is handled for diagnosing different diseases. Nevertheless, the particular diagnosis method is available for PCOS. Using the blood test, pelvic analysis, and ultrasound steps are followed for diagnosing PCOS leads to more cost and time [9]. The discovering of the gene combination, the PCOS disease can be diagnosed; nevertheless, the ultrasound images provide an effective outcome in the PCOS diagnosis [10].

Nowadays, Artificial Intelligence (AI) technology has been introduced that can predict diseases by image processing, and it produces minimal error and neglects unnecessary data from the process [11]. Machine Learning (ML) is a subdomain of AI in which algorithms are involved in diagnosing PCOS using the ultrasound imaging process. The k-nearest neighbor (KNN), logistic regression (LR), support vector machines (SVM), naïve Bayes (NB), and artificial neural networks (ANN)models have produced effective results in the diagnosis of PCOS [12]. Furthermore, the Hybrid ML methods, such as LR+RF is efficiently classify the PCOSovary or the normal ovary [13]. However, the ML techniques produce less accuracy in PCOS diagnosis while they face high-dimensional, unbalanced, complex data and noisy data, etc. [14, 15].

In recent advances, deep learning (DL) approaches are widely used in medical imaging, as they better allow extracting meaningful characteristics and building complicated patterns within the data and exhibit lower limitations of the ML technique. Convolutional Neural Networks (CNNs), in particular, have attained higher remarkable in the field of medical image analysis, including PCOS diagnosis, due to their hierarchical learning architecture and spatial feature extraction capabilities [16], [17]. Nevertheless, due to their effectiveness, existing CNN-based frameworks continue to encounter issues with redundant feature discovery, the disappearance of gradients in higher-level layers, and the lack of concentration on fine-grained image features, that concerning PCOS morphology, are essential. To overcome these limitations, this study proposes an Enhanced Feature Extraction Module Enclosed Hybrid Deep Learning (EFEM-HDL) model that integrates advanced attention mechanisms and hybrid feature fusion strategies within a DL framework to improve diagnostic accuracy for PCOS detection. The key contribution of the suggested methodology is as follows:

- ☞ To reduce the class imbalance problem and the overfitting issue using Generative Adversarial Network (GAN) for synthetic data generation, enhancing the diversity and representativeness of the training samples.
- ☞ To extract deep and discriminative features relevant to PCOS diagnosis using a novel Feature Interaction Channel Attention-enclosed Variational Autoencoder (FICA-VAE) that captures both spatial and channel-wise dependencies in the data.
- ☞ To accurately classify PCOS cases through a Cross Attention-based Convolutional Neural Network (CA-CNN), which leverages cross-attention layers and convolutional operations to emphasize relevant patterns and suppress irrelevant noise.

The rest of the paper is organized as follows: Section 2 describes the related work of PCOS ovary detection, Section 3 describes the proposed methodology, Section 4 describes the results, and lastly, Section 5 concludes and future direction of paper..

2. Related Works

This section provides a survey of various related techniques for PCOS detection is described as follows.

To effectively discriminate between PCOS and non-PCOS samples, Mahmud et al. [18] employ an integration of features in the form of intensity histograms, Gray-Level Run Length Matrix (GLRLM), and Gray-Level Co-occurrence Matrix (GLCM) from ultrasound images. The intensity and texture attribute, combined with ML and DL classifies, assisted in improving the diagnostic accuracy. Using a real-world dataset, the technique demonstrated a feasible accuracy from 85 to 90%. However, the limited size of the dataset influenced the model's generalizability.

To achieve correct automated PCOS diagnosis, Kaur et al. [19] presented a CNN-based model. CNNs can identify complex patterns and features of ultrasound images not perceived by physicians, offering an improved, faster, and more affordable method to PCOS diagnosis. Using a Kaggle dataset, the model reached an improved precision. The CNN faces poor scalability.

Pradeep Bedi et al. [20] developed an attention residual U-Net (AResUNet) model. This technique is utilized for efficient noise reduction and is able to process both multi-modal and 2D images. This technique obtains 98.1% for multi-modal images and 97.7% accuracy for 2D image. The overall accuracy of this model was 98%, and it limit its application to broader gynecological issues.

To detect the PCO, A.K.M. Salman Hosain et al. [21] developed a PCO with a CNN (PCONet). This technique utilized a fine-tuned InceptionV3 model, which is a pretrained CNN of 45 layers that classifies the polycystic ovarian ultrasound images using transfer learning. This technique achieves 98.12% accuracy for PCONet and 96.56% for fine-tuned InceptionV3. However, the limitation of the developed method was utilized less feature learning capability impact on the overall accuracy.

Raunak Joshi, et al. [22] developed a simple ML technique named Support Vector Machine (SVM), which is improved with an advanced framework using DL based Linear Discriminant Analysis (Deep LDA). It LDA was a linear dimensionality reduction algorithm utilized to classify the PCOS and enhance its performance. The technique achieves 98.35% as training accuracy and 90.90% as testing accuracy. The performance of PCOS detection was reduced when it was analyzed with a real-time dataset and utilized more parameters

Wenqi Lv et al. [23] developed an automated DL algorithm with an MLP for auxiliary detection of PCOS and segmenting the scleral image from the full-eye images. Finally, the multi-instance model utilized for classification achieves 0.979 average AUC and 92.9% accuracy. However, the limitation of the developed method requires a high time consumption.

Varada Vivek Khanna et al. [24] developed a 1-dimensional CNN (1D-CNN) to predict PCOS among fertile patients. The Multi-stack ML model is utilized to achieve efficient performance of 98% accuracy. It utilized Explainable artificial intelligence (EAI) for attribute importance with the RF for explaining the tree-based classifier. The quality of the dataset was low, which may reduce the overall performance of this technique.

Abhishek M. Gupta et al. [25] developed Discriminant Analysis in multidimensional and linear quadratic forms of a binary classification. This technique achieves efficient performance with less variation through Discriminant analysis. The classification algorithm achieves 97.37% training accuracy and 95.92% testing accuracy using Quadratic Discriminant Analysis. However, the limitation of the developed method was the class imbalance problem.

The analysis of features using ML and DL has shown promise in the diagnosis of PCOS, but some key challenges remain. Most of the used datasets are small and experience imposed imbalances, and model generalizability is a problem. Traditional CNNs cannot bring out the subtle features and can lead to misclassification. Another issue that influences reliability is overfitting with noisy and small data. In addition, the majority of the models do not incorporate attention mechanisms to provide individual spatial and channel-wise significance and do not include hybrid architectures to enhance the performance. To mitigate this, the paper introduces an Enhanced Feature Extraction Module Enclosed Hybrid Deep Learning (EFEM-HDL) model, which is composed of GAN-based data augmentation, a Feature Interaction Channel Attention-enclosed Variational Autoencoder (FICA-VAE), and a Cross Attention-based CNN (CA-CNN), as a robust and efficient method of PCOS detection.

3. Proposed Methodology

This section provides a fulldescription of the suggested methodology for classifying the PCOS and NonPCOS, as displayed in Figure 2.

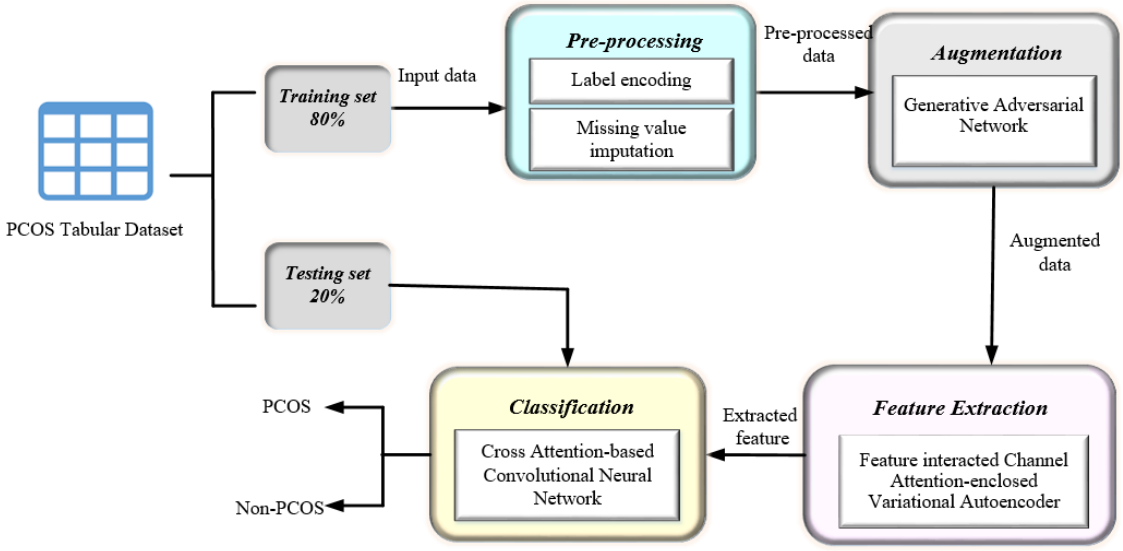


Figure 2: Workflow of the proposed EFEM-HDL model for PCOS detection using tabular clinical data.

As shown in Figure 2, PCOS dataset is collected from a publicly available Kaggle source. Then the dataset undergoes pre-processing, wherein data encoding techniques are applied to handle categorical variables and missing value imputation methods are employed to address any incomplete data points, ensuring the dataset's readiness for analysis. Before pre-processing, to balance the presented dataset, a GAN is used. Subsequently, a deep learning model, namely Feature Interaction Channel Attention-enclosed Variational Autoencoder (FICA-VAE), is utilized for feature extraction. This model is designed to enhance feature extraction by focusing on relevant parts of the input data and improving the representation of relevant information crucial for PCOS identification. Finally, PCOS detection is performed using a CA-CNN model, which incorporates cross-attention mechanisms to selectively emphasize pertinent features. The CA-CNN architecture employs convolutional layers and pooling layers to effectively extract features and reduce dimensionality. The proposed model successfully automates the process of detecting PCOS, resulting in improved accuracy and reliability.

3.1 Data acquisition and Splitting

The research utilizes the PCOS [26] dataset, available on https://www.kaggle.com/datasets/shreyasvedpathak/PCOS-dataset link. This dataset consists of 541 medical records,including 177 data of identified patients with PCOS and 364 data of those without this diagnosis. The data collection contains the necessary demographic and physiological data, which makes it possible to identify the patterns related to PCOS. It is formatted as a CSV and is particularly tailored to a binary classification exercise that would be conducted to predict whether or not a person has PCOS.To ensure a reliable and unbiased evaluation of the proposed model, the dataset is divided into two subsets as 80% Training set (432 samples) and 20% Testing set (109 sample).

A stratified sampling strategy is employed to preserve the original class distribution in both subsets. Consequently, the training set contains approximately 142 PCOS and 290 non-PCOS instances, while the testing set includes approximately 35 PCOS and 74 non-PCOS instances.

Furthermore, to prevent training–test data leakage, the testing set is strictly held out and remains completely unseen during all stages of model development, including preprocessing, data augmentation, and feature extraction. All model training and parameter tuning are performed exclusively on the training dataset, while final performance evaluation is conducted only on the independent test set.

3.2 Pre-processing

Data preprocessing [28] is a series of steps to transform unstructured raw data into a version suitable for analysis. Actual datasets from the world often contain various irregularities; indeed, many contain missing values, and have vastly different feature types, making the data extremely difficult to analyze [29]. Therefore, in this study, two preprocessing techniques are used to improve data quality and facilitate effective model training, which are label encoding and imputation of missing values. To ensure methodological rigor and to prevent training–test data leakage, all preprocessing operations are performed exclusively on the training dataset, and the derived transformation parameters are subsequently applied to the test dataset.

3.2.1 Label encoder

Categorical features are common attributes of many real-world datasets. However, most predictive modelling techniques, especially deep learning models, are only designed to operate on numerical input. Therefore, categorical features must first be preprocessed by encoding them into a numerical format. Label encoding [30] is used in this research to encode categorical features in numeric values, which is an essential preprocessing step for deep learning models. The PCOS data has categorical fields such as the types of blood groups and PCOS status coded as Yes or No. Converting these into numerical form enables the model to process the data more effectively.

3.2.2 Missing value imputation

The missing value imputation [31] process is performed to fill the missing value in a dataset by replacing the mean value of the non-missing values, as discussed below.

$$G_k = \frac{G_{k-1} + G_{k+1}}{2}, \quad k \in I \ (1)$$

Here, G_k is denoted as the missing values, G_{k-1} is denoted as the preceding values, I is denoted as the random number $(I = 1,2,..)$, and G_{k+1} denotes subsequent values from the missing values. Finally, these pre-processing steps improve the quality of the data.

3.3 Data Balance using GAN Model

The acquired dataset used to detect PCOS is extremely imbalanced in terms of class (the amount of PCOS-positive cases is far less than normal cases). This class imbalance can degrade the performance of DL approach by causing them to fit the majority case data, leading to poor sensitivity (low likelihood of detection) for the usual consideration of the minority class. To address this issue, a Generative Adversarial Network (GAN) is employed only on the training data to create synthetic data samples and augment the minority class, thereby balancing the dataset and improving generalization.

A classic GAN [27] system consists of two networks: a generator A, fed with random noise x, and generating artificial feature vectors, and a discriminator B, attempting to differentiate between real samples D_{real} and createdsamples D_{fake}. The creator converts noise to fake data simulated as:

$$D_{fake} = A(x) \ (2)$$

The discriminator learns the probability $Y(U \setminus D)$, where $U = 1$ for true samples, and $U = 0$ for generated ones:

$$Y(U \setminus D) = B(D); \qquad U \in \{0,1\} \ (3)$$

The purpose of the adversarial training process is to maximize the generator so that it produces synthetic data that the discriminator cannot distinguish from real artificial. To maximize the following log-likelihood function:

$$Max\{E[\log Y(U=1 \mid D_{real})]+E[\log Y(U=0 \mid D_{fake})]\} \quad (4)$$

Through this process, the GAN generates high-quality data records that resemble real PCOS-positive data records. Then, the generated synthetic data records are added to the real data to balance the class. Table 1 represents the before and after augmentation.

Table 1: Before and after augmented data details

Dataset Status	Total Records	PCOS	Non-PCOS
Before Augmentation	432	142	290
After Augmentation	582	291	291

Therefore, the data representation is reduce the overfitting issue, which improves the overall result of the models.

3.4 Feature extraction using FICA-VAE Framework

This research utilized a Feature Interaction Channel Attention-enclosed Variational Autoencoder (FICA-VAE) model to extract meaningful and discriminative features, as shown in Figure 3. The first utilizes the channel attention mechanism to learn the relationship between features in different channels and focuses on the most pertinent feature dimensions. Then the model uses a feature interaction module (FIM) that assesses various relevant feature and identifies those extracted features in the same manner as informative components of the features. Finally, the resulting features are then compressed into a latent representation of a Variational Autoencoder (VAE).

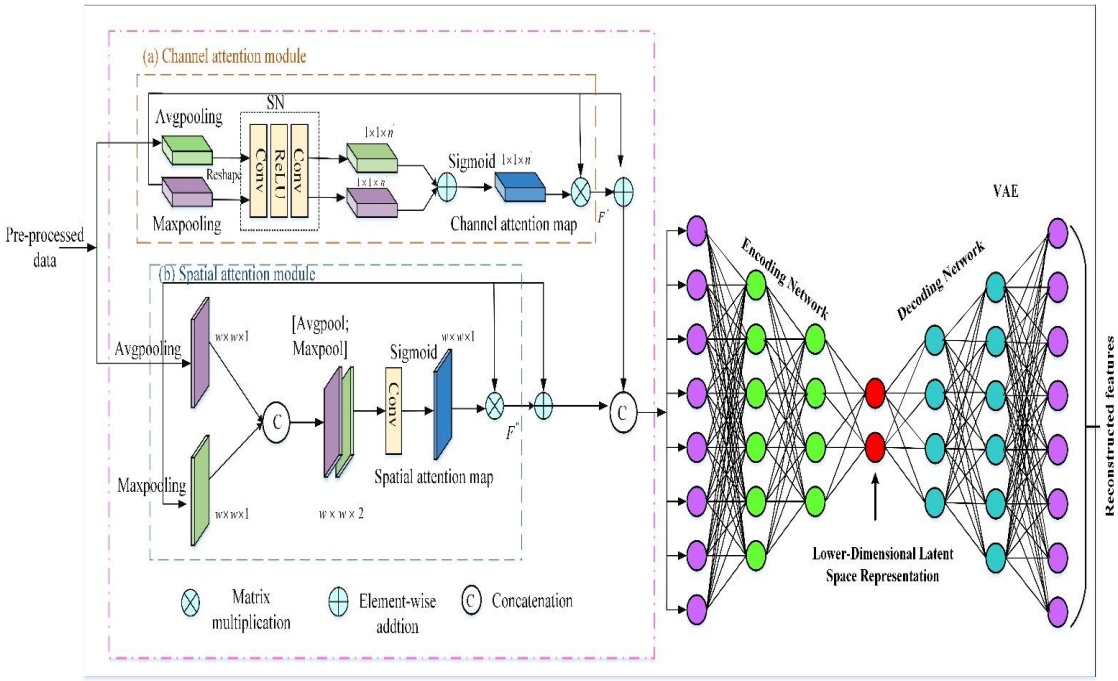


Figure 3: Architecture of the FICA-VAE model for feature extraction from tabular data.

In this case, the data is pre-processed before entering the attention module. First the channel attention module [32] assigns significance to every feature based on its contribution to the final decision. It applies global max and average pooling across all samples to produce two immediate vectors representing the significance of each feature. These vectors are passed through a shared network consisting of dense layers with ReLU and sigmoid activations to generate a channel attention map, which emphasizes informative features and suppresses irrelevant ones. Mathematically, this process is expressed as:

$$CA(F)=\delta\left(W_1\delta'\left(W_0\left(F^c_{avg}\right)\right)+W_1\delta'\left(W_0\left(F^c_{\max}\right)\right)\right) \quad (5)$$

Where δ and δ' is denoted as the sigmoid and ReLU activation function, W_0 and W_1 are trainable weights, F_{avg}^c and $F_{\max}^c$ is denoted as the pooled feature vectors. The output of this layer then multiplies the original feature vector element-wise to yield the channel-refined feature vector:

$$F' = CA(F) \otimes F \quad (6)$$

Here, F is denoted as the original input features and $CA(F)$ is denoted as the channel attention map.

Subsequently, the FIM [33] identifies feature interaction importance. It applies mean and maximum pooling on the channel dimension and then returns two descriptors, which are concatenated after being passed through a dense layer followed by a sigmoid to give the Inter-feature dependencies:

$$FIM(F) = \delta\left(f^{N\times N\times N}\left[F_{avg}^s; F_{\max}^s\right]\right) \quad (7)$$

Where, δ is denoted as the activation function of sigmoid, $f^{N\times N\times N}$ is denoted as the operation of dense layer, with $N \times N \times N$ refers the attention weight. This feature vector is once more multiplied with the input feature vector to obtain the refined feature vector:

$$F'' = SA(F) \otimes F \quad (8)$$

Here, $FIM\ (F)$ is denoted as the Inter-feature dependencies.

By combining both attention mechanismsis adapted to capture feature importance and inter-feature dependencies within tabular data. These refined features are then passed into the Variational Autoencoder (VAE), which encodes them into a latent space for improved feature representation. The VAE learns a probabilistic distribution of the input data and reconstructs it while minimizing reconstruction loss and regularization loss. Unlike a standard autoencoder [34], the VAE introduces a constraint by under the assumption that the latent variable follows multivariate logistic distribution. The encoder maps are input to two parameters, the mean and the log of the variance, which define the distribution. To allow gradient–based training, the model uses the refined- hyper parameterization to sample the latent variable z :

$$z = \mu + \sigma \cdot \in \sim N(0,1) \quad (9)$$

The decoder re-creates the input $\hat{x}$ from the latent variable z that has been sampled. The learning objective is to minimize a loss function that integrates the reconstruction accuracy and distribution regularization. This is achieved by using two terms: the Kullback-Leibler divergence and reconstruction loss. The total loss to be minimized is therefore written as:

$$L_{VAE} = E_{q\phi(z|x)}\left[\log p_\theta\ (x \mid z)\right] - KL\left(q_\phi(z \mid x) \| p(z)\right) \quad (10)$$

Where, encoder refers $q_\phi(z \mid x)$, $p_\theta(x \mid z)$ indicates decoder. $p(z)$ is denotes prior, which considered to be a $N(0, I)$ standard normal distribution, and $\phi \& \theta$ is denotes parameters of the encoder and decoder network, respectively. To extend this for a dataset with multiple samples, the objective function for all data points becomes:

$$L_{VAE} = \sum_{i=1}^{n}\left(\frac{1}{L}\sum_{j=1}^{L}\log p_\theta\left(x^{(i)} \mid z^{(i,j)}\right) - KL\left(q_\phi\left(z \mid x^{(i)} \| N(0, I)\right)\right)\right) \quad (11)$$

Here, the latent sample $z^{(i,j)}$ is generated using:

$$z^{(i,j)} = \mu^{(i)} + \sigma^{(i)} \cdot \in^{(j)} \quad (12)$$

This process enables the VAE to learn compact and meaningful representations of the input data. After processing through the attention-enhanced VAE, a refined feature vector consisting of 128 key features is extracted. The attention mechanisms integrate the VAE, allowing the model to retain important patterns and remove unnecessary information, resulting in more accurate and reliable PCOS detection.

3.5 Classifications Cross Attention-based Convolutional Neural Network (CA-CNN)

Then the extracted features are fed into the cross–attention–based convolution neural network (CA-CNN), which accurately classifies the PCOS and non-PCOS. The CA-CNN model combined two different components, such as the Cross-attention model and CNN model, as visually indicates in Figure 4.

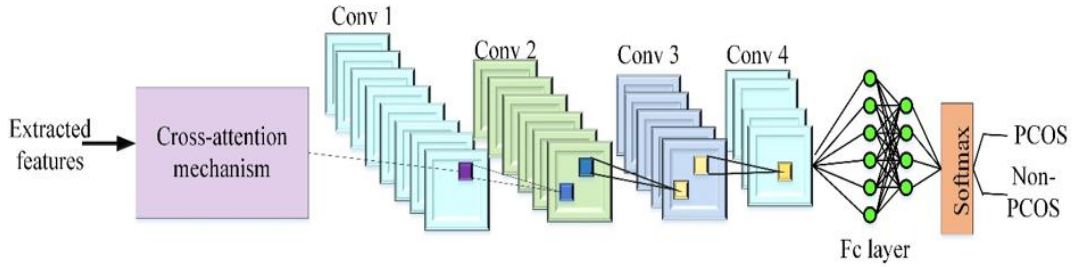


Figure 4: Architecture of the CA-CNN Approach

Here, the extracted features is fed into thecross attention mechanism [35], which enhances feature representation by learning relationship between different feature components. It emphasizes relevant feature while reducing noise.Through the Cross attention allows one sequence to another sequence. This is useful in tasks like machine translation, where the decoder attends to the encoder outputs to generate the translation. The CA modules takes the concatenated feature sequence a''^{l} as input and performs attention between the CLS feature and the feature embeddings is used as the query and key value. The CA can be written as:

$$q = a'^{l}_{cls} W_q,\ k = a' W_k,\ v = a'^{l} W_v \quad (13)$$

$$Attention = soft\max\left(\frac{qk^T}{\sqrt{\frac{c}{h}}}\right) \quad (14)$$

$$D\ \ atten\ \ (a''^{l}) = Attention \cdot\ value \quad (15)$$

In these equations, W_q , W_k ,and W_v are learnable parameters, D refer the dimension of embeddings, and h is the amount of heads. In equation (13), the attention weights describe the relative importance of each feature embeddings with regard to the CLS features. Equation (14) captures the features most informative.

Once the attention mechanism has refined the feature embeddings, the resulting enriched embeddings are passed to a CNN [36]for classification. The CNN captures 1D convolution and hierarchical information, which is enable the model learn discriminative structure of PCOS and Non-PCOS cases. The CNN component comprises multiple layers, including ReLU activation, batch normalization, fully connected (FC) layers, convolutional layers, and softmax output.

Specifically,Set of learnable filters W_c utilized in convolutional layers and a bias term b_c to the input embeddings X , yielding the output:

$$H_{conv} = \sigma(X * W_c + b_c) \quad (16)$$

Where * refers the convolution operation, and $\sigma(\cdot)$ indicatesReLU activation. The batch normalization layers then stabilize and normalize the activations across the batch, making the network more robust and accelerating training. The resulting attributevector are flattened followed by FC layers to aggregate features at the high level. The output layer matrix multiplies the offset matrix by the softmax activation to give an output probability distribution over the target classes as defined by:

$$p(y \mid X) = Soft\max(W_f h_{flat} + b_f) \quad (17)$$

Here, h_{flat} denotes the flattened feature embedding, W_f and b_f are the learnable weights and bias of the final classification layer, and $p(y \mid X)$ is the resulting prediction for the input X . Through this combined approach of attention and convolution, the CA-CNN model effectively captures both global context and fine-grained featureposition, making it highly suited for accurate and robust classification of PCOS versus Non-PCOS instances.

4. Results and Discussion

In this study, the suggested FICA-VAE and CA-CNNapproaches was tested to evaluate its performance in detecting PCOS. The suggested feature extraction technique was compared other technique, using the PCOS dataset. The findings indicated the suggested model captures important information better and improves classification accuracy. Then the suggested classification performance was also compared with other techniques. The suggested approach achieved higher F1 score, precision, AUC, recall, and accuracy, confirming its effectiveness and reliability for PCOS prediction. The system design of the suggested techniquesis detailed in Table 2, and Table 3 displays the hyper-parameter details as proposed methodology.

Table 2: System configuration of suggested approach

Installed RAM	8.00 GB (7.89 GB usable)
Packages	NLTK, NumPy, TensorFlow, Keras, Sklearn, Tweepy, Scikit-learn, etc.
Processor	Intel(R) Core(TM) i5-3570 CPU @ 3.40GHz 3.40 GHz
Experimental tool	Python

Table 3: Overall suggested approach Hyper-parameter details

Component	**Parameter**	**Details**
VAE - Input	Input Shape	(1, 43)
VAE - Encoder	Flatten	Applied before Dense layer
	Dense Units	64, activation = ReLU
	Latent Dimension	16
VAE - Latent Space	Mean Layer	Dense(latent_dim)
	Log Variance Layer	Dense(latent_dim)
VAE - Decoder	Dense Units	64, activation = ReLU
	Output Dense	units = 43, activation = Sigmoid
	Reshape	Output reshaped to (1, 43)
VAE - Spatial Attention	Pooling	Average & Max Pooling
	Conv1D	filters = 1, kernel_size = 7, activation = Sigmoid
VAE - Loss	Reconstruction Loss	Mean Squared Error (MSE)
	Regularization Loss	KL Divergence
VAE - Training	Optimizer	Adam
	Epochs	100
	Batch Size	32
CNN - Input	Input Shape	(1, 128)
Cross-Attention Module	Query Dense	16 units
	MultiHeadAttention	4 heads, key_dim = 16
	Layer Normalization	Applied
CNN Module	Conv1D	filters = 32, kernel_size = 3,

		activation = ReLU, padding = 'same'
	Global Pooling	GlobalAveragePooling1D on both attention & CNN
Classifier	Dense Layer	64 units, activation = ReLU
	Dropout	0.3
	Output Layer	Dense(2), activation = Softmax
CNN - Loss	Type	Sparse Categorical Crossentropy
CNN - Training	Optimizer	Adam
	Epochs	100
	Batch Size	32
	Validation Split	0.2

4.1 Performance metrics

The proposed work adds both the feature extraction and classification stages, and performances are evaluated according to a variety of measures, which is important for understanding the excellence of the extracted attributes and performance of the categorizing model for PCOS detection. Accuracy shows how well the model classified instances correctly. Precision shows how well the model classify relevant instance from all illustrations predicted positive by the approach. Recall shows how well the model find relevant instances from the dataset. F1 score measures both precision and recall in one single score (F1 score is especially relevant when the data is unbalanced). The following mathematical representation can be utilized to compute:

$$Accuracy = \frac{NP + PT}{PF + NF + PT + NF} \quad (18)$$

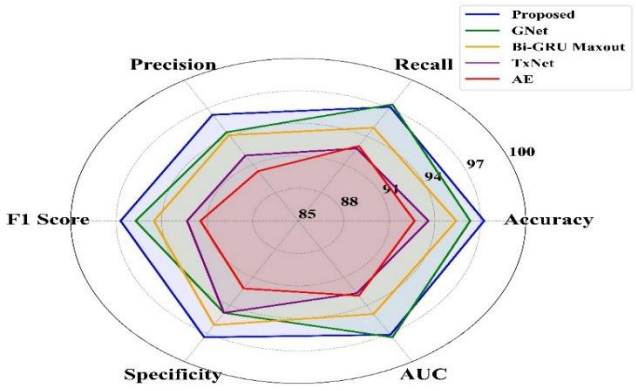
$$\Pr ecision = \frac{PT}{PF + PT} \quad (19)$$

$$\mathrm{Re}\, call = \frac{PT}{NF + PT} \quad (20)$$

$$F1\, score = 2 \times \left(\frac{\Pr ec \times \mathrm{Re}\, c}{\Pr ec + \mathrm{Re}\, c} \right) \quad (21)$$

Here, the NT represents true positive, NF is denoted as the false negative value, PT indicated the true negative, and PT is refers false positive.

4.2 Performance Comparison of Feature Extraction Models This section compares the proposed feature extraction model with other existing methods:Autoencoder, BiGRU-Maxout, TextNet (TxNet), and GateNet (GNet) using the PCOS dataset. Figures 5 visually depict the performance comparison of the suggested and existing approach.



Figures 5: Analysis of suggested and other approach performance

Figures 5 depict anassessment of the FICA-VAE model and existing feature extraction methods. SuggestedFICA-VAE model achieved higher performance at 98.49% accuracy, 97.85% precision, 98.96% F1 score, and 99.0% recall. Further existing models are performing poorly due to their inability to learn complex feature patterns in the PCOS dataset. To overcome this, the FICA-VAE has been presented. This method exploits the channel attention to grab the important relations across the feature channels, thus, it concentrates on the most relevant dimensions. Next, it exploits the spatial attention to decide the key local patterns, thus, it obtains the most informative features. These extracted features are then converted into a latent vector of the input space using a VAE, which gives the PCOS detection task a more reliable and accurate classification.Table 4provides the comparative analysis of proposed and existing feature extraction models.

Table 4: Comparative analysis of feature extraction model

Method	**Performance (%)**			
	Accuracy	**Precision**	**Recall**	**F1-score**
Proposed	98.49	97.41	98.96	99.03
GateNet	96.83	96.83	96.83	96.83
BiGRU Maxout	95.24	95.23	95.24	95.21
TxNet	93.65	93.99	93.65	93.72
Autoencoder	92.06	92.02	92.06	92.01

4.3 Overall Performance Comparison of proposed and existing model

This section compares the suggested approach with other approaches using the PCOS dataset. Figures 6 and Table 5 visually depict the performance of the CA-CNN approach in comparison to existing approach.

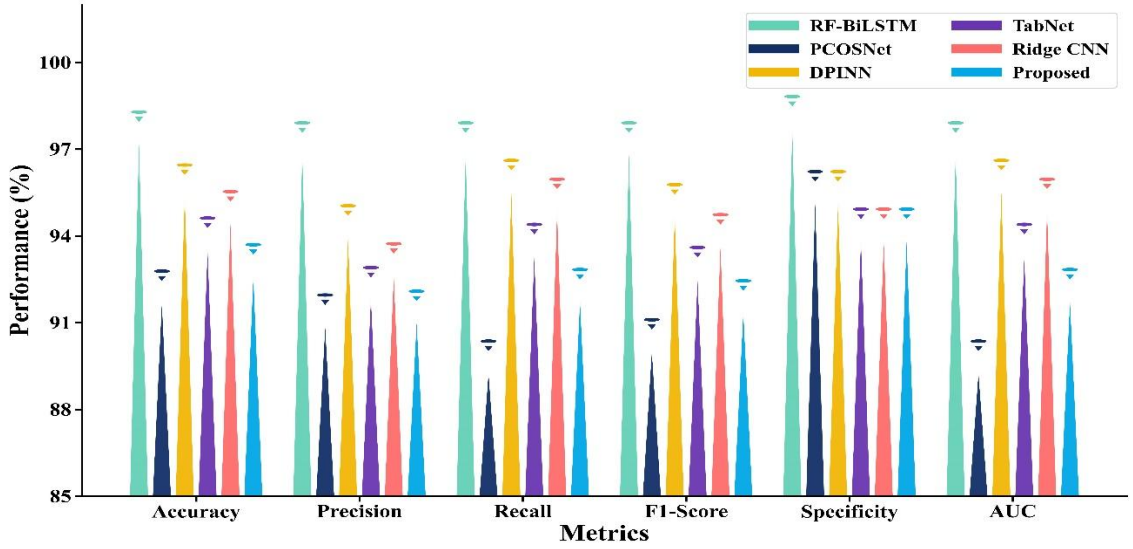


Figure 6: Analysis of the suggested and other approach classification performance

Figures 6display the performance of the suggestedagainst existing classification methods. The suggested approach provided superior results, including: 99.5% accuracy; 99.1% precision; 99.4 F1 score; 99.65 recall, and 99.7 AUM. In comparison, current methods underperformed because of shortfalls, including limited feature learning, computational overheads, class imbalance, and inadequate classification of PCOS and non-PCOS cases. These concerns usually result in dimensionality reduction issues, in addition to possible excessive overfitting and lower detection rates. The proposed method reduces these concerns with a proposed method of alleviating class imbalance whilst balancing the dataset. The FICA-VAE module developed a reliable feature extraction method and enhanced feature learning through the cross-attention block mechanism. Moreover, implemented advantages of the CA-CNN model were implemented to enhance the classification method. By combining these advances enabled the proposed method was enabled to provide more reliable and accurate results from PCOS and non-PCOS detection.

Table 5:PCOS classification Performance

Performance	**Method**				
	Accuracy	Precision	Recall	F1 Score	AUC
Proposed	99.5	99.11	99.65	99.38	99.65
RF BiLSTM	92.04	93.13	92.04	91.99	92.04
PCOSNet	96.59	96.6	96.59	96.59	96.59
DPINN	94.31	94.89	94.31	94.3	94.31
TabNet	95.23	95.51	95.23	95.2	95.23

Figure 7illustratesthe confusion matrix for the suggested classification approach.

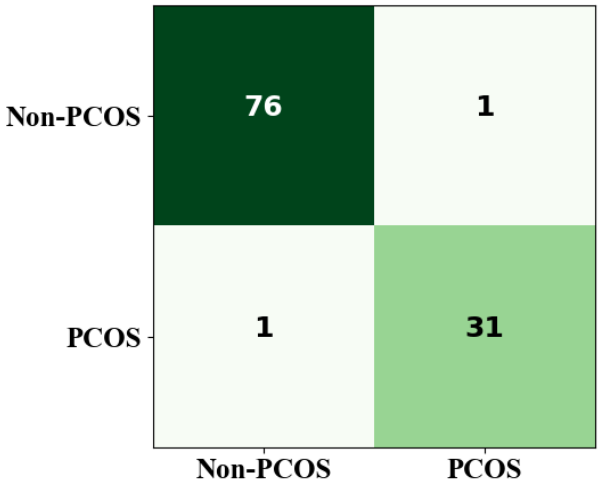


Figure 7: Confusion matrix of the proposed model on the test dataset

Figure 7 defines the confusion matrix for the normal and abnormal class movement in PCOS. The evaluation shows that the suggested approach has increasedperformance over previous works in terms of accuracy. The suggested approach outperformed on the testing PCOS dataset, 77 actual Non-PCOS samples, 76 were correctly classified as Non-PCOS, while only 1 sample was incorrectly classified as PCOS. Similarly, among 32 actual PCOS samples, 31 were correctly identified as PCOS, with only 1 sample misclassified as Non-PCOS. The suggested approach performance is great, which shows that it can classify the data for efficient PCOS classification. Figure 8illustrated the time analysis of the suggested and other approaches.

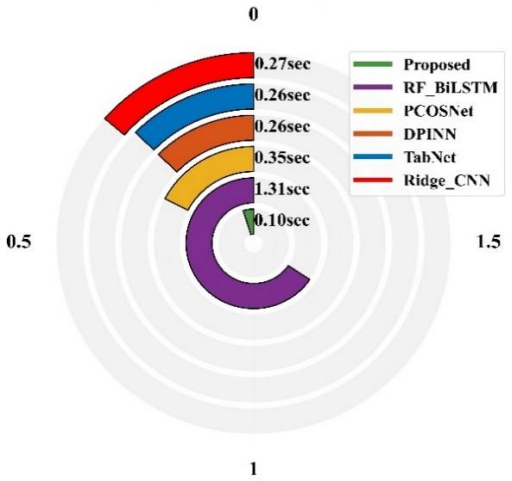


Figure 8: Analysis of Execution Time

The comparison of the suggested with other approaches'in Figure 8 indicates a high reduction of 0.245 seconds of execution time. This outcome indicates that the suggested strategy can reduce inspection time with high feature performance. However, in contrast, other methods take longer to process. The FICA-VAE model introduced in this paper is also an effective method of applying channel and spatial attention mechanisms to

extract the important characteristics of the PCOS dataset, and the Variational Autoencoder can extract latent characteristics with reduced time and provides a more accurate classification.

4.4 K-Fold validation

The K-Fold Cross-Validation is a popular method of testing the model and minimizing the chances of over-fitting. In this method the dataset has been divided into K equal sized folds. After that, the model is trained and validated K times, using the remaining folds as the training set and a different fold as the validation set each time. This not only gives a more accurate estimation as to how well the model will generalize, but also assists in determining possible bias in performance. This application uses K-fold cross-validation on our dataset, as shown in Figure 9.

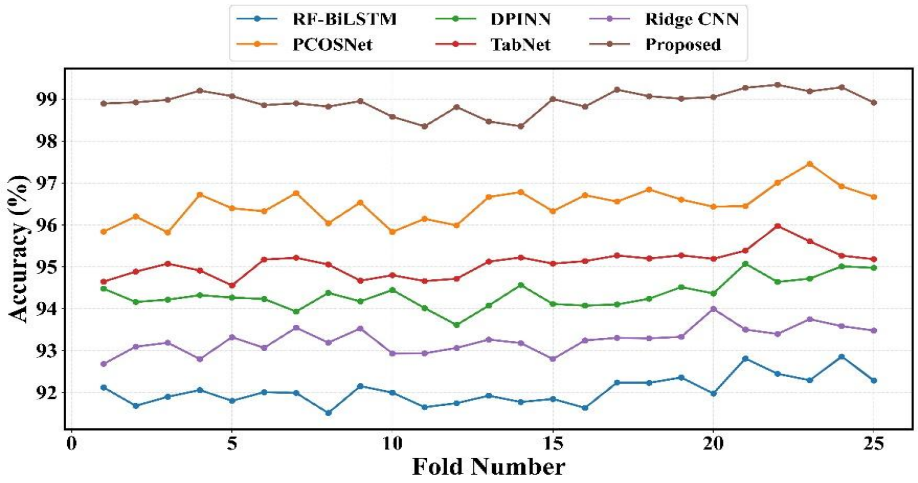


Figure 9: Analysis of K- Fold Validation performance of Accuracy

The suggested framework outperforms the other framework in all values of K , with impressive performance indicators at $K = 25$ yet 97.943% accuracy. The indicators reflect the capacity of the suggested framework to learn effectively since the data and remain highly accurate and stable.

4.4 Discussion

In this paper demonstrates the suggested model to improve PCOS classification outcomes compared to others. Table 8 compares the performance of the suggested model, PCOS, and non-PCOS classification to the existing literature, thus demonstrating the importance of the suggested approach.

Table 8: Comparison of state-of -the art model

Author and Reference	Method used	Accuracy
Mahmud et al. [18]	Intensity histograms, GLCM, and GLRL with ML& DL classifier	89.31%
Kaur et al. [19]	CNN	96%
Pradeep Bedi et al. [20]	AResUNet	97.7%
A.K.M. Salman Hosain et al. [21]	PCONet	98.12%.
Raunak Joshi, et al. [22]	SVM with Deep LDA	98.35
Wenqi Lv et al. [23]	MLP	92.9%
Varada Vivek Khanna et al. [24]	1D-CNN	98%
Abhishek M. Gupta et al. [25]	Discriminant Analysis	97.37%
Proposed	EFEM-HDL	99.51%

The proposed model shows very good overall performance for PCOS and non-PCOS classification when compared with other models in the literature, as shown in Table 8. The proposed approach adequately addressed the data and class imbalance challenges through innovations in GANs, which attempted to balance the data and minimize class imbalance as much as possible. The proposedFICA-VAE module captures meaningful features,

and the cross-attention improves the attribute learning process. The CA-CNN model improves classification performance.

5. Conclusion

This research presents the Enhanced Feature Extraction Module Enclosed Hybrid Deep Learning (EFEM-HDL) model, which marks a significant advancement in PCOS identification. The proposed method suggests employing Generative Adversarial Networks (GAN), which generates synthetic data, therefore enhancing the dataset size and aiding the approach in generalizing to variant populations. The model uses a FICA-VAE for the feature extraction step, enabling it to zoom in on the most relevant features in the data. For classification of PCOS and NonPCOS cases, the model used a Cross Attention-based Convolutional Neural Network (CA-CNN). The results show that EFEM-HDL achieved an accuracy of 99.1%, precision of 98.7%, and recall of 98.5%. As ways to improve the EFEM-HDL model in the future, the researchers will explore greater image augmentation, more narrowly defined feature selection, as well as a more robust classification method to more accurately and reduce overfitting, while working toward a model that can be relied upon in clinical practice to give a high level of real-time efficiency and an accurate diagnosis of PCOS.

References

1. Alamoudi, Abrar, Irfan Ullah Khan, Nida Aslam, Nourah Alqahtani, Hind S. Alsaif, Omran Al Dandan, Mohammed Al Gadeeb, and Ridha Al Bahrani. "A deep learning fusion approach to diagnosing the polycystic ovary syndrome (PCOS)." Applied Computational Intelligence and Soft Computing 2023 (2023).

2. Akshatha, M., Akhilaa C. Shekar, T. S. Bhamini, D. Vikas, and P. V. Vinutha. "Deep Learning Based Polycystic Ovarian Syndrome Detection Augmented By Image Processing."

3. Yadav, Neha, and Sagar Dhanraj Pande. "Comparative Analysis of Polycystic Ovary Syndrome Detection Using Machine Learning Algorithms." EAI Endorsed Transactions on Pervasive Health and Technology 10 (2024).

4. Zad, Zahra, Victoria S. Jiang, Amber T. Wolf, Taiyao Wang, J. Jojo Cheng, Ioannis Ch Paschalidis, and Shruthi Mahalingaiah. "Predicting polycystic ovary syndrome (PCOS) with machine learning algorithms from electronic health records." medRxiv (2023): 2023-07.

5. Berni, Thomas R., Christopher L. Morgan, and D. Aled Rees. "Women with polycystic ovary syndrome have an increased risk of major cardiovascular events: a population study." The Journal of Clinical Endocrinology & Metabolism 106, no. 9 (2021): e3369-e3380.

6. Elmannai, Hela, Nora El-Rashidy, Ibrahim Mashal, Manal Abdullah Alohali, Sara Farag, Shaker El-Sappagh, and Hager Saleh. "Polycystic ovary syndrome detection machine learning model based on optimized feature selection and explainable artificial intelligence." Diagnostics 13, no. 8 (2023): 1506.

7. Nasim, Shazia, Mubarak Saad Almutairi, Kashif Munir, Ali Raza, and Faizan Younas. "A novel approach for polycystic ovary syndrome prediction using machine learning in bioinformatics." IEEE Access 10 (2022): 97610-97624.

8. Lim, Jiekee, Jieyun Li, Xiao Feng, Lu Feng, Yumo Xia, Xinang Xiao, Yiqin Wang, and Zhaoxia Xu. "Machine learning classification of polycystic ovary syndrome based on radial pulse wave analysis." BMC Complementary Medicine and Therapies 23, no. 1 (2023): 409.

9. Batra, Harshita, and Leema Nelson. "DCADS: Data-Driven Computer Aided Diagnostic System using Machine Learning Techniques for Polycystic Ovary Syndrome." International Journal of Performability Engineering 19, no. 3 (2023): 193.

10. Wu, Yumi, QiWei Xiao, ShouDong Wang, Huanfang Xu, and YiGong Fang. "Establishment and Analysis of an Artificial Neural Network Model for Early Detection of Polycystic Ovary Syndrome Using Machine Learning Techniques." Journal of Inflammation Research (2023): 5667-5676.

11. Agrawal, Anushka, Ranjit Ambad, Radhika Lahoti, Parikshit Muley, and P. S. Pande. "Role of artificial intelligence in PCOS detection." Journal of Datta Meghe Institute of Medical Sciences University 17, no. 2 (2022): 491-494.

12. Nsugbe, Ejay. "An artificial intelligence-based decision support system for early diagnosis of polycystic ovaries syndrome." Healthcare Analytics 3 (2023): 100164.

13. Inan, Muhammad Sakib Khan, Rubaiath E. Ulfath, Fahim Irfan Alam, Fateha Khanam Bappee, and Rizwan Hasan. "Improved sampling and feature selection to support extreme gradient boosting for PCOS diagnosis." In 2021 IEEE 11th annual computing and communication workshop and conference (CCWC), pp. 1046-1050. IEEE, 2021.

14. Suha, Sayma Alam, and Muhammad Nazrul Islam. "Exploring the dominant features and data-driven detection of polycystic ovary syndrome through modified stacking ensemble machine learning technique." Heliyon 9, no. 3 (2023).

15. Fan, Junfang, Juanqin Liu, Qili Chen, Wei Wang, and Yanhui Wu. "Accurate Ovarian Cyst Classification with a Lightweight Deep Learning Model for Ultrasound Images." IEEE Access (2023).

16. GÜLHAN, Perihan Gülşah, Güzin ÖZMEN, and Hüsnü ALPTEKİN. "CNN Based Determination of Polycystic Ovarian Syndrome using Automatic Follicle Detection Methods." Politeknik Dergisi (2023): 1-1.

17. Alsibai, Mohammed Hayyan, and Seyed Youssef Heydari. "The Effectiveness of CNN in Evaluating Ultrasound Image Datasets: Diagnosing Polycystic Ovary Syndrome (PCOS) as an Example." Syrian Journal for Science and Innovation 1, no. 1-Volume 1 (2023).

18. Mahmud, Wan Mahani Hafizah Wan, Audrey Huong, and Nur Anida Jumadi. "Preliminary Analysis of Ultrasound Features for Detection of Polycystic Ovary Syndrome (PCOS) in Women." In Biomedical Engineering: AI and Technological Innovations, pp. 137-151. Singapore: Springer Nature Singapore, 2025.

19. Kaur, Trishvin, Syadia Nabilah Mohd Safuan, Azuwien Aida Bohari, Nor Izzati Ahmad, Nurul Izzatul Akma Katim, and Nor Akmal Alias. "Classification of PCOS Using Convolution Neural Network." In 2024 IEEE 12th Conference on Systems, Process & Control (ICSPC), pp. 148-153. IEEE, 2024.

20. Bedi, Pradeep, S. B. Goyal, Anand Singh Rajawat, and Manoj Kumar. "An integrated adaptive bilateral filter-based framework and attention residual U-net for detecting polycystic ovary syndrome." Decision Analytics Journal 10 (2024): 100366.

21. Hosain, AKM Salman, Md Humaion Kabir Mehedi, and Irteza Enan Kabir. "Pconet: A convolutional neural network architecture to detect polycystic ovary syndrome (PCOS) from ovarian ultrasound images." In 2022 International Conference on Engineering and Emerging Technologies (ICEET), pp. 1-6. IEEE, 2022

22. Joshi, Raunak, Abhishek Gupta, Himanshu Soni, and Ronald Laban. "Deep linear discriminant analysis with variation for polycystic ovary syndrome classification." In Intelligent Computing and Networking: Proceedings of IC-ICN 2022, pp. 25-33. Singapore: Springer Nature Singapore, 2023.

23. Lv, Wenqi, Ying Song, Rongxin Fu, Xue Lin, Ya Su, Xiangyu Jin, Han Yang et al. "Deep learning algorithm for automated detection of polycystic ovary syndrome using scleral images." Frontiers in Endocrinology 12 (2022): 789878.

24. Khanna, Varada Vivek, Krishnaraj Chadaga, Niranajana Sampathila, Srikanth Prabhu, Venkatesh Bhandage, and Govardhan K. Hegde. "A distinctive explainable machine learning framework for detection of polycystic ovary syndrome." Applied System Innovation 6, no. 2 (2023): 32.

25. Gupta, Abhishek, Himanshu Soni, Raunak Joshi, and Ronald Melwin Laban. "Discriminant analysis in contrasting dimensions for polycystic ovary syndrome prognostication." arXiv preprint arXiv:2201.03029 (2022).

26. GÜLHAN, Perihan Gülşah, Güzin ÖZMEN, and Hüsnü ALPTEKİN. "CNN Based Determination of Polycystic Ovarian Syndrome using Automatic Follicle Detection Methods." Politeknik Dergisi (2023): 1-1.

27. Alsibai, Mohammed Hayyan, and Seyed Youssef Heydari. "The Effectiveness of CNN in Evaluating Ultrasound Image Datasets: Diagnosing Polycystic Ovary Syndrome (PCOS) as an Example." Syrian Journal for Science and Innovation 1, no. 1-Volume 1 (2023).

28. Mahmud, Wan Mahani Hafizah Wan, Audrey Huong, and Nur Anida Jumadi. "Preliminary Analysis of Ultrasound Features for Detection of Polycystic Ovary Syndrome (PCOS) in Women." In Biomedical Engineering: AI and Technological Innovations, pp. 137-151. Singapore: Springer Nature Singapore, 2025.

29. Kaur, Trishvin, Syadia Nabilah Mohd Safuan, Azuwien Aida Bohari, Nor Izzati Ahmad, Nurul Izzatul Akma Katim, and Nor Akmal Alias. "Classification of PCOS Using Convolution Neural Network." In 2024 IEEE 12th Conference on Systems, Process & Control (ICSPC), pp. 148-153. IEEE, 2024.

30. Bedi, Pradeep, S. B. Goyal, Anand Singh Rajawat, and Manoj Kumar. "An integrated adaptive bilateral filter-based framework and attention residual U-net for detecting polycystic ovary syndrome." Decision Analytics Journal 10 (2024): 100366.

31. Hosain, AKM Salman, Md Humaion Kabir Mehedi, and Irteza Enan Kabir. "Pconet: A convolutional neural network architecture to detect polycystic ovary syndrome (PCOS) from ovarian ultrasound images." In 2022 International Conference on Engineering and Emerging Technologies (ICEET), pp. 1-6. IEEE, 2022

32. Joshi, Raunak, Abhishek Gupta, Himanshu Soni, and Ronald Laban. "Deep linear discriminant analysis with variation for polycystic ovary syndrome classification." In Intelligent Computing and Networking: Proceedings of IC-ICN 2022, pp. 25-33. Singapore: Springer Nature Singapore, 2023.

33. Lv, Wenqi, Ying Song, Rongxin Fu, Xue Lin, Ya Su, Xiangyu Jin, Han Yang et al. "Deep learning algorithm for automated detection of polycystic ovary syndrome using scleral images." Frontiers in Endocrinology 12 (2022): 789878.

34. Khanna, Varada Vivek, Krishnaraj Chadaga, Niranajana Sampathila, Srikanth Prabhu, Venkatesh Bhandage, and Govardhan K. Hegde. "A distinctive explainable machine learning framework for detection of polycystic ovary syndrome." Applied System Innovation 6, no. 2 (2023): 32.

35. Gupta, Abhishek, Himanshu Soni, Raunak Joshi, and Ronald Melwin Laban. "Discriminant analysis in contrasting dimensions for polycystic ovary syndrome prognostication." arXiv preprint arXiv:2201.03029 (2022).

36. Inan, Muhammad Sakib Khan, Rubaiath E. Ulfath, Fahim Irfan Alam, Fateha Khanam Bappee, and Rizwan Hasan. "Improved sampling and feature selection to support extreme gradient boosting for PCOS diagnosis." In 2021 IEEE 11th annual computing and communication workshop and conference (CCWC), pp. 1046-1050. IEEE, 2021.