Detection and Prediction of Polycystic Ovary Syndrome Using Attention-Based CNN-RNN Classification Model

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Abstract*—Polycystic Ovary Syndrome (PCOS) has many challenges when it comes to its diagnosis and treatment due to the diversity of presentation and potential long-term consequences for health. For this reason, sophisticated data pre-processing and classification methods are implemented to enhance the accuracy of PCOS diagnosis. A number of innovative techniques are employed in the process to enhance the accuracy and reliability of PCOS diagnosis. To identify ovarian cysts, real-time ultrasound images are pre-processed initially with the Contrast-Limited Adaptive Histogram Equalization (CLAHE) model to improve image contrast and sharpness. The ultrasound images are segmented with the K-means clustering algorithm, Particle Swarm Optimization (PSO), and a fuzzy filter, enabling precise analysis of regions of interest. An attention-based Convolutional Neural Network-Recurrent Neural Network (CNN-RNN) model is employed for classification and does so effectively to capture the temporal and spatial characteristics of the segmented data. The proposed model has a very good accuracy rate of 96% and works very well on a variety of evaluation metrics such as accuracy, precision, sensitivity, F1-score, and specificity. The results are evidence of the robustness of the model in minimizing false positives and enhancing PCOS diagnostic accuracy. Nevertheless, it is noted that bigger data sets are required to maximize the precision and generalizability of the model. The aim of subsequent research is to use Explainable AI (XAI) methods to enhance clinical decision-making and establish trust by making the model's predictions clearer and understandable for patients and clinicians. Along with enhancing PCOS detection, this comprehensive approach sets a precedent for integrating explainability into AI-based medical diagnostic devices.

Keywords*—*Polycystic ovary syndrome; contrast limited adaptive histogram equalization; particle swarm optimization; k- means clustering algorithm; convolutional neural network; recurrent neural network

I. INTRODUCTION

Polycystic ovarian syndrome (PCOS) is a common endocrinological disorder that affects one in ten pre-menopausal reproductive women worldwide [1]. According to several studies, women with PCOS are more likely to develop ovarian and endometrial cancer, both of which can be dangerous if not recognized early [2, 3]. The identification of PCOS is a major issue since it is a frequent illness that may endanger women's physical and mental health. Ovarian malfunction and an excess of androgen are the two main signs of PCOS [4]. Many factors are believed to cause this disorder, and the factors include genetics, puberty, physiological changes, mental state, and environmental effects. Patients who have PCOS usually exhibit hirsutism, obesity, insulin resistance, irregular menstruation, and cardiovascular problems. As a result, it is crucial for the accurate diagnosis and treatment of PCOS [5, 6]. However, a growing body of scientific research indicates that PCOS can be promptly diagnosed using a well-standardized diagnostic method and that it can be treated with appropriate, symptom-focused, long-term, and dynamic therapies [7].

The most common imaging technique used in the clinical assessment of a patient with ovarian disease is ultrasound. Compared to other medical imaging techniques like computed tomography (CT) and magnetic resonance imaging (MRI), ultrasound provides a number of benefits [8, 9]. This is because ultrasonography is inexpensive, widely available, safe, and delivers results instantly. The use of this imaging approach provides a fantastic chance to create a deep learning model for automatic analysis, improving the objectivity and diagnostic accuracy of the test. Patients are required to undergo ovarian ultrasonography in order to guarantee the correctness of the first PCOS diagnosis [10, 11]. For the purpose of evaluating their metabolism, some of them could even require venous samples. It is a substantial financial burden as the average cost of the initial diagnosis and evaluation of PCOS is estimated to be $740. There has been a lot of interest in using deep learning and machine learning to identify PCOS because artificial intelligence has developed so quickly [12-14].

Currently, a manual process is used to identify the polycystic ovary shape in ultrasound images. It is based on the collective expertise of professionals in identifying the shape and features of ovarian ultrasound images [15]. After reviewing images from the same instance, the specialist's judgment may occasionally be arbitrary and unpredictable. In order to identify PCOM, radiologists have to invest a great deal of time and effort due to the various follicle sizes and their relationship with veins and tissues. Additionally, it causes artefacts and speckle noise in the images. Additionally, this manual framework for diagnosis may increase examination errors, which is inconvenient for the patient. Therefore, it is advised to suggest clever computer-aided solutions that can provide gynecologists with decision-support tools [16]. Using clinical information and ultrasound images, a deep learning algorithm may be used to determine whether a woman has PCOS. It will also help remove barriers related to the manual review of ultrasound images and the assessment of clinical data for patients [17].

After PCOS was identified using a number of standard techniques, machine learning (ML) techniques were created and applied to clinical data [18]. The ML methods are time consuming, and yields poor detection accuracy results. On the other hand, neural networks are a well-known method for prediction [19]. Once more, some researchers used Convolutional Neural Networks (CNN) to diagnose PCOS from ultrasound images using deep learning techniques [20]. DL is a powerful method used in computer vision and image analysis. Although DL algorithms normally achieve a high degree of accuracy in classifying images. Random forest (RF) classifiers have been developed to classify PCOS and normal samples, yielding an accuracy of 72%. SVM, NB, CNN, and VGG-16 are a few machine learning and deep learning models used to analyze ovarian ultrasound images for diagnostic systems. However, several studies employed clinical data and ultrasound reports in text format rather than ultrasound images to diagnose PCOS [21-23]. PCOS is characterized by oligomenorrhea, anovulation, and biochemical hyperandrogenism. In some cases, it may occur due to the development of ovarian microcysts. Women are learning more about PCOS, which is becoming increasingly widespread. PCOS/PCOD is becoming more common in women and significantly impacts women.

According to a recent study, approximately 18 percent of women in India, especially from the East, suffer from this illness. Infertility, irregular ovulation, and preterm abortions are becoming prevalent issues for women. PCOS, a disorder that affects women of reproductive age, has been found to play a significant role in the cause of infertility. Doctors nowadays diagnose PCOS by manually counting the number of follicular cysts in the ovary, which is used to determine whether or not the condition exists. Variability, reproducibility, and efficiency issues may arise due to manual counting. The main objective of a proposed approach is listed in the following bulleted points,

- To design an effective polycystic ovary syndrome detection method using a machine learning algorithm.
- To eliminate additive noise and enhance the detection process, a dataset is pre-processed using the contrast-limited adaptive histogram equalization method.
- To present a particle swarm optimization (PSO) and K-means clustering algorithm with a fuzzy filter (FF) for the segmentation process.
- To implement an attention-based CNN-RNN deep model for increasing PCOS detection accuracy.

The proposed approach is highly accurate with low false positives and demonstrates impressive performance. The model provides a more accurate and efficient method for the diagnosis of PCOS using advanced deep learning methods, which ultimately leads to improved patient outcomes and clinical decision-making.

II. Related Work

NS. Nilofer et al. [24] developed a hybrid ML model for PCOS detection by extracting the GLCM features. The combination of an artificial neural network (ANN) and an improved fruit fly optimization approach (IFFOA) was developed. The suggested model had three main stages, namely pre-processing, segmentation, feature extraction, and detection. In the first phase, the image resizing and noise removal are executed using a medial filtering approach. Then, the enhanced K-means clustering model was utilized to perform the segmentation process. After attaining a segmented follicle part, the features from the particular portions are extracted using the Grey-Level Co-occurrence Matrix (GLCM). An enhanced optimization model was introduced in the detection model for the optimal two key parameters. The dataset used here was the US image dataset, and the performance measures of precision, recall, F measure, and accuracy are analyzed.

C. Gopalakrishnan et al. [25] presented a detection method of PCOS from the ultra sound image of the ovary. The ovary's size, number of follicles, and location may all be learned by ultrasound imaging. Due to the different follicle sizes and the complex relationship between tissues and blood vessels, diagnosing PCOS in real time can be challenging for radiologists. This frequently leads to incorrect diagnosis. Initially, the pre-processing stage was performed, and in this stage, RGB to Gray conversion, ROI extraction, and speckle noise reduction were executed. The ovary image was binarized for segmentation using the modified Otsu approach. The contour initialization concerns were resolved since the binary mask had foreground and background areas organized properly to segment objects. Additionally, based on the distributed grey level, a thresholding strategy was added to remove the objects from the ovary image. Finally, an improved outcome in terms of accuracy had been achieved. As a result, the modified Otsu method proved effective for follicle extraction.

Recently, medical professionals have been able to identify and categorize illnesses using image recognition techniques. Traditional methods for detecting PCOS have several drawbacks, therefore, Dongyun He et al. [26] developed a probabilistic method. To ensure accurate cue recognition, the training images were first split into several grids of identical sizes. Furthermore, each grid in the supplied image had a quality score that roughly corresponded to its grayscale and texture properties. As a result, one may consider each image to be a scoring matrix. The feature vectors might be provided using the statistically based model while taking into account the score matrix. The probabilistic model was used to train the identified feature vectors, and the learned feature vectors were subsequently transformed into an SVM kernel to identify PCOS.

To identify PCOS from ultrasound images of the ovary, C. Gopalakrishnan et al. [27] developed a model based on scale-invariant feature transform (SIFT) descriptors. Initially, the Canny edge detection method was utilized to enhance image quality and delineate the margins of follicles in the ultrasound image. This approach involved pre-processing, gradient computation, non-maximum suppression, and thresholding as integral steps of the Canny edge detection process. SIFT descriptors are used to identify the feature descriptors for diagnosing the condition. Then, a support vector machine (SVM) was used to ultimately perform data training and classification. Better accuracy, mean squared error, and normalized absolute error has been achieved for PCOS identification.

In order to identify PCOS using ultrasound images, Untari N. Wisesty et al. [28] suggested a modified back propagation method. Typically, stereology calculations or feature extraction and classification were the key foundations for PCO follicle identification. The extraction and categorization of features served as the foundation for this PCOS detection. The Gabor wavelet was taken into consideration for the feature extractor, while the modified back propagation model was employed as a classifier. Levenberg-Marquardt optimization (LMO) and Conjugate Gradient-Fletcher Reeves (CGFR) were the modified backpropagation algorithms. LMO was used to achieve the highest level of accuracy by considering 33 neurons and 16 vector characteristics.

A PSO model to partition follicles and identify PCOS was reported by E. Setiawati et al. [29]. Here, the follicles were segmented using a novel clustering model created with PSO and a modified non-parametric fitness function. The primary goal of the fitness function would be to detect faults based on pixel values and improve the likeness to human vision. Then, normalized mean square error (NMSE) and the mean of the modified non-parametric fitness function and structural similarity index (MSSIM) approaches were used to create convergent and compact clusters. The PSO fitness function also led to more convergent solutions. The performance of the examined PSO also impacted the extracted follicular size and contrast enhancement.

The chan-vase model and split-Bregman optimization were introduced by H. Prasanna Kumar and S. Srinivasam [30] for quick segmentation of PCOS. A thorough understanding of the size and quantity of follicles might be gained through PCOS diagnosis using ultrasound images. Using an increased active contour without an edge model, the tiny follicles could be identified. In addition, by using the split-Bregman optimization model, the segmented image’s accuracy and computation time are enhanced. Results demonstrated that the split-Bregman optimization model produced superior outcomes with less computing time and iteration.

Onyema et al. [31] applied the AI-based Granger panel model approach to provide an empirical analysis of apnea syndrome. The MIT-BIH polysomnographic database (SLPDB) was the source of the data. MATLAB software was utilized for the implementation, and the panel consisted of eighteen patients. The findings indicate a substantial correlation between ECG-blood pressure (BP), ECG-EEG, and EEG-blood pressure (BP) for the eighteen sleep apnea patients.

Tiwari et al. [32] developed a model that diagnoses based on a clinical dataset Kottarathil provided and made available through its Kaggle repository. A variety of machine learning techniques for patient screening without the need for intrusive diagnostics are assessed using non-invasive screening metrics. The experiments demonstrate that the Random Forest (RF) approach outperforms the other well-known machine learning algorithms with an accuracy of 93.25%. Moreover, the model possesses high complexity.

Alamoudi et al. [33] suggested a data set containing an ultrasound image of the ovary and clinical information about a patient classified as either PCOS or non-PCOS is presented. Then, using the Inception model, a deep learning model was built to diagnose the PCOM based on the ultrasound image and achieved 84.81% accuracy. Then, in order to determine whether or not the patient has PCOS, a fusion model that combines clinical data with the ultrasound picture was suggested. By combining clinical features with mobile net architecture to extract image data, the most advanced model to date has achieved 82.46% accuracy.

Lv et al. [34] suggested an automated deep learning method that investigates the possibility of scleral alterations in PCOS identification for auxiliary PCOS detection. After utilizing an enhanced U-Net to separate scleral photos from full-eye images, the method was run on the dataset. From there, deep features were extracted from the scleral images using a Resnet model. In order to accomplish categorization, a multi-instance model was created. A variety of performance metrics, including AUC, F1-score, recall, precision, and accuracy of classification, are used to evaluate the effectiveness of the method. The results demonstrate the high potential of deep learning in PCOS diagnosis, achieving an average AUC of 0.979 and a classification accuracy of 0.929. The comparison with existing methods is shown in Table I.

Gaps Identified in the Literature Review and Contributions of the Work

- Data Scalability and Flexibility: Some of the models mentioned, such as the probabilistic model with SVM, the Canny edge detection method, and the adaptive k-means clustering with GLCM feature extraction and ANN network, struggle with different types of image datasets and large databases.
- Complexity and Parameter Tuning: Support Vector Machine (SVM), Random Forest (RF), and Decision Tree models require high-fidelity parameter tuning and can be computationally intensive, leading to inefficiencies in real- world applications.
- Temporal analysis and feature extraction: Spatial feature extraction is the prime focus of traditional models like active contour with altered Otsu threshold value, Particle Swarm Optimization with a new revised non-parametric fitness function, and LMO (Local Min-Orthogonal) CGFR (Centered Gaussian Fit Regression) algorithms. They cannot capture the temporal dependencies of the data sufficiently.

The CNN-RNN model's strong architecture makes it better placed to deal with large and diverse datasets.

- With the addition of attention mechanisms, the CNN-RNN model enhances model performance and efficiency while reducing the need for manual parameter tuning.

- The CNN-RNN model excels in this aspect by combining Convolutional Neural Networks for spatial feature extraction and Recurrent Neural Networks for temporal sequence analysis, providing a more comprehensive approach to diagnosing PCOS.

- By combining recurrent neural networks for analysis of temporal sequence and convolutional neural networks for spatial feature learning, the CNN-RNN model excels at this task and provides a more comprehensive approach to PCOS diagnosis.

TABLE I. COMPARISON WITH STATE-OF-THE-ART TECHNIQUES

References	Method	Advantages	Disadvantages
[24]	Adaptive k-means clustering, GLCM feature extraction, and ANN network model	The system is used for alternative medical data, and a number of criteria are used to evaluate its efficacy.	Various algorithms can be employed to optimize the parameters of an artificial neural network.
[25]	Active Contour with modified OTSU threshold value	High accuracy	A large database cannot be applicable
[26]	Probabilistic model and SVM with kernel function	Image quality diagnosis may assess early alterations in endometrial thickness and blood flow and perform early illness diagnosis and therapy.	Accuracy can be improved.
[27]	The Canny Edge detection method	The suggested methods are more suited to extracting and identifying follicles from ovarian images.	Different kinds of image datasets cannot be used.
[28]	LMO and CGFR algorithm	It has high accuracy	The conjugate gradient parameter is not considered
[29]	PSO with a new modified non-parametric fitness function.	The retrieved follicular size may be made to resemble the real follicular size by using contrast enhancement.	The follicles cannot be identified automatically.
[30]	Improved active contour without edge method.	The performance is high	High cost
[31]	AI-based Granger Panel model approach	Valuable statistical source for the analysis of dynamic behaviours	Give less performance in prediction
[32]	RF	Attain accuracy of 93.25%	Highly complex in computation
[44]	Random forest	High accuracy and robustness; handles missing data well.	Can require a great deal of processing power and overfit noisy data.
[45]	Decision tree	It needs minimal data preparation and is easy to analyze and represent.	Vulnerable to overfitting and subject to instability when data is slightly different
[46]	Convolutional neural network (CNN)	Extracts and categorizes features automatically.	High computing power and large data sets are required,
[47]	Transfer learning (e.g., VGG16) [48]	Uses pre-trained models to improve performance.	Require huge processing power.

III. METHODOLOGY

PCOS is caused by a hormonal imbalance that can lead to various illnesses and occurs in one in ten women of reproductive age from 18 to 44. In the proposed approach, machine learning-based techniques are proposed to detect PCOS disorder efficiently. The main novelty of the proposed work lies in the integration of several advanced techniques to address the challenge of diagnosing PCOS using ultrasound images: CLAHE takes it a step further by limiting the amplification of noise in relatively homogeneous regions. This helps in enhancing the contrast of ultrasound images, which is crucial for identifying subtle details like ovarian cysts. This combination of K-means clustering and PSO with fuzzy filtering allows for more accurate segmentation of ultrasound images. K-means clustering partitions the image into clusters based on pixel intensity, while PSO optimizes the clustering process by finding the optimal centroids. Fuzzy filtering further refines the segmentation by considering the uncertainty in pixel classification, improving the regions of interest identification.

CNN-RNN architecture is designed to effectively capture both spatial and temporal features within the segmented ultrasound images. The attention mechanism allows the model to focus on the most relevant regions, while the CNN component extracts spatial features, and the RNN component processes temporal sequences. This holistic approach enables more accurate classification of ultrasound images, aiding in the diagnosis of PCOS. By combining these techniques, the proposed approach offers a comprehensive solution for PCOS diagnosis. The proposed approach comprises three stages for PCOS detection they are;

- Pre-processing
- Segmentation
- Classification.

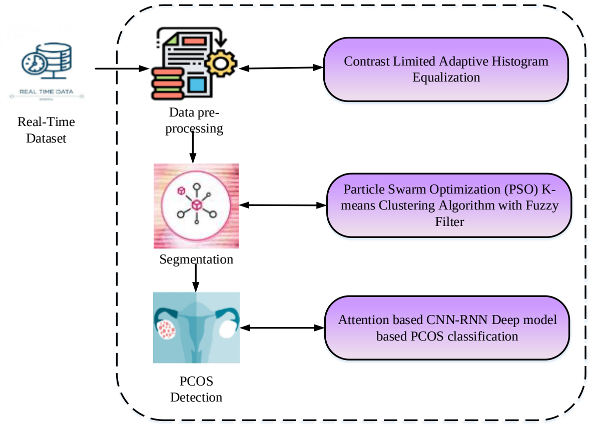

Fig. 1. Workflow for proposed approach.

Fig. 1 represents the step-by-step process involved in the proposed approach. In the first stage of the proposed approach, the real-time dataset is pre-processed to enhance the performance of PCOS detection. After that, the segmentation process is done for pre-processed data using particle swarm optimization (PSO) K-means clustering algorithm with FF. Then, the detection process was done by attention-based CNN-RNN deep model. The proposed classification model applies to many technical problems with reduced complexity. The proposed model provides the best optimal outcome and improves classification accuracy effectively. The step-by-step process of PCOS detection using machine learning techniques will be discussed briefly in subsequent sections.

A. Pre-processing

The initial stage of the proposed work is pre-processing, which is aimed at enhancing the quality and clarity of ultrasound images specifically for the purpose of identifying ovarian cysts, which are a hallmark of PCOS diagnosis. CLAHE is applied to improve image contrast and detail. This enhancement is crucial for subsequent steps in the analysis pipeline, such as segmentation and classification, as it enables more accurate regions of interest identification and characterization within the ultrasound images. Therefore, the pre-processing is focused on preparing the ultrasound images for further analysis and diagnosis of PCOS. The proposed approach pre-processes the real-time dataset using the CLAHE method [35]. The use of CLAHE for pre-processing is attributed to its effectiveness in enhancing image contrast and improving local details, particularly in medical imaging applications like detecting polycystic ovary syndrome. CLAHE is specifically designed to address the limitations of traditional histogram equalization by limiting contrast amplification in regions with high contrast variations, thereby avoiding over-enhancement artifacts.

Additionally, CLAHE's adaptive nature allows it to adjust parameters locally based on the characteristics of different image regions, which is crucial for maintaining diagnostic information integrity in medical images. This flexibility guarantees the preservation and highlighting of pertinent characteristics linked to polycystic ovary syndrome, improving the overall efficacy of later analysis algorithms. Moreover, CLAHE is a better option for pre-processing tasks due to its ease of integration into current pipelines and low computational overhead brought about by its simplicity and efficiency. Image quality consistency between datasets is guaranteed by using CLAHE to standardize pre-processing. Input image in the CLAHE model is classified into non-overlapping contextual regions known as blocks/sub-images/tiles. In the CLAHE model, two main metrics are Clip Limit-CL and Block Size-BS. Using these metrics in the CLAHE model maintains and enhances image quality. When the CL is higher then, the histogram becomes flatter, and the image's brightness is increased due to the low intensity of the input image. In addition, if BS is higher, the image contrast is increased, and the dynamic range becomes higher. An optimal image quality is generated using the image entropy when the two metrics are determined at the point with the huge entropy curvature. The major steps of the CLAHE model are defined below:

Step 1: Classify the intensity of an original input image into non-overlapping contextual regions. In which, $m \times n$ is considered the total number of image blocks and 8×8 is considered the optimal value for preserving the chromatic data in the image.

Step 2: Based on the values of the grey level present in the image of the array, evaluate the contrast-limited histogram for each contextual zone.

Step 3: By using the CL value, the limited contrast histogram for the contextual region is calculated, and the mathematical equation is given below:

$$N(Avg) = \left[\frac{N(U)_r \times N(V)_r}{N(GL)} \right] \tag{1}$$

Here the average number of pixels is represented by $N(Avg)$, the number of gray levels in the contextual region is represented as $N(GL)$, $N(U)_r$ *and* $N(V)_r$ represents the number of pixels in the U dimension, and V dimension for the contextual region. The actual CL is calculated by the following equation;

$$N(CL) = Nor(CL) \times N(Avg) \tag{2}$$

Here $N(CL)$ represents the actual CL, $Nor(CL)$ represents the normalized CL. The total number of clipped pixels is determined as $Nor\sum(CL)$. Finally, the average of the remaining pixels to be distributed into each gray level is defined in the following equation;

$$N(Avg)Nor(CL) = \left[\frac{Nor\sum(CL)}{N(GL)} \right] \tag{3}$$

By using the following condition, the histogram clipping rule is calculated;

If $His_{reg}(x) > N(CL)$ then;

$$His_{reg\_clip}(x) > N(CL)$$

Else if $(His_{reg}(x) + N(Avg)N(CL) > N(CL)$ then

$$His_{reg\_clip}(x) > N(CL)$$

Else $(His_{reg\_clip}(x) = His_{reg\_clip}(x) + N(CL)$

Here the original histogram is represented as $His_{reg}(x)$, and the clipped histogram for each region at x^{th} gray level is represented as $His_{reg\_clip}(x)$.

Step 4: Reallocate the other pixel until all have been allocated. The step for reallocating the pixel is represented in the following equation;

$$S(PI) = \left[\frac{N(GL)}{N(\mathrm{Re}\,main)}\right] \tag{4}$$

Here $S(PI)$ represents the step of a positive integer of at least one, $N(GL)$ represents the number of gray levels, and $N(\mathrm{Re}\,main)$ represents the remaining number of clipped pixels. The program begins its search process from the lowest to the highest order of gray level using the above step. The program will allocate one pixel to the gray level if the number of pixels in the gray level is less than $N(CL)$. If the distribution of the pixels is not even performed when the search is complete, the program computes a new step using Eq. (4) and starts a new search round until all of the remaining pixels are dispersed.

Step 5: Each region's intensity values are improved using the Rayleigh transform model. The clipped histogram is distorted to cumulative probability $CP_{inp}(x)$; it is used to generate a transfer function. The PCOS image shows as another original when the Rayleigh distribution is applied. The mathematical equation of using the Rayleigh forward transform is represented in the following equation;

$$RFT(x) = \left[PV_{LB} + \sqrt{2\delta^2 In\left(\frac{1}{1-CP_{inp}(x)}\right)}\right] \tag{5}$$

Here RFT represents the Rayleigh forward transform, PV_{LB} represents the pixel value of the lower bound, and δ represents the scaling parameter of the Rayleigh distribution. The output of probability density is defined below:

$$CP(RFT(x)) = \left[\frac{RFT(x)-PV_{LB}}{\delta^2} \bullet Exp\left(-\frac{(RFT(x)-PV_{LB})^2}{2\delta^2}\right)\right] \quad for\ RFT(x) \geq PV_{LB} \tag{6}$$

Where a higher δ value results in more effective contrast improvement in PCOS image to enhance the rate of saturate value and reduce the level of noise.

Step 6: Limiting the effect of a sudden change. Linear contrast stretch is used to resize the transfer function output dynamically. The linear contrast stretch is represented in the following equation;

$$RFT(x) = \left[\frac{TF(x) - TF_{Min}}{TF_{Max} - TF_{Min}}\right] \tag{7}$$

Here $TF(x)$ represents the transfer function.

Step 7: In order to prevent border artefacts, the new grey level task of pixels inside a sub-matrix contextual region is computed via a bi-linear interpolation between four mappings.

By using CLAHE, the dark area in the images is clearer and more prominent for higher contrast. As a result, the CLAHE model is suggested to improve PCOS detection performance by eliminating boundary artefacts.

B. *PSO-Based K-means Model with Fuzzy Filter for PCOS Segmentation*

In the proposed approach, PCOS segmentation is considered an essential stage to extract significant objects lying in images and segment the images into nearby semantic regions. The segmentation process of PCOS images is commonly difficult because the images are complicated, diverse and differ from person to person. Various methods are proposed for segmenting the follicles in ultrasound images. In the proposed approach, the segmentation process is performed by a particle swarm optimization (PSO) based K-means clustering algorithm with an FF to enhance the performance [36]. In the proposed approach, FF is used in image processing to enhance the performance of classifiable filters. The main objective of using an FF in the proposed approach is to reduce the unwanted noises in contaminated images when there are many uncertainties. In the fuzzy filtering approach, a pixel is denoted by the membership function and a set of fuzzy rules that consider adjacent information in a limited area or other data to remove the noise with blurry edges of the PCOS image. Recently, the K-means method has become one of the most prominent models in medical technology. The k-means clustering method is considered the most significant algorithm used in centre-pivot clustering techniques in clustering. The initialization of cluster centres and other factors in the K-means clustering method begins with allocating Euclidean distance criteria to one cluster with the shortest distance among the cluster centres. PSO is a population-based search algorithm; each individual in PSO is considered a particle and "flown" via hyper-dimensional space. Individuals' social psychological behaviour causes particles to shift their position in the search space to replicate the success of others. The neighbours' knowledge and experience impact the changes in the particles within the same swarm. The search behaviour of a particle is influenced by the behaviour of other particles in the equivalent swarm.

K-means Clustering: K-means clustering is a form of unsupervised learning used when no groupings or categories exist in the data. The main objective of a K-Learning algorithm is to detect groups in data, where the variable K indicates the number of groups. In the proposed approach, every PCOS image waits to be segmented while the data points set is represented in the following equation;

$$x = [x_1, x_2, \dots, x_n] \quad (8)$$

Here n represents the dimension vector. Using the K-means segmentation process in the proposed approach, PCOS images are divided into K-cluster. The normal method detects the subset $S = \{Cl_1, Cl_2, \dots, Cl_k\}$ in a set x to reduce the target function $TF = \sum_{i=1}^{k} \sum x_j \in s_j D_{ij}(x_j, Cl_i)$. In which $D_{ij}(x_j, Cl_i)$ represents the Euclidean distance from the data point x_j to a clustering centre Cl_i. The target function is represented in the following equation;

$$TF = \left[\sum_{i-1}^{k} \sum_{x_j \in Cl_i} \left\| x_j - Cl_i \right\|^2 \right] \quad (9)$$

The target function TF is closer to clustering with the clustering effect. As a result, to get the optimum clustering effect, the target function value and all the clustering centres should be set as zero, and the mathematical equation is given below:

$$Cl_i = \left[\frac{1}{N_i} \sum_{j=1}^{n_i} x_j \quad (i = 1, 2, \dots, k) \right] \quad (10)$$

Here N_i represents the number of data points in the cluster i. The clustering centre of K-Means is constantly updated by reducing several iterations of the target function. The similarity of data points in the same clustering rapidly enhances as the clustering centre is updated, whereas the similarity of data points in separate clustering gradually decreases. The clustering process is over when no new information exists in the clustering centre.

PSO: In the proposed approach, PSO-based K-means clustering is used for segmentation to detect the approximate solutions for PCOS detection. PSO is an artificial intelligence (AI) based technique used to find approximate solutions to numerical maximizing and minimizing problems that are exceedingly difficult or impossible to solve. In PSO, the best solution for each problem may be computed into a single particle with no quality or volume in N-dimensional space. The step-by-step process involved in the PSO-based K-means clustering algorithm is as follows;

Let's consider the particle P_i present in the dimension space D; then the position is represented in the following equation;

$$P_i = [P_{i1}, P_{i2}, \dots, P_{iD}] \quad (11)$$

Then, the speed is represented in the following equation;

$$SD_i = [SD_{i1}, SD_{i2}, \dots, SD_{iD}] \quad (12)$$

During the update process, the best position of a particle is detected, and the iteration is represented in the following equation;

$$P_i = [P_{i1}, P_{i2}, \dots, P_{iD}] \quad (13)$$

Then, its best position is;

$$P_B = [P_{B1}, P_{B2}, \dots, P_{BD}] \quad (14)$$

Then, the speed calculation of each particle is represented in the following equation;

$$SD_{ij}(T+1) = \left[WSD_{ij}(T) + LF_1 R_1 \left(P_{ij} - X_{ij}(T) \right) + LF_2 R_2 \left(P_{Bi} - X_{ij}(T) \right) \right] \quad (15)$$

The calculation of particle position is represented in the following equation;

$$X_{ij}(T+1) = \lfloor X_{ij}(T) + SD_{ij}(T+1) \rfloor \quad j = 1, 2, \dots, D \quad (16)$$

Here, the inertia coefficient is represented as W, learning factors are denoted as $LF_1 R_1$ and $LF_2 R_2$ in that order, denoting the capacity for self-learning and learning from an excellent group of particles. In a PSOK-based algorithm, the linear regression model is used to assist the inertia coefficient and enhance the convergence and optimization of the quality speed rate.

PSO-based K-means Clustering with FF for PCOS Segmentation: In the proposed approach, PSO-based K-means clustering (PSOK) is proposed to enhance the segmentation process of PCOS detection. The cluster centres in PSOK are recognized as the particle positions, and the weakest particle is removed by searching for the optimal solution using the PSO algorithm to enhance the computation. The proposed approach proposes the K-means clustering algorithm to update the particle positions. In PSOK, n particles are initialized, with their positions and velocities updated as needed, and the fitness values evaluated and arranged in decreasing order in a list. The iteration process continues until the maximum number of iterations is met or the minimal error condition is reached.

Step 1: Choose m particles known as the initial population number, and feed the particles into the initial swarm called IS is represented in the following equation;

$$IS_1 = [P(1), P(2), \dots, P(m)] \quad (17)$$

Then, initialize the position x_{id} for the swarm S by utilizing the K-means clustering algorithm.

Step 2: Arbitrarily begins the velocities v_{id}

Step 3: Fitness evaluation for each particle by using $\left(x_{id}(T) \right)$.

Step 4: The exploration stage is given below:

$$p_{id}(T+1)=\begin{cases} p_{id}(T) & FitVal(p_{id}(T)) > FitVal(x_{id}(T)) \\ x_{id}(T) & FitVal(p_{id}(T)) \le FitVal(x_{id}(T)) \end{cases} \quad (18)$$

Step 5: Determine the global best $p_{GB}(T+1)$ for the particle position by the best fitness value computed in the swarm.

Step 6: Based on the K-means clustering algorithm, the position of every new particle is optimized in the $S(T+1)$ new swarm.

Step 7: Based on the below equation, the velocity vector $(v_{id}(T+1))$ for each particle is varied.

$$\begin{pmatrix} v_{id}(T) = wv_{id}(T-1) + LF_1 Rand()[p_{id}(T-1) - x_{ii}(T-1)] \\ + LF_2 Rand()[p_{id}(T-1) - x_i(T-1)x_{id}(T)] \\ = x_{id}(T-1) + v_{id}(T) + v_{id}(T-1) \end{pmatrix} \quad (19)$$

Step 8: In which, i^{th} particle in a D dimensional space is represented by $(x_{id}(T))$ at the time step T velocity v_{id} of $p_{id}(T)$. Here LF_1 and LF_2 represents the learning factor, w represents the inertia weight, and $Rand()$ represents the random function.

Step 9: Then update each particle in $S(T+1)$.

Step 10: Stop the process until the maximum number of iterations reached of the minimum error condition is satisfied, or else repeat the process.

Therefore, the proposed approach uses a PSOK clustering-based fuzzy filter model for partitioning the ultrasonic image of PCOS into several segments. It uses an appropriate suppression factor for perfect segmentation of PCOS to enhance detection performance.

C. Attention-Based CNN-RNN Deep Model for PCOS Classification

In the classification stage, the segmented PCOS features are fed into the detection model for PCOS detection. An attention-based CNN-RNN deep model is proposed for PCOS detection. The proposed approach is a combination of a CNN and an RNN [37]. The attention-based CNN-RNN deep model is essential for classifying PCOS because it can capture complex temporal dynamics and spatial patterns in medical image sequences. The model gets a thorough knowledge of PCOS-related features by incorporating RNN for modeling temporal dependencies and CNN for extracting spatial information. The inclusion of attention mechanisms concentrates on pertinent areas or time steps in the data, which improves the interpretability of the model even more. By ensuring resilience to the individual variations in PCOS symptoms, this hybrid architecture enhances generalization performance. Furthermore, the interpretability of the model helps physicians comprehend the logic underlying its predictions, enabling well-informed decision-making. All things considered, the Attention-based CNN-RNN deep model makes a substantial contribution to medical image analysis and diagnosis by providing a strong and adaptable framework for precise, comprehensible, and clinically useful PCOS classification.

Using a combination of cutting-edge NN components, the attention-based CNN-RNN deep model is a sophisticated architecture designed for the complex problem of PCOS categorization. Its purpose is to extract valuable information from medical image sequences. CNNs, well-known for their ability to extract spatial characteristics from images, serve as the model’s foundation. CNNs are particularly good at detecting minute patterns and structures in ultrasound scans and other medical images, which is important when it comes to differentiating between ovaries that are damaged and those that are not. CNNs are enhanced by RNNs, who are skilled in simulating the temporal dependencies in sequential data. This skill is essential for documenting dynamic changes in ovarian morphology over time, as these alterations may be markers for diagnosing PCOS. The model can identify temporal patterns and fluctuations that could indicate the onset or progression of PCOS due to RNNs.

The capacity of the model to rank pertinent areas or time steps in the input data is improved by the addition of attention mechanisms. Attention processes enable the model in the setting of PCOS classification to concentrate on particular areas of interest within medical images or sequences, removing unnecessary information and highlighting important diagnostic signals. The model obtains a comprehensive grasp of PCOS-related factors by merging temporal dynamics recorded by RNNs with spatial data recovered by CNNs. This combination of temporal and spatial data improves diagnostic accuracy by allowing the model to identify intricate patterns and changes in both domains.

Attention techniques in the hybrid CNN-RNN architecture give the model robustness and allow it to generalize well to various PCOS symptoms seen in clinical practice. This resilience guarantees the model’s strong performance in various patient demographics and imaging situations, improving its clinical usefulness and dependability. Beyond its potential for classification, the attention-based CNN-RNN deep model is interpretable, giving physicians an understanding of the machine’s decision-making process. The clinical applicability and acceptance of the model are eventually increased by this openness, which also promotes trust and cooperative decision-making between clinicians and AI systems. Using the synergy of CNNs, RNNs, and attention mechanisms to extract, integrate, and interpret complex information from medical image sequences, the Attention-based CNN-RNN deep model advances state-of-the-art PCOS diagnosis and improves patient care.

Here, CNN consists of three layers: convolution, fully connected, and pooling layers. The convolution layer is first used in CNN to extract the required features from input PCOS images. The edges and corner information about the images are extracted using a feature map. The second fully connected layer is used for classification, which uses the convolution layer output to detect the image class effectively. The pooling layer reduces the convolved feature map size to minimize computational costs. RNN is a neural network (NN) type in which the previous output is considered the current input. The input layer contains the initial data for the NN, the hidden layer acts as an intermediate layer among input and output layers, and the output layer generates the final results. In the proposed approach, the CNN model contains seven layers; the initial two are convolution layers with 64x3x3 kernels. The local features of a PCOS image are extracted using 64x1x1 kernels of a locally connected layer. Each RNN unit in the sequence modelling stage has a probability of 0.5 and a dropout of 512 hidden units, followed by a P-way fully connected layer and a softmax classifier.

The integration of CNN and RNN with attention processes may elevate the possibility of overfitting, particularly in scenarios involving small dataset sizes. In order to mitigate this risk, the suggested model incorporates dropout layers. P represents the number of polycystic ovaries to be predicted. The final class of PCOS image is predicted using the average pooling of a softmax output. RNN consists of encoding contextual information and feedback loops of a temporal sequence. Let's consider the input sequence $\{S_1, S_2, \ldots, S_T\}$ segmented from the input PCOS, $\{H_T\}$ represents the hidden state and $\{O_T\}$ represents the output state. Therefore, the mathematical equation is defined below:

$$\{H_T = Height(W_{InH} F_T + W_{HH} H_{T-1} + B_H)\} \quad (20)$$

$$\{O_T = W_{HO} H_T + B_0\} \quad (21)$$

The weight matrices of the three layers are represented as $\{W_{InH}, W_{HH}, W_{HO}\}$. In the proposed approach, long short-term memory (LSTM) is used to improve the standard of RNN from the vanishing of gradient issue. In LSTM, each unit contains an input gate, forget gate, cell gate, and output gate, and their equations are given below;

$$\{In_T = \delta(W_{In}[H_{T-1}, F_T] + B_{In})\} \quad (22)$$

$$\{F_T = \delta(W_F [H_{T-1}, F_T] + B_F)\} \quad (23)$$

$$\{O_T = \delta(W_O [H_{T-1}, F_T] + B_O)\} \quad (24)$$

$$\{\hat{C}_T = TanH(W_C [H_{T-1}, F_T] + B_C)\} \quad (25)$$

$$\{C_T = F_T \bullet C_{T-1} + In_T \bullet \hat{C}_T\} \quad (26)$$

$$\{H_{T-1} = O_T \bullet TanH(C_T)\} \quad (27)$$

Here $In, F, OandC$ represents the input, forget, output, and cell gate activation and δ represents the logistic sigmoid function. In the proposed approach, an attention layer is proposed to improve the hybrid CNN-RNN performance is expressed in the following equation;

$$A_T = TanH(W_H H_T) \quad (28)$$

$$\alpha_T = SM(W^T M_T) \quad (29)$$

$$R = \sum_{T=1}^{T} \alpha_T H_T \quad (30)$$

Here H_T represents the output of T^{th} hidden layer in the RNN module, α_T represents the T^{th} attention weight, W_H and W^T represents the weighted matrices, and the attention module is denoted as R. The output R is followed by a P-way fully connected layer and softmax classifier. The loss function of the detection model is represented by the following equation;

$$LF = [\alpha.L_{Att} + \beta.L_{Att} + \lambda.\|W\|]^2 \quad (31)$$

Here LF represents the attention loss, L_{Att} represents the target replication loss, and W represents the regularization term. α, β, λ represents the three weight parameters.

$$L_{Att} = \left[\frac{1}{TS}.l(G_1(x), y)\right] \quad (32)$$

$$l[P_1(x), y] = \left[-\sum_{i=1}^{P} 1_i(y) Log\, P_1(x)^i\right] \quad (33)$$

$$P_1(x) = [F_S(F_a(F_H(x_1), F_H(x_2), \ldots, F_H(x_T)))] \quad (34)$$

Here x represents the PCOS detected, T represents the number of time steps of RNN, P represents the number of polycystic ovaries to detect, $P_1(x)^i$ represents the i^{th} dimension of $P_1(x)$ and $P_i()$ is the indicator function. F_S, F_h and F_a represents the hybrid CNN-RNN framework, attention module, and the last softmax layer, respectively.

$$L_{Tar} = \left[\frac{1}{TS}\sum_{T=1}^{TS} l(P_2(x_T), y)\right] \quad (35)$$

$$l[P_2(x_T), y] = \left[-\sum_{i=1}^{P} 1_i(y) Log\, P_2(x_T)^i\right] \quad (36)$$

$$P_2(x_T) = [F_S(F_H(X_T))] \quad (37)$$

Here x_T represents the T^{th} sub-segment of x and $P_1(x)^i$ represents the i^{th} dimension of $P_1(x)$. F_S and F_h represents the softmax layer.

IV. Result and Discussion

The proposed model is trained using a real-time dataset collected from clinical sources and meticulously augmented to enrich its diversity and enhance training efficacy. The dataset size amounts to 1.32MB, comprising images categorized into two distinct classes: “affected” and “not affected.” The dataset’s sources encompass a broad spectrum of clinical scenarios, ensuring a representative sample that captures the variability inherent in polycystic ovary syndrome cases. The images were collected from the Kerala hospital containing nearly 20 women’s scan reports. The augmentation process involves rotation, scaling, and flipping to expand the dataset’s size and improve model generalization. This comprehensive approach to dataset preparation underscores the robustness and reliability of the proposed model in real-world clinical applications. In the result and discussion section, all machine learning methods are compared with a proposed model using a graph. The proposed approach is implemented in the PYTHON platform and assessed using accuracy, precision, sensitivity, and F1-score. The experimental outcomes are evaluated and compared with the earlier methods like SVM, logistic regression (LR), naive Bayes (NB), random forest (RF), and classification and regression tree (CART) [38]. The detailed description is given below;

- SVM is a supervised learning algorithm. It is based on SVM and can handle multiclass. The SVM classifier model is placed near a classifier’s margin to enhance the performance.
- The LR model is an ML algorithm that solves categorization issues. Binary values are calculated using classifications and determined by a group of different values. The detection probability is used, and the value remains between zero and one.

A. *Performance Analysis*

Accuracy: The performance accuracy for a proposed approach is considered a significant metric for computing the efficiency and the improved rate of any proposed classification method compared with existing methods. The following equation calculates the accuracy performance of a proposed approach;

$$Accuracy = \left[\frac{TruePos + TrueNeg}{TruePos + TrueNeg + FlasePos + FlaseNeg} \right] \tag{38}$$

Where Acc represents the accuracy performance, $TruePos$ represents the true positive, $TrueNeg$ represents the true negative, $FalsePos$ represents the false positive and $FalseNeg$ represents the false negative value. The proposed approach considers accuracy a significant task in defining classification performance to detect PCOS.

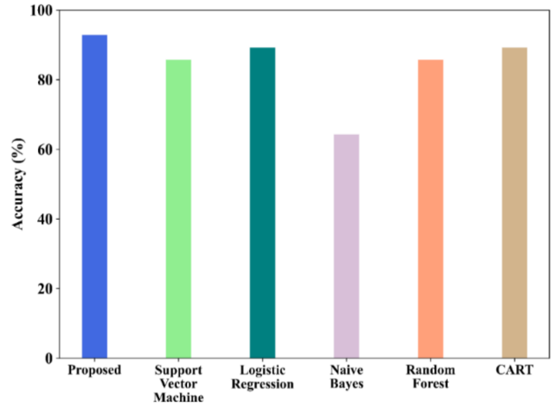

Fig. 2. Accuracy performance.

Fig. 2 illustrates the accuracy analysis. It shows that the proposed approach provides an effective accuracy rate in detecting PCO or non-PCO follicle classes. The proposed approach attains 96% accuracy in detecting PCOS, which is more reliable than existing approaches like support vector machine (85%), logistic regression (89%), naive Bayes (64%), random forest (85%), and CART (89%). Evaluating other methods proves that the defined model provides better results in classifying the PCO or non-PCO follicle class than existing methods.

Precision: Precision performance is considered the most important metric for computing the classification results in the proposed approach. The following equation calculates the performance of precision;

$$\Pr ecision = \left[\frac{TruePos}{TruePos + FalsePos} \right] \tag{39}$$

Here $\Pr e$ represents the precision performance, $TruePos$ represents the true positive, and $FalsePos$ represents the false positive values. Precision performance is used to establish the images that are exactly classified to authenticate the overall accuracy of the detection system of PCOS. The performance result of precision in proposed and existing methods is represented in Fig. 3.

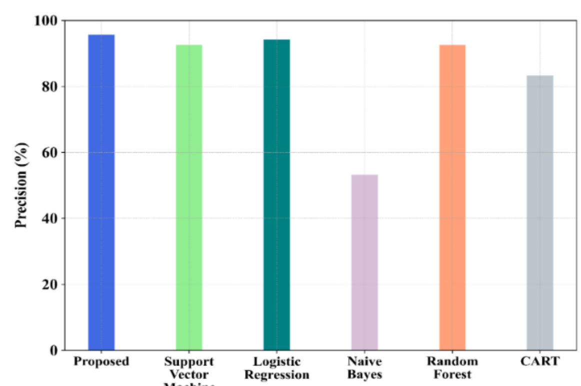

Fig. 3. Precision performance.

Fig. 3 illustrates the precision performance for a proposed model. The proposed approach provides an effective precision rate in detecting PCO or non-PCO follicle class. The proposed approach attains 96% precision in detecting, which is more reliable than existing approaches like SVM (92%), LR (94%), NB (53%), RF (92%), and CART (83%). The proposed method offers exceptional results in identifying the PCO or non-PCO follicle class, as demonstrated by the evaluation of alternative approaches.

Sensitivity: Sensitivity performance is another significant metric for detecting the overall sensitivity of the system model. The following equation calculates the performance of sensitivity;

$$Sensitivity = \left[\frac{TruePos}{TruePos + FalseNeg} \right] \tag{40}$$

Here $\mathrm{Re}c$ denotes the performance of sensitivity, $TruePos$ denotes the true positive, and $FalseNeg$ denotes the false negative value. $FalseNeg$ denotes the actual value is true, but the obtained result is false. By using sensitivity performance, classification errors are detected significantly. The sensitivity performance analysis for proposed and existing approaches is represented in the following Fig. 4.

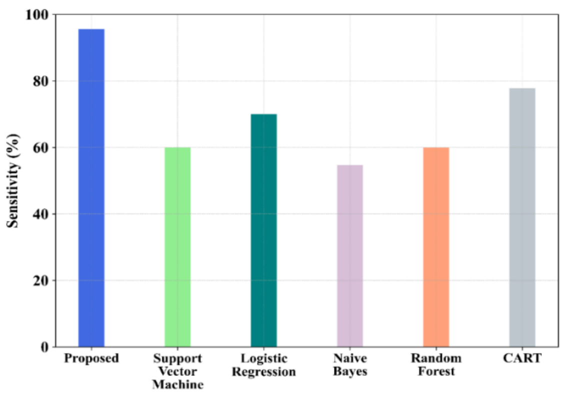

Fig. 4. Sensitivity performance.

Fig. 4 illustrates the sensitivity performance. The proposed approach provides an effective rate of sensitivity performance in detecting. The proposed approach attains 97% sensitivity, which is more reliable than existing approaches like SVM (60%), LR (70%), NB (54%), RF (60%), and CART (77%).

Specificity: It is considered a significant metric for detecting the PCO or non-PCO follicle class in an image without any modifications. Specificity performance is used to detect the negative results, which correctly detect the negative class. The following equation analyzes the performance of a TNR metric;

$$Specificity = \left[\frac{TruePos}{FlasePos + TrueNeg} \right] \tag{41}$$

Here $specificity$ represents specificity performance, $FalsePos$ represents the false positive, $TruePos$ represents the true positive, and $TrueNeg$ represents the true negative value. The following Fig. 5 represents the TNR performance analysis for proposed and existing approaches.

Fig. 5 illustrates the specificity performance for proposed and existing models. The proposed approach provides an effective rate of sensitivity performance. The proposed approach attains (96%) specificity, which is more reliable than existing approaches like SVM (92%) specificity, LR (94%) specificity, NB (53%) specificity, RF (92%) specificity, and CART (83%) of specificity.

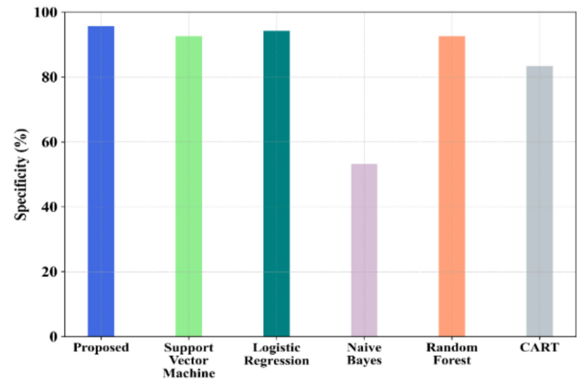

Fig. 5. Specificity performance.

F1-measures: The performance of an F1-measures is calculated between the recall and precision performance. The harmonic mean of the precision and recall performance is called an F-measure. The following equation calculates the F-measure performance;

$$F1 - measure = \left[\frac{2 \times sensitivity \times \mathrm{Pr}ecision}{sensitivity + \mathrm{Pr}ecision} \right] \tag{42}$$

Here $F1 - measure$ represents the F-measure performance, and $sensitivity \times \mathrm{Pr}ecision$ denotes the harmonic mean. The F-measure performance for proposed and existing approaches is depicted in the following Fig. 6.

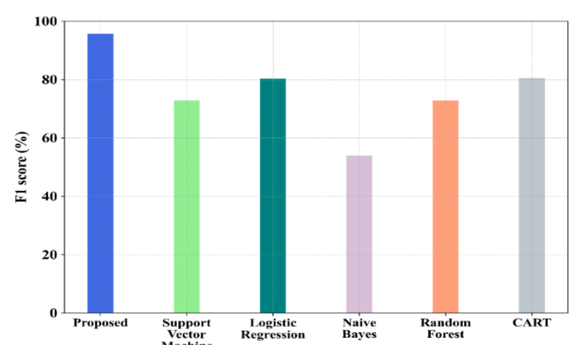

Fig. 6. F1-Measure performance.

Fig. 6 illustrates the F1-measure performance for a proposed and existing model. The proposed approach provides an effective rate of F1-measure performance in detecting PCO or non-PCO follicle class. The proposed approach attains (97%) of F1-measure in detecting PCO or non-PCO follicle class, which is more reliable than existing approaches like support vector machine (72%) F1-measure, logistic regression (80%) F1-measure, naive Bayes (53%) F1-measure, random forest (72%) F1-measure and CART (80%) F1-measure.

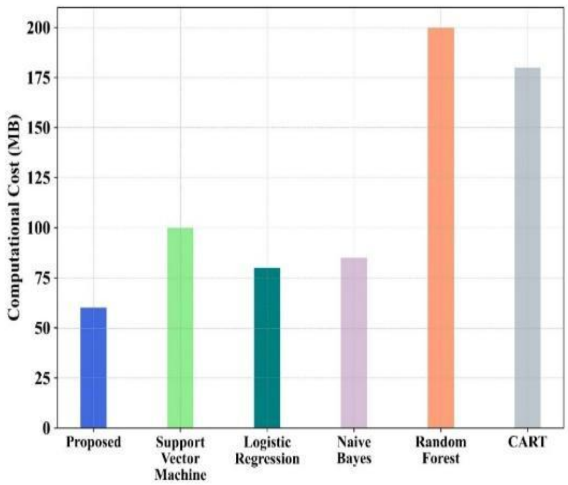

Fig. 7. Comparative analysis of the proposed model in terms of computational cost.

Fig. 7 provides an intricate analysis of the computational costs associated with the proposed model versus existing counterparts, elucidating the efficiency of our approach. The model exhibits a computational requirement of just 60MB, a substantial reduction compared to the other models, which have 100MB, 80MB, 85MB, 200MB, and 180MB of computational cost, respectively. This meticulous examination underscores the superior efficiency of the model, signaling its suitability for adoption in resource-constrained settings without compromising performance. The minimal computational cost underscores the streamlined complexity of the proposed model, making it a compelling choice for widespread implementation. The proposed model is compared with other models with a different dataset, as shown in Table II.

TABLE II. DATASET COMPARISON OF THE PROPOSED MODEL

Dataset	Method	Accuracy [%]
PCOS dataset from Kaggle [39]	HRFLR	87
PCOS dataset from UCI[40]	Red deer algorithm and RF	89.81
PCOS [41][42] [43]	PSO-SVM	90.18
Proposed	CNN-RNN	96

The proposed model outperforms its counterparts, trained on diverse datasets such as UCI and Kaggle. Despite the variations in dataset composition and characteristics, our model consistently demonstrates superior performance. This comparison encompasses thorough accuracy and illustrates the robustness of the approach across different data sources. The comprehensive analysis underscores the adaptability and efficacy of the model across a wide range of datasets, further bolstering its suitability for real-world applications across various domains. The Comparative value analysis of the proposed and other existing ML methods is given in Table III.

The comparative analysis of the proposed model with several performance measures is shown in Table III, and it shows that the proposed model reveals a better outcome.

TABLE III. COMPARATIVE VALUE ANALYSIS OF PROPOSED AND OTHER EXISTING ML METHODS

Methods	Accuracy [%]	Precision [%]	F1-measure [%]	Sensitivity [%]	Specificity [%]
SVM	85	92	72	60	92
Logistic Regression	89	94	80	70	94
Naive Bayes	64	53	53	54	53
Random Forest	85	92	72	60	92
CART	89	83	80	77	83
Proposed	96	96	97	97	96

V. LIMITATIONS OF THE STUDY

Based on the study, the attention-based CNN-RNN classification model is a reliable and valid approach to identifying Polycystic Ovary Syndrome (PCOS). The model is based on the efficiency of the PSO-based K-means clustering algorithm with a fuzzy filter and Contrast-Limited Adaptive Histogram Equalization (CLAHE) in pre-processing and segmenting ultrasound images. It is anticipated that performance metrics such as specificity, F1-score, sensitivity, accuracy, and precision effectively capture the strength of the model. However, there are flaws in the study, primarily the need for a larger dataset to enhance accuracy and minimize misclassification errors. The resilience of the model needs to be enhanced by testing it on smaller datasets. In addition, the ability of the model to be used broadly can be limited to the specific dataset and imaging conditions utilized in the study. Because it is based on ultrasound scans, the model may not account for other PCOS diagnostic criteria.

VI. FUTURE SCOPE

The application of Explainable AI (XAI) methods would significantly enhance the current research in identifying and predicting PCOS based on attention-based CNN-RNN classification models. Ensuring that the predictions of the AI model are understandable, comprehensible, and trustworthy to both doctors and patients would be the primary objective of these advances. By applying XAI methods such as Local Interpretable Model-agnostic Explanations (LIME) or SHapley Additive exPlanations (SHAP), it would be shown what factors or areas of the ultrasound images have the most impact on the conclusions of the model. Simplifying the AI decision-making process, these approaches would help healthcare professionals have more confidence in and trust the predictions of the AI.In addition, in order to further enhance the accuracy of the predicted model, additional research can focus on incorporating multiple data sources of different modalities, including genomics, hormonal profiles, and clinical data. Explainable AI with these numerous data sources has the potential to give a broader picture of the patient's disease, leading to more personalized and effective treatment regimens. In addition, the model's generalizability and robustness to different populations would be increased through the utilization of a larger and more diverse dataset during training. Aside from enhancing PCOS detection, this approach would set a precedent for the incorporation of explainability in AI-based medical diagnostic systems.

VII. Conclusion

The conclusion of this study highlights the significance of the proposed approach in the early detection of PCOS in women. The proposed method employs a real-time dataset, pre-processed using the Contrast-Limited Adaptive Histogram Equalization (CLAHE) model, to improve image quality by reducing noise. Subsequently, segmentation is performed using a Particle Swarm Optimization (PSO)-based K-means clustering algorithm with a Fuzzy Filter (FF) to enhance detection performance before classification. Finally, PCOS detection is carried out using an attention-based Convolutional Neural Network-Recurrent Neural Network (CNN-RNN) model. The approach implemented in Python exhibits superior performance when compared to existing methods. The model achieved impressive accuracy (96%), precision (96%), sensitivity (97%), F1-score (97%), and specificity (96%) metrics. These results underscore the reliability and precision of the proposed approach in PCOS detection, surpassing other models in the field. However, there are some limitations to the proposed methodology. Particularly, the model’s performance should be evaluated with larger dataset samples to enhance accuracy and minimize misclassification errors. Furthermore, validating PCOS detection with smaller dataset samples is essential for refining the model’s robustness. Although the proposed approach demonstrates better results, continuous refinement and validation efforts are vital to guarantee its effectiveness in real-world PCOS detection scenarios.

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