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Original Article

Polycystic Ovarian Syndrome (PCOS) Detection Through Deep Learning

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Abstract *- Polycystic Ovarian Syndrome (PCOS) is a complicated endocrine condition that is influenced by inherited predisposition as well as environmental circumstances. PCOS is characterized by several symptoms involving cardiovascular disease, hirsutism, acne, hyperandrogenism, and infertility. It is important to diagnose and treat PCOS at the earliest as it can lead to infertility and cardiac issues. Earlier, it was difficult for physicians to distinguish between benign cysts and malignant cysts in PCOS as they typically relied on manual ultrasound tests. This paper introduces a Python based algorithm of Convolutional Neural Network (CNN) to improve diagnostic speed as well as its accuracy. It mainly aims to develop a CNN based ultrasound image classifier that can distinguish between cysts using ultrasound images. This technique simplifies the diagnosis and accelerates the start of the treatment. It can speed up the initial treatment and streamline the diagnostic process, which are crucial in lowering the risk of PCOS related side effects like cardiac problems and infertility. Diagnosis of PCOS can be extremely complicated due to the intricate visuals, which are characterized by follicular overlap and operator variability. This paper discusses a novel approach to overcome these difficulties. The proposed method focuses on CNN-based image processing for feature extraction. The algorithm is trained on a dataset obtained from Kaggle that contains a range of PCOS-related situations to get the discriminative properties required for accurate classification. It is possible to evaluate classification performance using defined metrics by retesting on different datasets. This paper highlights not only the implications for diagnosis but also the significance of early detection of the reproductive system shortcomings. Results demonstrate that CNN exhibits the best testing accuracy of 97.76% and a recall value of 99.27%.*

Keywords *- Polycystic Ovarian Syndrome (PCOS), Convolutional Neural Network (CNN), Ultrasound image classifier, Infertility, Kaggle dataset.*

1. Introduction

PCOS is an endocrine disorder, sometimes referred to as Stein-Leventhal syndrome, which causes ovaries to generate many fluid-filled sacs that impede regular ovulation [1]. It is characterized by elevated androgen levels. Clinical management of PCOS is guided by the presence of cardinal features, including anovulation, hyperandrogenism signs, and menstrual dysfunction [2]. These cardinal features are often accompanied by several symptoms, such as pelvic pain, hirsutism (excessive hair growth), acne, and acanthosis nigricans (velvety skin patches). The presence of these symptoms aids healthcare professionals in the diagnosis and implementation of appropriate treatment strategies for PCOS. The female reproductive system is vital in women's physiology, comprising key components like the uterus, which nurtures the developing foetus and aids in sperm transfer to the fallopian tubes and the ovaries, responsible for egg cell production. Throughout the reproductive cycle, the egg releases specific molecules essential for guiding and binding with sperm, initiating fertilization. While fertilization commonly occurs in the oviducts, it may also take place in the uterus. PCOS has most likely been diagnosed if the ovaries have a volume greater than or equal to 10 cm3. Also, there is a high probability of PCOS getting diagnosed if there are 10 or more follicles with diameters ranging from 2 to 9 mm[3]. The condition affects an estimated 8–13% of women of reproductive age, and up to 70% of cases are undiagnosed [4]. Timely and accurate diagnosis of PCOS via minimally invasive tests and imaging is vital, as it can significantly reduce the risk of ovarian dysfunction, miscarriage, infertility, and even gynecological cancer, while also sparing patients from the emotional and financial toll of delayed treatment, including the anguish of wasted time and resources [5]. However, this process of investigation is much more costly in terms of the developing and least developing countries. Moreover, it entails medical acumen and the subjectivity of the clinician, as nicely as the intrusion of privateness of the women; also, the emotional wellness of the ladies is not considered. Due to shyness as well as lack of awareness, this condition goes undetected for years in women, which causes serious issues in the long run [6]. In the women's reproductive system, a normal ovary contains several small size follicles at various stages of development, which eventually mature and release an egg during the menstrual cycle. In contrast, the PCOS infected ovary normally contains several small, immature follicles that do not fully develop or release eggs on a regular basis, which further leads to anovulation. These follicles are described as cysts, although they are not true cysts in the medical sense. Figure 1 shows the difference between a normal ovary and a PCOS ovary.

Using deep learning approaches, a model has been created that processes ultrasound images by utilizing Convolutional Neural Networks (CNN) as a machine learning methodology through the installation of 64 kernels at convolutional 3D layers, which generate feature maps for the user-provided ultrasound picture/image as an input. Relu is an activation function that is utilized to provide nonlinearity, allowing the network to learn complex patterns of cysts from ultrasound images. Additionally, "2 x 2 max pooling" is developed. A probability distribution is produced at the model's output by using the "SoftMax" activation function. The main aim of this research is to use CNN algorithms and data augmentation techniques to recognize PCOS at an early stage better and reduce the prospect of serious consequences. It evaluates a variety of machine learning techniques and datasets to provide insight into the best methods for diagnosing PCOS.

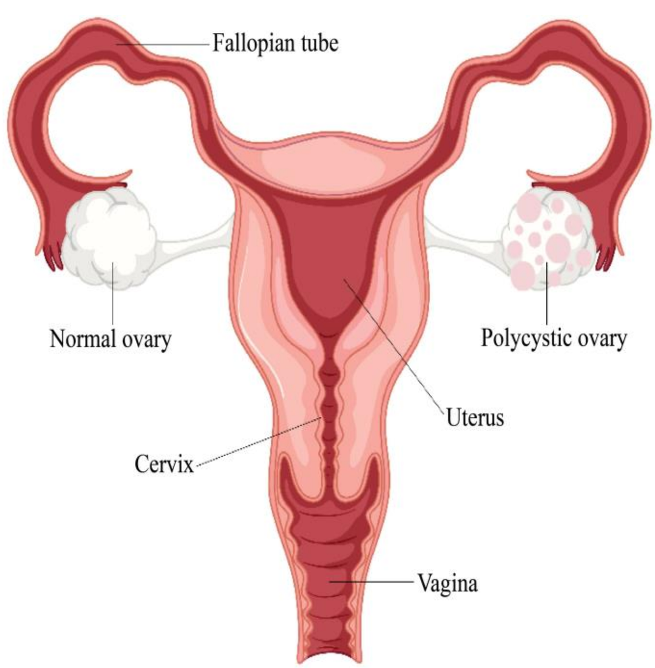

Fig. 1 Polycystic and Normal ovary [7]

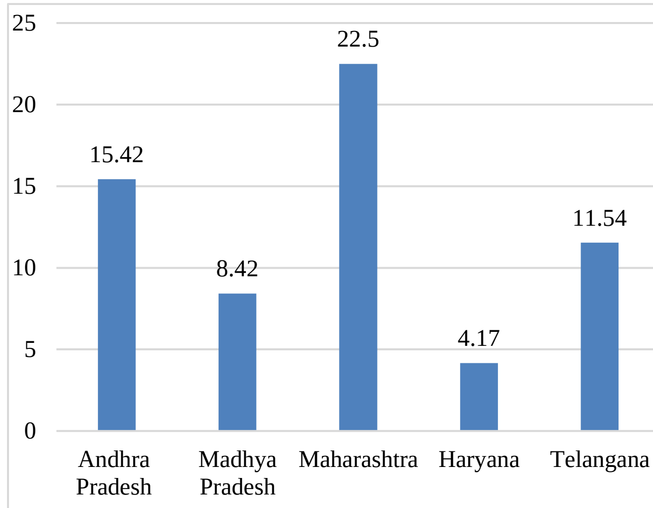

Fig. 2 State wise prevalence of PCOS [8]

Figure 2 shows the prevalence of PCOS among women in different states of India. While Maharashtra has the highest incidence of around 22.50 %, Haryana has the lowest incidence of 4.17 %. In Andhra Pradesh, it was 15.42%, followed by Madhya Pradesh with 8.42% and Telangana with 11.54%. This information highlights genetic factors that contribute to PCOS in women.

1.1. Types of Ovaries

Various ovarian types and their characteristics are described as

1.1.1. Normal Ovary

An ovary typically consists of eight to ten follicles, which range in size from two to twenty-eight millimeters(mm). The antral follicles are the group of follicles smaller than 18 mm where, whereas dominant follicles have a group of follicles larger than 18 mm.

When a developed follicle is ready to ovulate, its diameter ranges from 18 to 28 mm. A woman's pre-ovulatory follicle has a size of 18 to 28 mm [9]. An ultrasonography scan of a normal ovary is shown in Figure 3a.

1.1.2. Polycystic Ovary

Ovarian cysts are just one of the fluids found in a normal, healthy ovary. Cysts are of different types and sizes and are found in the gynaecological area. During ovulation, a woman usually produces a small amount of fluid around the egg. This fluid combines with some other secretions to form a structure about the size of a pea called a follicle. On the other hand, sometimes the ovary may enlarge inside due to excess fluid coming from the surrounding cells. A follicular cyst remains when fluid has collected up to 3-4 inches in diameter. Typically, 12 or more follicles less than 9 mm in diameter are the characteristic appearance of polycystic ovaries, which are surrounded by a thick layer of intercellular space [9].

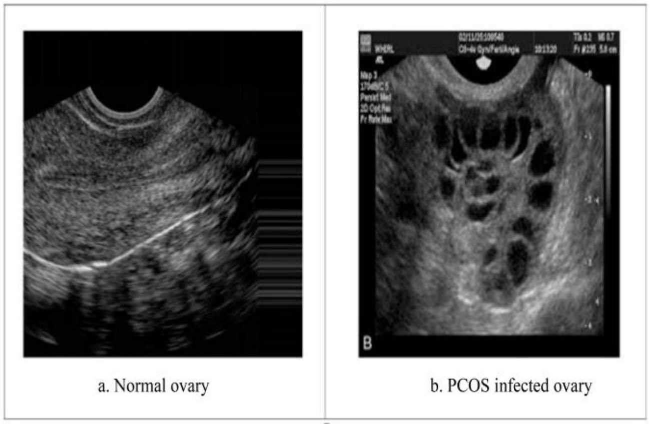

Fig. 3 Ultrasonography scan of normal and PCOS ovary [9]

Additionally, ultrasound measurements will show the presence of cysts as well as more follicles and numbers in polycystic ovaries. The main difference between ovarian cysts and polycystic ovaries is that ovarian cysts have many small endometrial follicles that form the area where eggs are stored. However, these cysts cannot grow and do not grow well, making ovulation difficult. An antral follicle is the presence of numerous small cystic structures, which causes a distinctive "polycystic" appearance seen on ultrasound images of polycystic ovaries [9]. PCOS infected ovary is shown in Figure 3b.

2. Literature Review

The study in [10] proposes a YOLO algorithm for automatic PCOS detection in sonography images using a single CNN for accurate real-time identification. In PCOS detection using the YOLOv3 algorithm, a notable concern arises from the algorithm's novelty and lack of established reliability for medical diagnosis. Authors in [11] mention that PCOS, a significant disorder during reproductive years, arises from excess androgen levels, impacting fertility. Many women remain undiagnosed. This research employs advanced machine learning, featuring Gaussian Naive Bayes, to predict PCOS with 100% accuracy, aiding early detection through key factors like prolactin, blood pressure, and thyroid hormone.

Around one in ten women in their childbearing years experience PCOS [12]. It is important to have early detection of PCOS for prompt treatment. The authors use a self-developed CNN based approach to detect PCOS accurately. The ultrasound ovary images are classified into PCO and non-PCO categories. The CNN's filters handle follicle segmentation, while classification is done by the fully connected layer. The study in [13] utilizes hybrid machine learning models, including CatBoost and HRFLR, to detect PCOS using a comprehensive dataset. CatBoost achieves 92% accuracy, highlighting its effectiveness in PCOS detection. A key requirement here is to prioritize addressing data imbalance through appropriate techniques for future research directions. A Pelvic ultrasound alone is not sufficient for diagnosis. A comprehensive approach combines ultrasound and blood tests. To enhance diagnostic accuracy, authors of [14] have developed a MATLAB-based diagnostic model using a Kaggle dataset. K-Nearest Neighbours is used to excel in sensitivity. Authors in [15] have explored PCOS diagnosis using ultrasound images through threshold-based segmentation algorithms. Results indicate Otsu's algorithm is most effective for follicle detection and accurate PCOS identification, suggesting its potential integration into clinical diagnosis systems.

The study in [16] introduced PCONet, a CNN and fine-tuned InceptionV3 for detecting PCOS from ultrasound images. PCONet outperforms InceptionV3 with 98.12% accuracy compared to 96.56%, offering promising advancements in PCOS detection using deep learning. K. P. Harish et al. mentions in [17] that PCOS affects 5-10% of women aged 15-45. Balancing techniques like SMOTE were used on a dataset with 541 instances.

XGBoost achieved 96% accuracy in supervised learning using ensemble stacking on the balanced dataset. This study could benefit from utilizing ultrasound image datasets for PCOS diagnosis, potentially achieving improved results through the implementation of diverse deep learning models. Authors in [18] aim to classify PCOS in women using machine analysis of ultrasound images, which is crucial for early diagnosis without medical supervision. It addresses BMI imbalance, irregular menstrual periods, and related health problems using CNN and SVM techniques with a huge dataset.

Women's lives are profoundly affected by PCOS, which frequently results in problems like infertility. To minimize difficulties, early diagnosis is essential. Machine Learning (ML) has shown promise in this regard because of its feature extraction capabilities. A thorough review of machine learning methods, such as decision trees, SVM, and CNN, for PCOS diagnosis is given in [19]. Authors in [20] introduce a CAD system named ESDPCOS, designed for the detection of PCOS. The ESDPCOS system utilizes a blend of deep learning and handcrafted features. ESDPCOS first extracts deep features through a CNN model, simultaneously employing GLCM to capture texture features. Notably, the proposed ESDPCOS model achieves an impressive peak accuracy of 96.06%, surpassing the performance of the existing PCONet model. Table 5 gives a comparison of different models for the detection of PCOS.

3. Methodology

3.1. Dataset Description

In this study, the dataset is primarily collected from Kaggle Anagha Chowdhary, encompassing a total of 1924 images with a resolution of 224 x 224, out of which 781 images were infected ultrasound images and 1143 images were non-infected ultrasound images [9].

Table 1. Parameters for 10x augmentation

Sr. No.	Parameters	Details
1	Horizontal flips	Flipped an image horizontally with a 50% chance.
2	Vertical flips	Vertically flipped an image with a 50% probability.
3	Random rotations	Applied transformation to an image, rotating it randomly between -30 and 30 degrees
4	Brightness change	Multiplied the pixel values of an image by a random factor between 0.8 and 1.2
5	Gaussian noise	Adds Gaussian noise to an image ranging from 0 to 0.05 times the maximum pixel intensity
6	Random crops	Randomly crops an image, removing up to 10% of its width or height
7	Adjust Gamma contrast	Adjusts the gamma contrast of an image by scaling its pixel values using a random factor between 0.5 and 2.0
8	Adjust linear contrast	Adjusts the linear contrast of an image by scaling its pixel values using a random factor between 0.75 and 1.5
9	Scaling	Applies an affine transformation to an image, randomly scaling it between 80% and 120% of its original size

Table 2. Database specification [21]

Dataset Name	Total Images	Resolution	Extension
Kaggle Anaghachoudhari	18,240	224*224	JPG

Data augmentation with a 10x scale is used to increase the variations of the dataset. This process helped the CNN model to enhance performance by providing more examples for training.

The augmentation process involves a series of transformations applied to images to diversify the dataset for training the machine learning model. Firstly, images are subjected to horizontal flips with a 50% probability, effectively doubling the dataset size with mirror images.

Additionally, vertical flips are applied with the same 50% chance. Random rotations are performed within a range of -30 to +30 degrees, adding variability to aid in model generalization.

The image brightness is adjusted between 80% and 120% of the original brightness to simulate lighting conditions. Next up, Gaussian noise is added to the images of the dataset with a scale of range 0% to 50%. This noise contributes to the random nature of the dataset.

Random cropping is carried out in the images, which removes up to 10% of pixels. Gamma contrast is adjusted between 0.5 and 2.0, which alters the brightness and contrast of images. Linear contrast is modified within the range of 0.75 to 1.5.

Finally, images are scaled randomly between 80% and 120% of their original size. In this way, the augmentation of datasets is carried out to enrich the dataset, resulting in variability and improving the robustness of the trained model. After performing 10x data augmentation, a finalized dataset of 18,240 images, as explained in Table 2, was obtained.

3.2. Dataset Splitting Methodology

In the development of the model, a meticulous data splitting methodology was employed to ensure the robustness and applicability of the diagnosis. The dataset was split into two distinct subsets: testing and training.

3.2.1. Training Set

This set consists of 70% of the original data, which is utilized for training the deep learning model, providing a substantial number of examples.

3.2.2. Testing Set

Accounting for 30% of the data, remained independent of the training and validation processes. Its purpose is to impartially assess the final model's performance, offering an unbiased evaluation of its predictive efficacy.

3.3. Edge Detection

At the initial convolutional layers, edge detection of the input ultrasound image takes place. This layer applies edge detection filters to identify important features such as contours and other anatomical structures.

This process is important as it can help in accurately distinguishing between normal and polycystic ovaries.

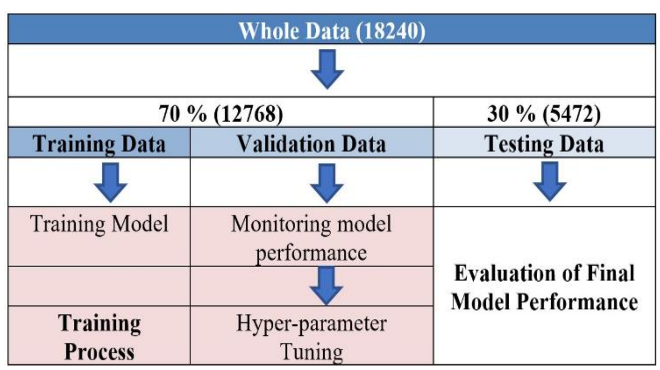

Fig. 4 Dataset splitting for the model

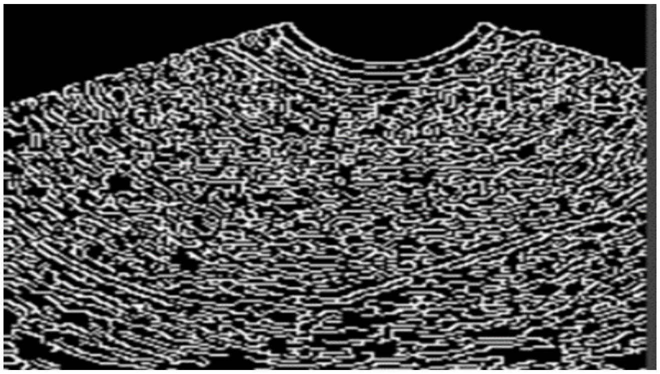

Fig. 5 Edge detection of PCOS non-infected ultrasound image

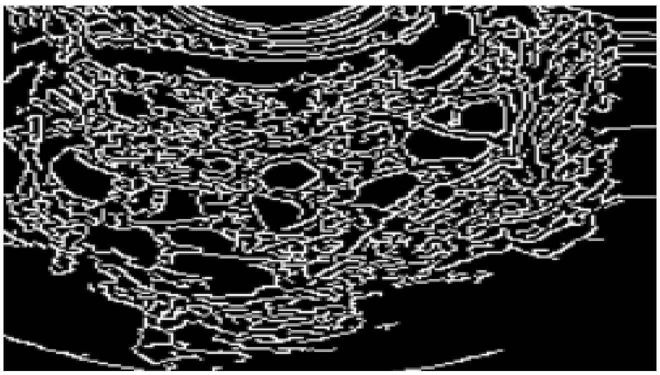

Fig. 6 Edge detection of PCOS infected ultrasound image

3.4. Preprocessing of Images

Preprocessing is a crucial initial step in which, the image is scaled in the required dimensions. In this step, variations caused due to the image conditions are minimized. Furthermore, images are resized to uniform dimensions of 224 x 224 pixels. In this way, the preprocessing of an image is carried out. Figures 7 and 8 are extracted from the intermediate stages of a CNN and represent the preprocessing of ultrasound images of both infected and non-infected PCOS cases, respectively.

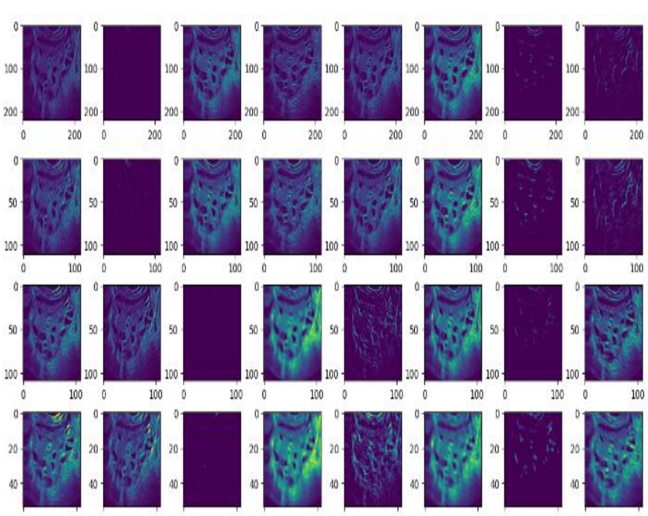

Fig. 7 Preprocessing of infected PCOS ultrasound image

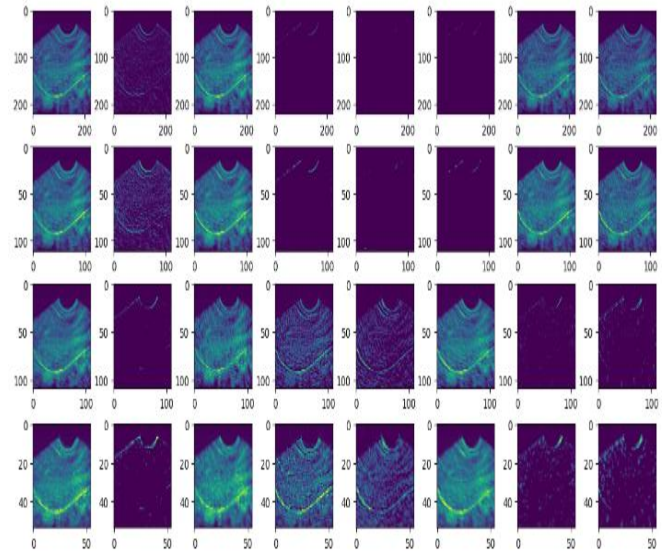

Fig. 8 Preprocessing of non-infected PCOS ultrasound image

4. System Workflow

The process of developing a CNN-based PCOS detection model involves several crucial steps, as outlined in the workflow diagram shown in Figure 9. Initially, the dataset containing ultrasound images of ovaries is loaded into memory. This dataset serves as the foundation for training and evaluating the model. By including both PCOS-infected and normal/non-infected ovary images, the dataset has provided the necessary input for the model to learn and generate predictions.

The dataset is now divided using a 70-30 split technique into a training set and a testing set, respectively. The custom CNN model is trained using the training set, which makes up 70 % of the dataset. Throughout the training phase, the model trains from the collection of ultrasound images. The algorithm learns to identify patterns linked to both normal and PCOS infected ovaries by repeatedly being exposed to the images and their parameters adjusted depending on the prediction errors. Once the training set has been created, the CNN model is built and trained with a custom design.

In this architecture, specified layers like convolutional layers, pooling layers and fully connected layers are defined. This design carries out the feature extraction from the input image and provides an accurate PCOS diagnosis. When the model is trained, the testing set is utilized to assess the model. To identify the accuracy with which the trained model can diagnose PCOS infected ovary, random ultrasound images from the testing set are fed into the model. The model predicts if the test image indicates a case of PCOS or not. This binary classification process provides insights into the model's accuracy and reliability in identifying PCOS-infected ovaries. Ultimately, the displayed result indicates whether each test image is classified as PCOS or not, aiding in medical diagnosis and decision-making processes.

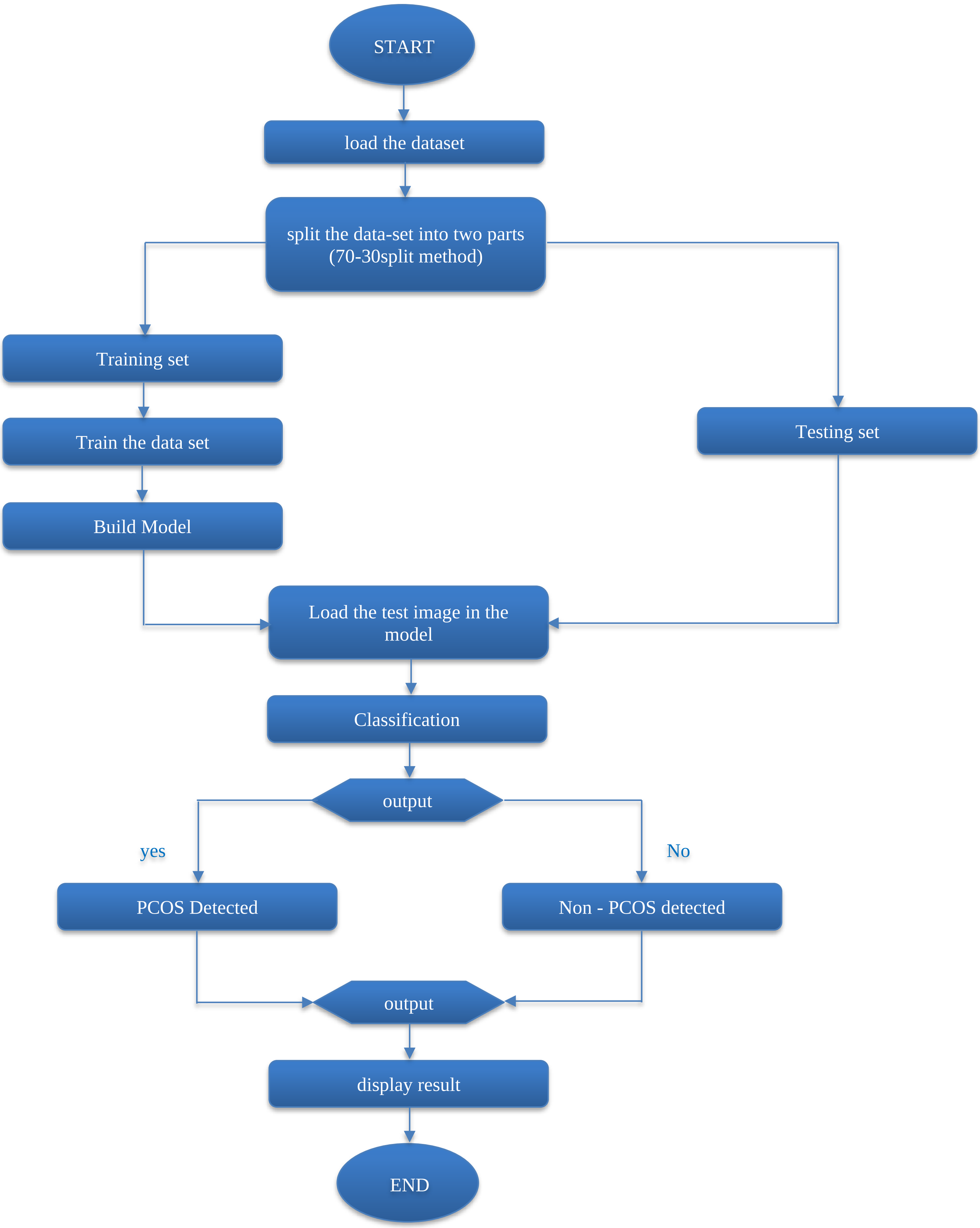

Fig. 9 Workflow diagram

5. Mathematical Modelling

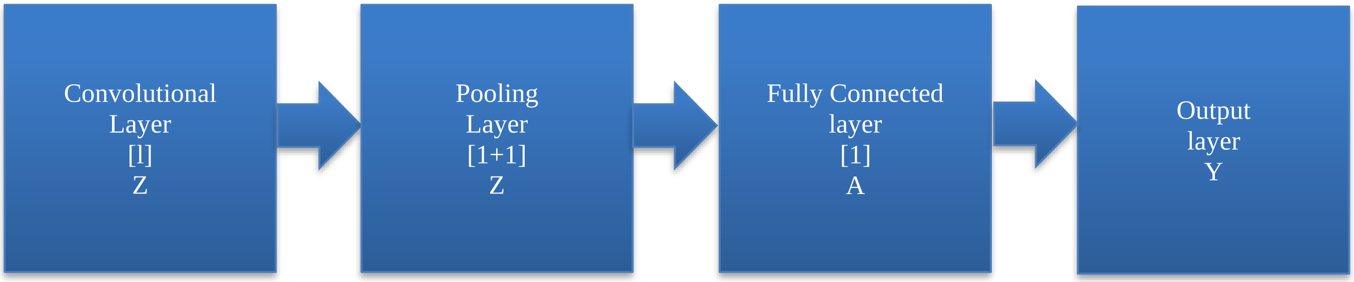

Fig. 10 System model set theory

5.1. Input Layer

- Let X be the input given in the form of an ultrasound sonography image.
- Let the dimensions of the input image be H x W x C (height, width, channel)

5.2. Convolutional Layer

- Let $Z^{[l]}$ be the output feature map of layer (l).
- The equation for the convolutional layer is given as:

$$Z^{[l]} = f\,(X * W^{(l)} + b^{(l)}) \quad (1)$$

Where,

- ➢ X = Input image or the input feature map from the prior level.
- ➢ $W^{(l)}$ = The weight matrix (also known as kernels or filters) of the respective convolutional layer. This matrix is learned during the training period of the model.
- ➢ (*) = It represents the convolutional operation that includes sliding input $W^{(l)}$ over the input X and computing the dot product at every position to produce a feature map.
- ➢ $b^{(l)}$ = It is the bias vector for the lst convolutional layer which is added to all elements of the feature map.
- ➢ f = Activation function applied elementwise to introduce non-linearity into the model. Here we have used ReLu (Rectified Linear Unit).

5.3. Pooling Layer

- The pooling layer is the second layer. The spatial dimensions of the feature maps are reduced by the pooling layer. It also maintains the most important features.
- The equation for the pooling layer is given by:

$$Z^{[l+1]} = P(Z^{[l]}) \quad (2)$$

Where,

- ➢ $Z^{[l-1]}$ = The output feature map from the previous layer.
- ➢ P = Pooling operation (Height and width get reduced, but depth remains the same)

5.4. Fully Connected Layer

- The function of a fully connected layer is to combine the characterized features from the prior layer to make the predictions.
- The equation for the fully connected layer is as follows:

$$A^{[l]} = f(W^{[l]}.\ A^{[l-1]} + b^{[l]}) \quad (3)$$

Where,

- ➢ $A^{[l-1]}$ = Flattened output from the previous layer.
- ➢ $W^{[l]}$: Weight matrix of the l-th fully connected layer.
- ➢ Dot product operation
- ➢ $b^{[l]}$ = Bias vector for the l-th fully connected layer.
- ➢ f = The activation function

5.5. Output Layer

- At the output layer, the final prediction of the network is made. The sigmoid activation function is used for the binary classification, and the SoftMax function is used for the multiclass classification, respectively.
- Binary classification is given as,

$$Y = \sigma(W^{[L]}.\ A^{[L-1]} + b^{[L]}) \quad (4)$$

Where,

- ➢ σ: Sigmoid activation function for binary classification.
- ➢ $W^{[l]}$: The weight matrix of the output layer.
- ➢ $b^{[l]}$ = Bias vector for the output layer
- ➢ Here L indicates the last layer of the network

5.6. Summary of the Mathematical Model

In this way, the model functions in the 4 layers to classify the PCOS ultrasound images:

a) Convolutional Layer: Applies filters to extract the features from the input ultrasound image taken from the user.
b) Pooling layer: Removes the spatial dimensions (height and width but no depth reduction) while maintaining the required features.
c) Fully Connected layer: Will combine the features from the previous layers to make assumptions.
d) Output Layer: Generates the final predictions using different functions like Sigmoid or SoftMax.

By thorough collaboration of these layers, the CNN model serves as a robust framework for the automated detection of PCOS, which could result in early diagnosis and personalized treatment.

5.7. Limitations
- A large database may require more time to retrieve the information.
- Hardware malfunction.

5.8. Advantages
- It is fully analyzed through the available datasets for the necessary information.
- The user receives results quickly in accordance with their needs.

6. Results and Discussion
The assessment of the CNN model on the transvaginal ultrasound test dataset indicates a need to improve specificity. The algorithm has a propensity to correctly identify more True Positives than True Negatives, suggesting challenges in reliably identifying instances that are not PCOS. To address this problem, epidemiological methods that reduce False Positives should be prioritized above those that highlight True Negatives. From Figure 11, it can be inferred that the proposed model's accuracy on both training and testing is growing as the number of epochs is growing, which means that the model is successfully learning from the training data and improvising its ability to detect PCOS in ultrasound images.

Figure 12 shows the graph of model loss with an epoch of 300. As the number of epochs grows, the loss appears to be decreasing. This implies that our model is learning from the training dataset and improving its ability to detect PCOS ultrasound images. The Receiver Operating Curve (ROC) is shown in Figure 13. The area under the curve is 1, which means that it is a good classifier. The hyperparameters selected to train a machine learning model are shown in Table 3. Although the model does not explicitly learn them, these parameters govern how the model learns from the data. The model will be trained on the full dataset a total of 30 times, according to the number of epochs provided.

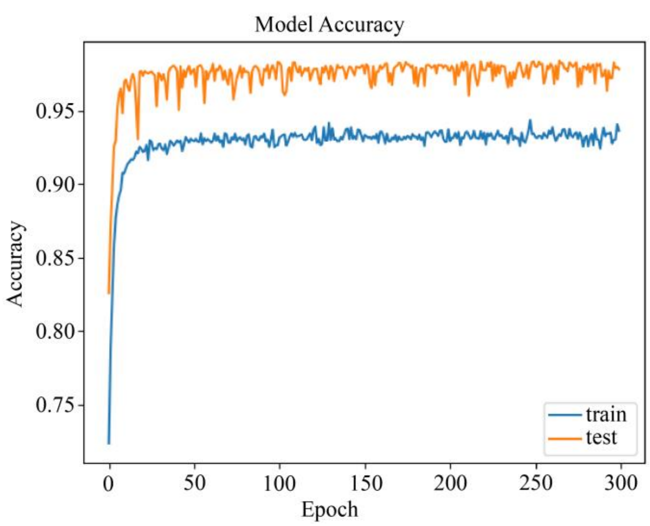

Fig. 11 Model accuracy

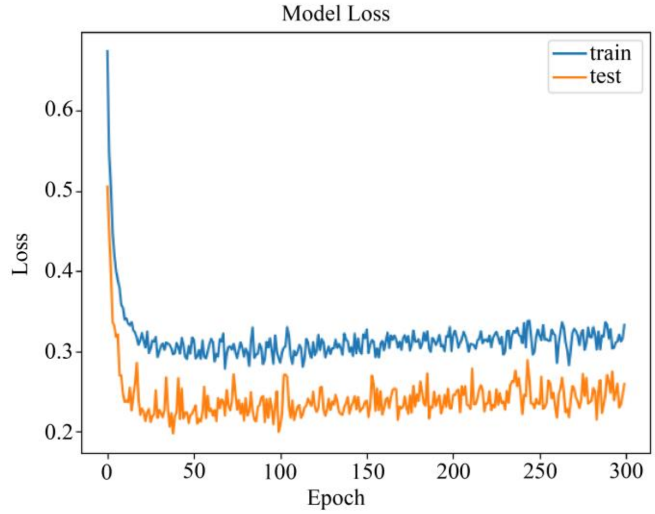

Fig. 12 Model loss

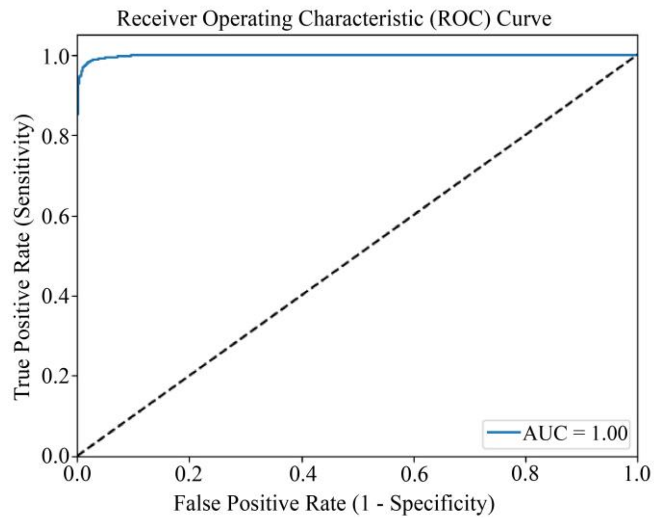

Fig. 13 Receiver operating curve

A validation split (0.3) sets aside some data so that the performance of the model may be tracked throughout training. The model's internal parameter changes are managed by the Adam optimizer method, which is utilized to enhance the model's predictions. The loss function, also known as binary cross entropy, is a useful tool for discriminating between two alternatives since it quantifies how well the model's predictions fit the real data. Additionally, a certain picture size of 224 x 224 is expected by the model. There are three convolutional layers it is essential for image recognition. Fully linked dense layer 2, then utilize these extracted characteristics to get the final categorization. To strike a compromise between model complexity and training duration, the number of dense layers and the number of processing units inside each layer (layer size, 64, adjustable) may be changed based on certain characteristics. Through meticulous selection and adjustment of these hyperparameters, the training procedure has been optimized to attain the best results for the PCOS classification.

Table 3. Hyperparameters for custom CNN model

Sr. No.	Hyperparameters	Value
1.	Batch Size	32
2.	Epoch	30
3.	Validation Split	0.3
4.	Optimizer	Adam
5.	Loss Function	Binary Cross entropy
6.	Dimensions	224 x 224
7.	Number of Convolutional Layers	3
8.	Number of Dense Layers	2 (can be modified based on 'dense layers')
9.	Layer Size	64(can be modified based on 'layer sizes')

6.1. Performance Evaluation and Comparison

A comparative analysis of research work done in this paper and nine other research studies was conducted utilizing the same dataset, focusing on metrics such as accuracy and precision. The findings of the analysis revealed that the proposed model exhibited superior performance in predicting PCOS responses. Table 4 provides a detailed comparison of results obtained across different experiments, including accuracies, sensitivity, F1 score, specificity, precision, and processing time reported by relevant studies. Notably, our research demonstrated the highest accuracy of 97.76% and exhibited variability in precision rankings. Table 4 shows the outputs of different CNN models. The confusion matrix for the proposed model is shown in Figure 13.

The number of negative data points that were correctly identified (2140) and falsely labelled as positive (100) is displayed in the top row. The number of positive data points that were correctly identified (3296) and incorrectly classified as negative (24), respectively, is displayed in the bottom row.

<table>
<tr><td></td><td></td><td colspan="2">Predicted</td><td></td></tr>
<tr><td></td><td></td><td>Positive</td><td>Negative</td><td></td></tr>
<tr><td rowspan="2">Actual</td><td>Positive</td><td>2140</td><td>24
Type II
Error</td><td>Sensitivity
TP/(TP+FN)
=0.9889</td></tr>
<tr><td>Negative</td><td>100
Type I
Error</td><td>3296</td><td>Specificity
TN/(TN+FP)
=0.978</td></tr>
<tr><td></td><td></td><td>Precision
TP/
(TP +
FP)
=0.9553</td><td>Negative
Predictive
Value
TN/
(TN +
FN)
=0.9927</td><td>Accuracy
(TP + TN) /
(TN+TN+FP+FN)
=0.9777</td></tr>
</table>

Fig. 14 Confusion matrix of the proposed model

Table 4. CNN models outputs

Sr. No.	Model	Test Accuracy (%)	Sensitivity (%)	F1 Score (%)	Specificity (%)	Precision (%)	Processing time (s)
1.	Custom CNN	97.76	99.27	98.15	95.53	97.05	2628.18
2.	KNN	94.7	087.05	93.07	100	92.00	1.19
3.	SVM	95.6	100	99.60	76.00	99.40	0.1286
4.	InceptionV3	51.43	59.33	59.33	39.73	59.33	179.76
5.	Logistic	96.7	94.19	95.90	98.49	97.68	11.86
6.	XgBoost	96.1	97.70	98.80	100	100	183.3
7.	Naïve Bayes Classifier	85.27	75.03	80.54	92.28	86.94	3.00
8.	EfficientNet	59.17	92.46	73.00	88.69	60.31	21.46

Table 5. Comparison of different models

Reference Paper (Year)	Model	Dataset	Accuracy (%)	Sensitivity (%)	Specificity (%)	Precision (%)	F1 Score (%)
Custom CNN		Kaggle *(10X augmentation)*	97.76	99.27	95.53	97.05	98.15
[1] (2024)	Ensemble (LR, CatBoost and AdaBoost)	541 patient datasets from Kaggle Prasoon Kottarathil	93	88	96	95	96
[2] (2020)	RFLR	541 patient datasets from Kaggle Prasoon Kottarathil	91.01	90	68.6	89.90	89.6
[3] (2023)	VGG1 & ResNet50 (Hybrid)	Kaggle- Anagha Choudhari	95	100	90	91	95

[5] (2019)	Random Forest Classifier (RFC)	541 cases from various infertility treatment centers at Thrissur.	89.02	74.19	98.03	95.83	41.82
[6] (2023)	Random forest classifier	Kaggle and UCI	93.74	93.74	93.7	93.75	93.74
[12] (2023)	CNN	70 Images Private dataset	83	93	83.48	85.6	88
[13] (2022)	CatBoost	541 patient datasets from Kaggle Prasoon Kottarathil	92	84	94.63	95	89
[14] (2022)	Linear	541 patient datasets from Kaggle Prasoon Kottarathil	92.60	92.20	93.55	97.6	94.8
[15] (2023)	Otsu's Threshold Segmentation	Kaggle- Anagha Choudhari	96	96	96	99	97
[20] (2023)	ESDPCOS	Kaggle- Anagha Choudhari	96.06	96.5	95.48	96	96
[22] (2024)	Random Forest	Private dataset	92	90.5	89	94	92
[23] (2022)	Logistic Regression	Online source	90	83.5	38.65	89	85.5
[24] (2021)	Decision Tree	Private dataset	81	41	94	70	94
[25] (2021)	XGBoost	Kaggle- Prasoon Kottarathil	95.83	95.50	99.20	96.07	95.74
[26] (2023)	YOLO	Private dataset	87.24	87.58	87.68	87.08	87.24
[27] (2023)	Radial Kernel SVM	Private dataset	96	95	-	96	89

7. Conclusion

The presented study provides a foundation for the automated assessment of PCOS data quality through the utilization of a Convolutional Neural Network. Progress in image processing could support healthcare professionals in achieving early detection of PCOS, leading to prompt initiation of therapy and care for patients. Late detection of PCOS not only affects physical health but also has implications for mental health conditions. This research illustrates the amalgamation of various segmentation techniques to enhance the follicle segmentation process. To address the issue of class imbalance in medical datasets, an augmentation technique was suggested to amplify minority samples while eliminating outliers from the dataset. Subsequently, significant and distinctive features reflecting the PCOS condition were selected and incorporated into a CNN model. Extensive evaluation of a reference dataset indicates the substantial potential of the proposed integrated solution. Experimental results demonstrate that CNN exhibits the best testing accuracy of 97.76% and a recall value of 99.27%. To enhance the model, the incorporation of CNN in an optimal form is considered for future research.

Better dataset balance might be attained by using data preprocessing techniques, which could improve the model's robustness. Furthermore, increasing data in the training set might enhance the model's overall efficacy and performance. Additionally, for improved performance, a more thorough adjustment of hyperparameters in machine learning algorithms and enhanced feature selection are desired.

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