Polycystic Ovary Syndrome (PCOS) Detection and Prevalence Report using Computational Intelligence

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Abstract

Polycystic Ovary Syndrome (PCOS) is a common endocrine disorder which impacts 6–12% of women worldwide and can result in infertility and metabolic disorders. Despite how common it is, PCOS is often underdiagnosed simply because it relies on subjective diagnostic measures. This project attempts to navigate this issue by applying DenseNet121, a deep learning model, to automatically detect PCOS from the ultrasound images. DenseNet121 has an efficient architecture that allows for substantial accuracy with often the smallest of datasets. This feature makes it a fantastic application in medical images where data can sometimes become extremely limiting. The model was trained and developed on labeled ultrasound images to classify ultrasound images with and without PCOS lesions as a diagnosis, which were found to be reliable. After detection, the cysts were analyzed manually to extract valuable diagnostic metrics including type, shape, clustering, and severity. These metrics then were combined to construct web-based reports that are user friendly with even more detail to diagnostics and recommendations to action. Combining this technology with clinical expertise, allows for an enhancement in the accuracy of diagnosing PCOS, while providing a practical tool for patients and health care professionals to enhance early detection and management of PCOS.

Keyword: Polycystic Ovary Syndrome (PCOS), DenseNet121, Ultrasound Imaging, Medical Diagnosis, MONAI, Cyst Analysis.

1. Introduction

Polycystic Ovary Syndrome (PCOS), or Polycystic Ovarian Disorder (PCOD), is one of the most common endocrine disorders in women of reproductive age all over the world. PCOS presents with a complex, heterogeneous combination of hormonal, metabolic (mild to moderate), and reproductive abnormalities. The prevalence of PCOS globally is about 6% to 12%, with a higher prevalence reported in specific populations. In India the prevalence of PCOS is approximately 9% to 22%. The rates are generally higher in urban populations, likely due to associated rapid urbanisation, sedentary lifestyles, and a change in diet usually associated with urbanization. Nevertheless, amongst the high prevalence, many women with PCOS are either undiagnosed or untreated due to low awareness, stigma around reproductive health topics, and lack of widely accepted criteria for diagnosing PCOS.

The diagnosis of PCOS often applies the Rotterdam criteria, which recommend having at least 2 of the following 3 features: hyperandrogenism (whether clinical or biochemical), ovulatory dysfunction (regular menses vs. absent or irregular cycles) and polycystic ovarian morphology (PCOM) seen by ultrasound. Each of these symptoms requires subjective observations, such as those with hirsutism, acne, weight gain, or infertility may have very different symptoms attributable to PCOS. Additionally, PCOS has very serious long-term health risks, such as insulin resistance, type 2 diabetes, cardiovascular diseases and endometrial cancer. The impact of PCOS does not end there; the psychological impact including anxiety and depression, alongside decreased quality of life warrants identification and early diagnosis of PCOS.

PCOS has a multifaceted etiology, relying on a variety of genetic, hormonal, metabolic, and environmental components. Genetic predisposition appears to be a driving factor with family history being a strong risk factor. Hormonal abnormalities play a central role in pathogenesis, primarily driven by elevated levels of androgens (male hormones) and dysregulation of the hypothalamic-pituitary-ovarian (HPO) axis. Insulin resistance (60–70% of women with PCOS) further aggravates hyperandrogenism and contributes to a metabolic abnormality. Environmental factors, including poor diet, sedentariness, chronic stress, and exposure to endocrine-disrupting chemicals, also play a role in new onset and progression of PCOS.

PCOS is not simply a reproductive disorder; it affects the entire woman's health system. The hormonal and metabolic changes associated with PCOS can lead to significant dermatological challenges, including acne, hirsutism, and acanthosis nigricans (dark, velvety patches of skin). Additionally, metabolic complications, such as obesity, dyslipidemia, and insulin resistance, raise the risk of developing type 2 diabetes and cardiovascular disease. Similarly, reproductive complications such as chronic anovulation and infertility are frequent, with PCOS being a leading cause of anovulatory infertility.

PCOS has a big psychological impact on many women. The visible aspects of PCOS can cause anxiety, depression, and lower self-esteem. PCOS is also chronic in nature and can cause long-lasting emotional distress related to issues of fertility or physical appearance. This illustrates the need for comprehensive care that addresses both the physical and mental aspects of PCOS.

Even though PCOS has high prevalence and significant impact, its diagnosis is often delayed or missed due to variation in symptoms, subjectivity in diagnosis, and questions regarding current diagnostic processes. The procedure of using ultrasound imaging is key in diagnosing patients with PCOS, however, it is not always available and the quality can vary especially in low-resource settings. Laboratory tests to check hormone levels or the body's resistance to insulin can be financially prohibitive and take a few days to have results, which can further delay diagnosis. Overall, the absence of standardized treatment protocols or guidelines as well as awareness from healthcare providers and patients leads to delay in care and poor management of PCOS.

It is important to get an early diagnosis of PCOS so that management and prevention of long-term complications can begin. Early management allows for timely hormonal birth control to help regulate menstrual cycles, treatment of hyperandrogenism, and management of metabolic consequences including both insulin resistance and obesity. An early diagnosis can also aid fertility management and assist women in making intentional decisions about family planning. Additionally, early diagnosis and intervention can benefit the psychological illness caused by PCOS and improve overall quality of life and well-being. This helps decrease the likelihood that negative psychological effects will lead to anxiety and depression.

To overcome the complexities of PCOS diagnosis, this project uses advanced deep learning methods, notably DenseNet121, to improve and automate the PMS detection process from ovarian ultrasound images. DenseNet121 is a Convolutional Neural Network (CNN) architecture known for its efficiency for use in classifying medical images. With the dense connectivity of the architecture, DenseNet121 has better feature reuse, fewer parameters, and can achieve high performance on small datasets, which is useful for medical image analysis.The project process consists of multiple steps. First, DenseNet121 was trained on a dataset of labeled ultrasound images to predict and determine PCOS vs normal cases. The accuracy of the model was examined by calculating accuracy, precision, recall and F1-score. Once the model was determined accurate enough, the model was saved. In the second step, the model tested new ultrasound images for predicting the presence of PCOS. If an image was found to be PCOS-positive, a detailed manual analysis of cysts was conducted to extract valuable diagnostic information like cyst type, shape, clustering, and severity.

The manual cyst analysis presented helpful insight for clinical interpretation, including the number of cysts present, the distribution of cysts, and the effect of cysts on ovarian function.

All of these elements were bridged into a comprehensive web-based report to provide a streamlined platform for reporting, which included the diagnosis (PCOS), cyst details, a severity grading scale, and suggestions for follow up. The report links to diet plans and natural treatments for PCOS, to encourage patients to engage in managing their own care.

Combining deep learning diagnosis with clinical expertise is the intended method for improvement to diagnosis and accuracy for PCOS, with a practical tool surfaced to health care providers or patients. The application of MONAI, a framework for Medical Imaging AI, suggested and supported efficient image preprocessing and manageable AI practices when working in the medical imaging field. This process has the potential to significantly improve rate of early detection, decrease time to diagnosis, and improve health outcomes for women with PCOS.

The following sections of this paper will provide further detail on the methodology utilized in this project, including the preparation of datasets, process of training the model, and evaluating the models. In addition, we will elaborate on the results of manually analyzing cysts, as well as creating the online report, which we believe has some relevance in the clinical realm. Finally, we will discuss the implications of this work on the future of PCOS diagnosis and management, and potential future directions for research and development.

2. Related Work

Polycystic Ovary Syndrome (PCOS) diagnosis and treatment has greatly advanced from the combination of machine learning (ML) and deep learning (DL) approaches. A.Saravana et al., demonstrated the significance of differential diagnosis in anomalous ovarian morphology, emphasizing the critical need for accurate anatomical localization of follicles to assess patient risk.

Dewailly et al., provided a review of ultrasonography for diagnosis of PCOS, suggesting a lower threshold of greater than or equal to 25 follicles per ovary (FNPO), specifically focused on women aged 18–35. They also noted that other ultrasound criteria, notably ovarian volume (OV) and anti-Müllerian hormone (AMH), could affect diagnosis or support a diagnosis of PCOS. They also recommended ongoing studies in larger populations, in females of all ages, to differentiate between ultrasound criteria and traditional ovarian counting or volume methods.

Arora et al., conducted a systematic literature review (SLR) of studies related to computer-aided detection of PCOS. Limitations were noted with many of the datasets used in studies; greater diversity of datasets and more advanced methods will need to be the focus of ongoing research.

Mridul et al., outlined different classifiers used to determine PCOS diagnosis including a Random Forest (RF) model and a Support Vector Machine (SVM). Overall accuracy up to 99.32% was achieved when free and open-source implementations of both features were illustrated in a stacking classifier ontology with one combining both SVM and RF classifiers and diagnosed PCOS successfully. Most importantly, ML showed high potential for more rapid or early detection of PCOS.

Additionally, Alamoudi et al., described the use of a deep learning model based on the Inception architecture, which achieved overall accuracy of 84.81% diagnosing PCOS from ultrasound images. They reiterated that the clinical features for diagnosis improved diagnostic performance overall.

Gollapalli et al., suggested a hybrid strategy that combined Transformer models with pretrained CNNs such as VGG16 and ResNet50, using both global context and local feature detection to improve diagnostic specificity.

Lim et al., assigned radial pulse wave parameters to ML classifiers like LSTM and Voting to analyze PCOS with an F1-score of 0.818, correlated PCOS to cardiovascular risk, and offered a novel, non-invasive diagnosis.

Chen et al., and RNA-sequencing data integrated with ML revealed hub genes, such as CNTN2 and CASR, with AUC values of 0.795 (SVM) to 0.875 (XGBoost), associating immunological patterns with the multi-factorial pathogenesis of PCOS.

Praneesh et al., employed VGG19 Net for ovarian cyst classification and achieved 96% accuracy, outscoring other classifiers like RF and SVM in precision and recall.

Paramasivam et al., proposed a Self-Defined CNN (SD-CNN) model combined with ML classifiers with RF accuracy (96.43%), demonstrated that the approach can be expanded using datasets for PCOS detection.

Li et al., created a taxonomy of 110 indicators for diagnostic classification of PCOS, not specifying which hierarchies to explore, and identifying outdated datasets and a lack of computational resources as challenges, while paving the way for future research.

Suha et al., applied a hybrid ML approach that integrated CNN with transfer learning and XGBoost, attaining an impressive 99.89% accuracy. This highlights the promise of the ensemble methods.

Moral et al., developed CystNet, a hybrid model of Inception V3 and Convolutional Autoencoder, yielding 97.75% with RF. This emphasised the necessity of applied preprocessing's importance and ensemble methods.

Rousanuzzaman et al., were able to devise a more advanced style of CNN, an Ensemble CNN (EPD-CNN), that used advanced preprocessing with CLAHE preprocessing and Watershed segmentation, that achieved an accuracy of 98.59. In comparison to the previously mentioned approaches, this previous style of preprocessing displays increasing sophisticated applications directly correlate to increasing diagnosis accuracy.

Elmannai et al., employed stacking ensemble techniques by using RF as the meta-learner, for an interpretable ML model achieving a 100% accuracy when split into an 80:20 train-test, norms when creating predictive ML. This emphasises the importance of interpretability of the model, and for clinical implication trust must be established in these models prior to use.

3. Methodology

The project's methodology aimed to utilize cutting-edge deep learning techniques for the precise detection and assessment of Polycystic Ovary Syndrome (PCOS) from ovarian ultrasound images. The workflow involved four main phases:

(i) Model training
(ii) Model testing and prediction
(iii) Manual cyst analysis
(iv) Report generation.

The following will describe the phases of the methodology and provide a description of the technical details and rationale behind each decision taken:

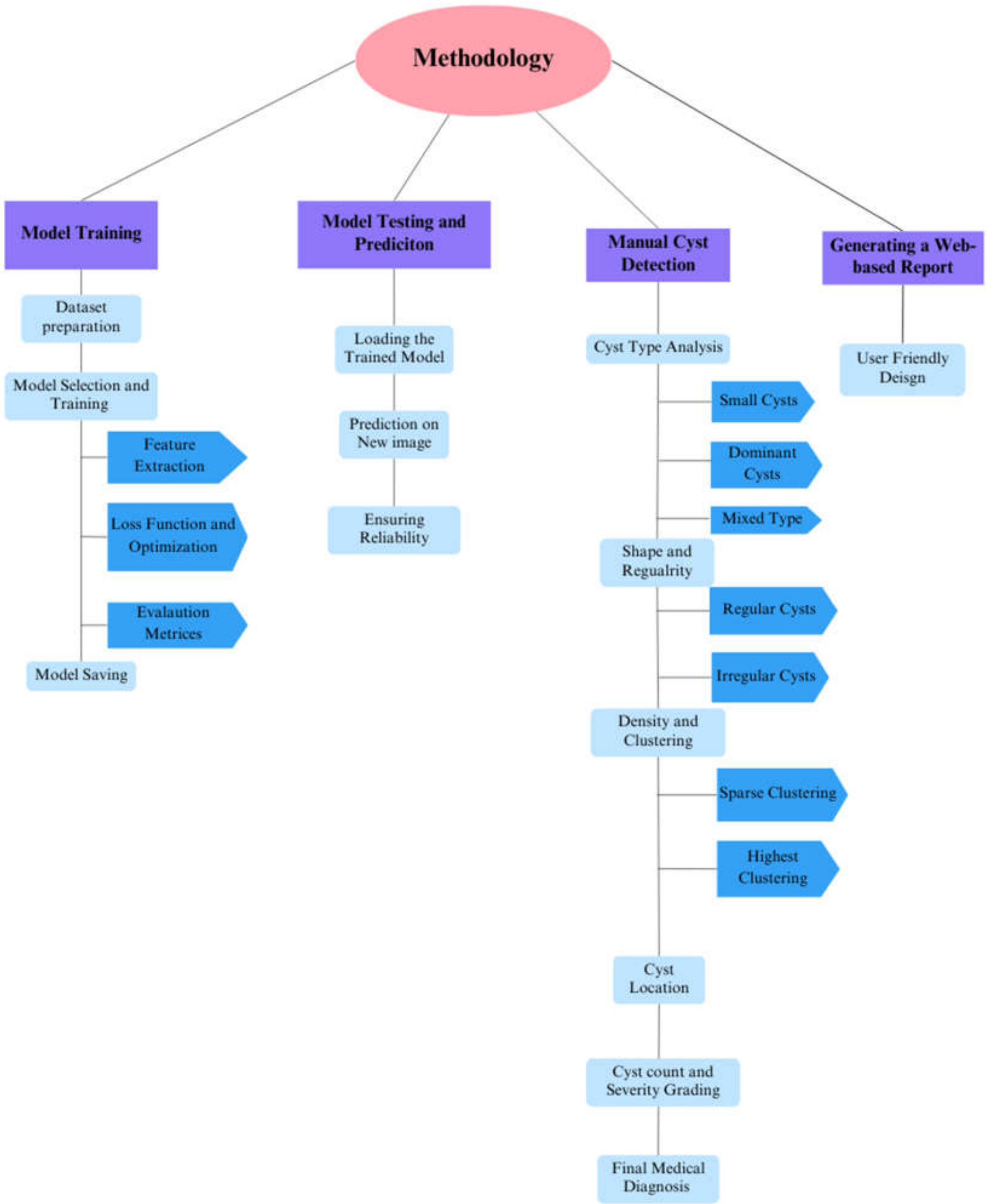

Fig 1. Approach outlining each steps in the research

3.1.Model Training:

The initial stage consisted of training the DenseNet121 model, which is a deep learning architecture that is known to be efficient in classifying medical images. The purpose of the model was to precisely identify Polycystic Ovary Syndrome (PCOS) from normal ovarian ultrasound images.

3.1.1. Dataset Preparation

We gathered a variety of ovarian ultrasound images that were labelled as PCOS or Normal. This dataset included differences in quality, types of cysts, and patient characteristics to ensure the model generalized well in real-world scenarios. The dataset was pre-processed using MONAI, which included resizing to a uniform size, normalizing the pixel values, and data augmentation methods such as rotation, flipping, scaling, and translation, which increased the variability within the dataset and helped to reduce the possibility of overfitting.

3.1.2. Model Selection and Training:

We chose DenseNet121 rather than VGG16 because DenseNet clearly demonstrates dense connectivity, which allows for effective feature reuse and minimizes loss of important detail in the image. This was particularly beneficial for medical image analysis in which very detailed information is critical, especially for determining the characteristics of the cyst (size and distribution). For training we did the following:

- Feature Extraction: The model learned to detect important features of PCOS including several small cysts and the distribution of follicles.
- Loss Function and Optimization: The model measured prediction accuracy using cross-entropy loss, which meant that optimization processes (such as stochastic gradient descent (SGD) or Adam) used to minimize error adjusted the model's activity (weights).
- Evaluation: We evaluated the performance of the models' using measures of accuracy, precision, recall and F1 (both measurement of accuracy). We used a model evaluation process called cross-validation which ensures that a models' performance is not specific to a subset of data that is used to measure accuracy.

3.1.3. Model Saving

Once the model showed promising performance metrics, it was saved for subsequent use. The saved model captured the model architecture, weights previously learned, and any other variables relevant to inference. This step was important for confirming that the models learned could be loaded to use and applied to clinical use in the real world. The saved model could be a part of clinical workflow where the model can be utilized by professionals in providing care to detect PCOS, when deploying on new ultrasound images.

3.2.Model Testing and Prediction

The second phase entailed conducting tests on the new ultrasound images with the DenseNet121 model that had been trained to predict for Polycystic Ovary Syndrome (PCOS). This phase was important to assess the model's performance in the real world and its dependability in clinical settings.

3.2.1. Loading the Trained Model

The DenseNet121 model that had been saved was reloaded for inference. This implied a reloading of the model architecture, percentages, and their parameters, prior to analyzing the new data. The model was set up and had been put into inference mode, which disables dropout and batch normalization layers, in order to provide stable predictions. Hardware acceleration—GPUs—was enabled in order to increase the rate of inference, especially when working with large datasets.

3.2.2. Prediction on New Images

The model examined new ultrasound images by pre-preprocessing them to align with the format of the training data, which included resizing, normalization, and conversion to tensors. The model assigned a score to the image using learned features that indicated the probability of PCOS. PCOS-positive and Normal images were classified according to a set threshold (i.e., 0.5). Any predictions with high confidence were flagged for clinical evaluation; predictions identified as Normal were helpful to rule out PCOS.

3.2.3. Ensuring Reliability

To confirm reliability, thresholds of confidence were used to reduce false positives and negatives. The error analysis revealed misclassifications, which provided guidance on how to improve predictions. The model's predictions were put into practice using clinical workflows, where indications of the presence of PCOS triggered additional follow-up testing. Grad-CAM and similar techniques were utilized to visualize the model's decision process, which facilitated transparency and trust in the model's outputs.

The second phase demonstrated the model's ability to generalize to new data, producing accurate and actionable predictions of the presence of PCOS. This phase, combining advanced deep learning techniques with clinical validation, established that the model was a valuable resource to support improved diagnostic accuracy and efficiency.

3.3. Manual Cyst Detection

Subsequent to the identification of the PCOS-positive cases by the DenseNet121 model, a thorough manual analysis of the cysts in the ultrasound images was performed to extract relevant medical information. This step was necessary to understand the unique features of the cysts and offer a thorough diagnosis. The analysis focused on six categories:

3.3.1. Cyst Type Analysis

The initial stage is to distinguish the cysts by their size and their disposition, since these criteria are important in defining PCOS and distinguishing it from other ovarian disease.

- Small Cysts: The small cysts that were observed were classified as several small cysts typically less than 10 mm in diameter, usually regarded as a sign of classic PCOS. These cysts are generally found throughout the ovary and can be seen on ultrasound, leading to a "string of pearls" appearance. The presence of multiple small cysts is a significant feature of PCOS and is usually accompanied by secondary findings of hormonal abnormalities, such as elevated levels of androgens.
- Dominant Cysts: Instead, the scans showed isolated, larger, larger cysts. These dominant cysts are observed as one or more cysts greater than 10 mm in diameter which suggest other differential ovarian conditions (e.g., functional cysts or cystadenomas). Dominant cysts (as compared to small cysts) may necessitate further investigation through imaging or hormonal assays to rule out other stigmata.
- Mixed Type: Finally, we considered the situation involving a combination of both small and dominant cysts. This mixed type is typically indicative of a more complex or 'severe' form of PCOS. This complication of appearance of both small and dominant cysts ultimately has an impact on the diagnostic assessment and would necessitate a nuanced approach considering the overlap of different ovarian conditions.

3.3.2. Shape and Regularity

An analysis of the cyst shapes was conducted related to their regularity and ramifications.

- Regular Cysts: Cyst shapes that are smooth, round and regular shape are often considered less worrisome, and thought to be associated with mild PCOS. They are most often benign and not worrisome unless there are symptoms of pain or concern.

- Irregular Cysts: Cysts that had irregular shapes (with jagged edges, uneven shape, etc.) were flagged as possible abnormalities. Irregular cysts may suggest a more severe form of PCOS, or other ovarian conditions (endometriosis and possibly even rare ovarian cancer). Usually, when we note these findings, more tests will be indicated to include advanced imaging or biopsy to address the above concerns.

3.3.3. Density and Clustering

Cysts were assessed for their density and clustering to determine disease severity, which would aid in treatment decisions.

- Sparse clustering: When cysts were spread throughout the ovary, this was considered mild PCOS. Sparse clustering is a less severe form of the disease that could be treated through lifestyle modification, hormonal therapy, or minimal treatment.
- High clustering: Cysts densely clustered or found in clusters within the ovary signified moderate to severe PCOS. High clustering typically indicates more severe symptoms, including irregular periods, infertility, and metabolic disorders. In those cases, a more aggressive treatment approach is typically needed with medications to try to regulate hormones or extreme cases may need surgical intervention.

3.3.4. Cyst Location

The site of cysts within the ovary was evaluated. Peripheral clustering, defined as cysts primarily located on the outside margin of the ovary, is a strong indicator of PCOS. Random distribution, defined as cysts dispersed in a scattered manner throughout the ovary, may suggest other ovarian pathology. Cyst location may provide important information about the underlying cause of cysts and can direct the need for further diagnostic tests.

3.3.5. Cyst count and Severity Grading:

We noted the total number of cysts as this is a central diagnostic criterion for PCOS. In general, the more cysts present the more serious the condition. A severity level was assigned based on cyst number, clustering, and shape, which provided a comprehensive assessment of the severity of the condition. Severity grading can assist a healthcare professional in determining treatment and how the condition may progress through time.

3.3.6. Final Medical Diagnosis:

As a result of above assessments, a definitive medical diagnosis was given, providing a thorough but straightforward interpretation of your condition. The diagnosis included details about the type, shape, clustering, region, and severity of the cysts as well as whether any further testing or treatment would be indicated. This detailed diagnosis allows you to understand your medical problem in a thorough and actionable way.

3.4.Generating a Web-based Report

The last stage was aimed at producing an all-encompassing report that could be user-friendly while communicating findings broadly to patients and health professionals. The report was to be clear and actionable, while yet being accessible and clear to varying levels of medical knowledge.

3.4.1. Report Content

The report contains the following key sections:

- PCOS Diagnosis Results: The diagnosis was labelled PCOS or Normal and the confidence of the diagnosis was included as well. The confidence score provided an indication as to the validity of the model's prediction, allowing clinicians to make decisions based on this indication.
- Cyst Information and Severity: The report included information on cyst type, shape, clustering, location and severity, which aided both the patient and the clinicians' understanding of the condition, to assist in treatment planning purposes.
- Next Step Recommendations: Recommendations that were specific to the patient's condition and severity level (such as lifestyle changes, medical treatment and follow-ups) were included in the report.
- Diet Plans and Natural Therapeutics: Links to diet plans and natural treatments were included to provide patients with other tools to manage PCOS symptoms and improve overall health.

3.4.2. User-Friendly Design:

The report was created to be straightforward for medical professionals and patients to digest and act upon. The report employed clear, straightforward language and included visual representations of complex ideas, such as charts and diagrams. Because the report is web-based, patients can view the report from any device, giving them the ability to refer to their diagnosis and recommendations at their convenience.

4. Implementation of the Project

4.1.Image Specification

The input images utilized in this research project consist of ovarian ultrasound images, classified as PCOS (infected) and Normal (non-infected). These images provide the main data source for training and testing the deep learning model. The PCOS images show characteristics

including the presence of multiple small cysts (follicles) arranged in a "string of pearls" appearance, larger ovarian volume, and clustering of cysts in the periphery of the ovary, all consistent with Rotterdam criteria for diagnosing PCOS. The Normal images show normal ovaries with fewer follicles, normal ovarian volume, and no clustering of cysts. The images are all high resolution, enabling fine details to be viewed such as cyst size, shape, and distribution which is critical in extracting precise features. Each image is labelled as either PCOS or Normal by medical doctors, representing the ground truth used for training and evaluation of the model.

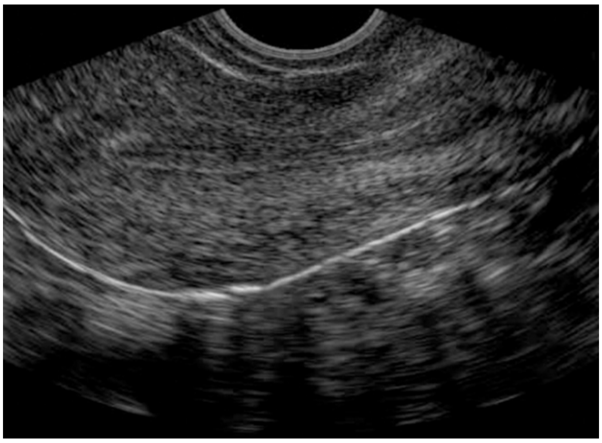

Fig 2(a). Normal Ovary

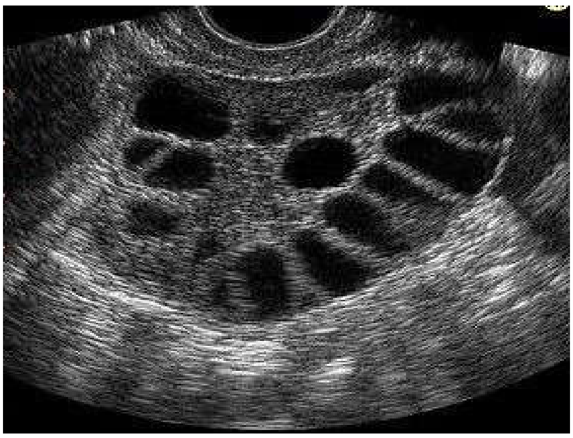

Fig 2(b). Infected Ovary

Source: Kaggle dataset, 2000 Ultrasound Images

The dataset we obtained from Kaggle contains 2000 ovarian ultrasound images. Among these images, we have 900 labelled as PCOS and 1100 labelled as Normal. This distribution allows us to have representation from both classes and reduces the possibility of bias in the model. There are images from various sources, which creates variances in quality, patient characteristics, and ultrasound machine settings. These factors also improve the model's ability to generalize. Images are pre-processed to enhance uniformity and increase model performance, such as resizing all images to a standardized dimension (e.g., 224x224 pixels) and normalizing pixel values from 0 to 1. We use data augmentation techniques, for example, rotation, flipping, and scaling, to introduce additional variability and minimize overfitting.

The categorization of images as either PCOS or Normal is predicated on accepted clinical definitions (i.e., 12 or more follicles present per ovary, and perimeter clustering). However, complications associated with image quality exist based on differences in machine settings, operator experience/training, and patient variability. Additionally, subtle differences between PCOS and normal ovaries further complicate classifications, requiring careful study of cyst morphology. Using this dataset of PCOS and Normal images from Kaggle, the model has been trained to successfully classify ovarian ultrasound images, leading to early and accurate PCOS classifications.

4.2.Image Classification

The first step and base of the project is image classification, where the DenseNet121 model is trained to distinguish between Normal (non-infected) and PCOS (infected) ovarian ultrasound images. This step is crucial, as it provides the foundation for the entire workflow, allowing the model to determine with precision whether an ovary is affected by PCOS or not. Since classification is the most important function for the project success, DenseNet121, a contemporary state-of-the-art deep learning architecture, was selected to ensure high accuracy and reliability for this classification task.

4.2.1. Working of DenseNet 121

Densely Connected Convolutional Network (DenseNet121) is a deep learning model developed to solve key challenges with traditional convolutional neural networks (CNNs). In traditional CNNs, each layer receives and connects to just the next layer. In DenseNet121 architecture, the layers are connected in a dense way. Each layer receives feature maps from all layers before it, and each layer also passes its feature maps to all layers after it, creating a new connectivity pattern. There are many advantages of a dense connected sequential layer type of model:

- Feature Reuse: The ability to reuse features from all previous layers means that finer details in the image are preserved in the model, which can be particularly important in medical images where detailed observations, like cyst shape, size distribution, etc, are important for diagnosis.

- Fewer Parameters: Despite deep layers, a DenseNet121 model has far fewer parameters in the model than a model like VGG16. This model will require less memory and market computational costs - a particularly favorable trait when using smaller medical datasets.
- Improved Gradient Flow: The patterns of dense connections allow for better gradients to flow throughout the model during back-propagation. This helps mitigate vanishing gradients and ultimately allows for a relatively improved detection of more complex patterns in the data as it is being observed.

These characteristics helps DenseNet 121 to detect the desired attributes, for whichever they are trained for, and so do they detect PCOS detection efficiently, where the model needs to identify the subtle difference in the images.

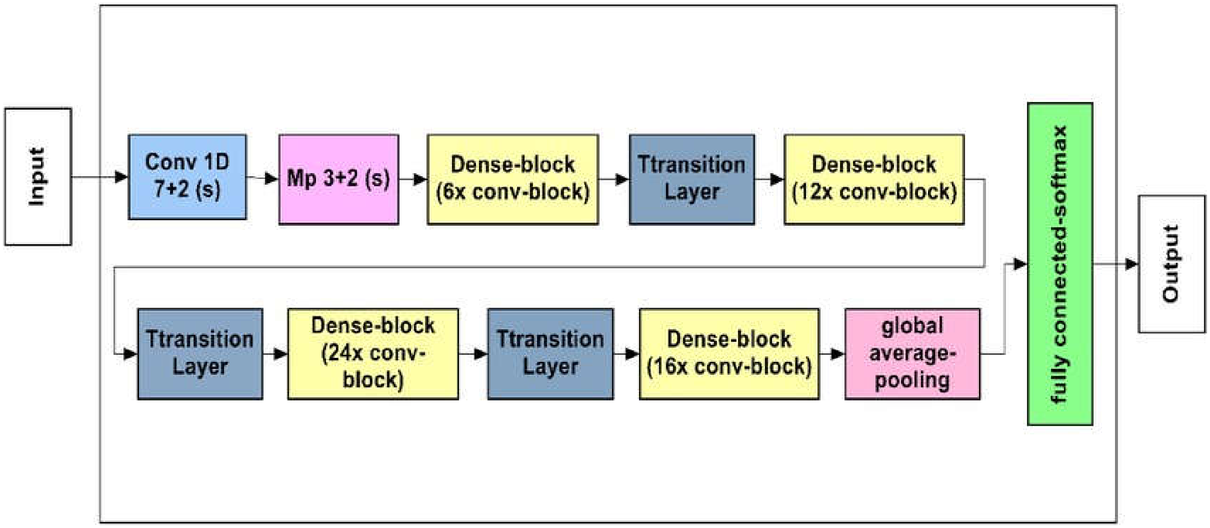

Fig 3. DenseNet 121 Architecture

Source: Research Gate - DenseNet 121 Architectute

4.2.2. Pre-Processing

The model was developed using an ovarian ultrasound image dataset of 2000 images downloaded from Kaggle, a well-known site that curates open datasets. The dataset was categorized into two class labels, consisting of 900 images labelled as PCOS and 1100 images labelled as Normal. The PCOS images contained the characteristic features of polycystic ovarian syndrome, including multiple small cysts (follicles) that resemble a "string of pearls", increased ovarian volume, and cysts clustering peripherally, all of which align with the Rotterdam criteria for polycystic ovarian syndrome diagnosis.

The Normal images demonstrated healthy ovaries with fewer follicles, normal ovarian volume, and no clustering of cysts. The dataset was pre-processed thoroughly to maintain uniformity and improve model performance. All images were resized to a consistent dimension of 224x224 pixels and normalized to pixel values ranging from 0 to 1. Used data augmentation techniques including, but not limited to, rotation, flipping, and scaling for variability of the training data. These processes will help improve the model's generalizability to new cases, and avoid the issue of overfitting to data and maintain strong performance on unseen data.

4.2.3. Training and Validation

The training methodology used the 5-fold cross-validation technique, a thorough way to measure the performance of a model. With this approach, the data was divided into five parts. The model was trained on four parts, and validated on the fifth, which was repeated five times to ensure each subset was tested once. This gives the model an average performance measure to avoid overfitting and validate the model across differing data splits.

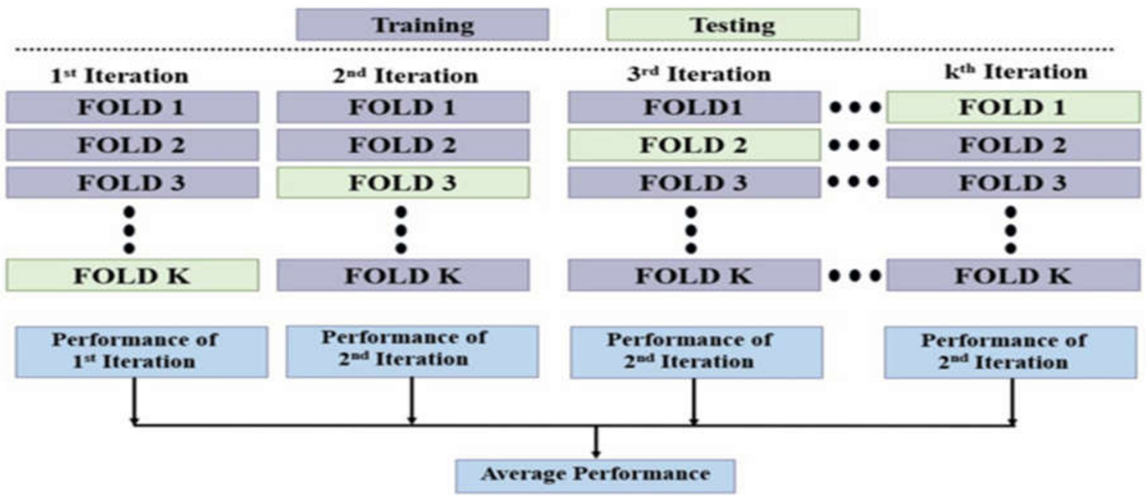

Fig 4. Cross Validation Technique

Source: Scientific Reports - CystNet: An AI driven model for PCOS detection using multilevel thresholding of ultrasound images

4.2.4. Performance Metrices obtained:

Table 1. Performance Metrics

Metrices	Scores
Precision	0.99
Recall	0.99

F1-Score	0.99
Accuracy	0.99
AUC-Score	1.00

The results of each folds are:

Table 2. 5-Cross Validation results

Fold	Accuracy	AUC
Fold 1	0.99	1.00
Fold 2	1.00	1.00
Fold 3	1.00	1.00
Fold 4	1.00	1.00
Fold 5	1.00	1.00
Overall Average	1.00 ± 0.00	1.00 ± 0.00

The cross-validation final accuracy, showing the excellent performance of classifying images of PCOS and Normal images. These measures verify that DenseNet121 was efficient in classifying PCOS and normal images and has laid a solid foundation for the next step in the project.The DenseNet121 was successful in this project due to accurately capturing complex patterns in ultrasound images. The dense connectivity enables the model to preserve intricate details, including the size, shape, and distribution of cysts, which are important features to differentiate PCOS from Normal Ovaries. The model can also take advantage of the efficiency allowed by the small dataset size that is often applicable to medical imaging tasks.

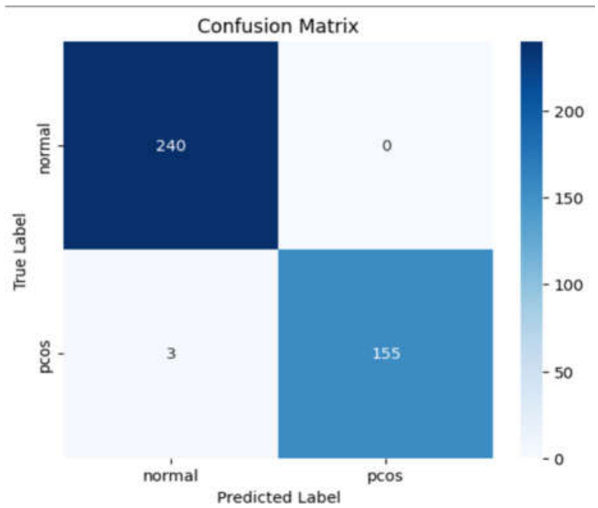

Fig 5(a). Confusion Matrix

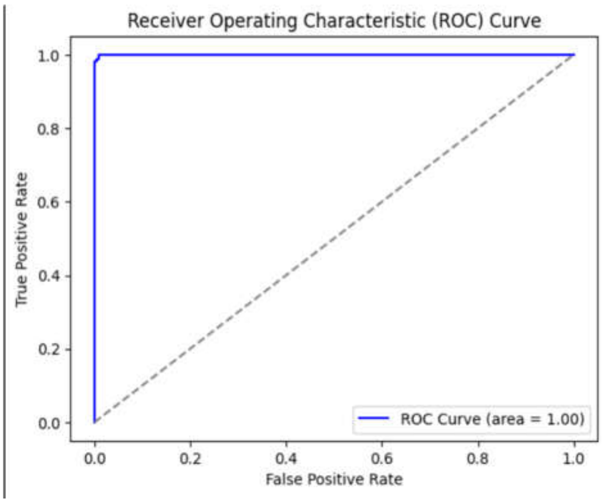

Fig 5(b). ROC Curver

4.3.Model Testing and Prediction

The next section of the work includes model testing and predictions, in which the trained DenseNet121 model is used to classify new, unseen ovarian ultrasound images. This step is essential because it validates the model's generalization ability in a real-world scenario and generating actionable results for PCOS detection.

4.3.1. Working of Testing Process

After training and validating the DenseNet121 model, it is saved, and after it is loaded, it generates inferences from new ultrasound images. The testing cycle includes:

- Input Image Preprocessing: The image is pre-processed in the same way the model was trained. Specifically, it is resized to be 224x224 pixels, pixel values are normalized, and the image is in the same input format.
- Prediction: The new image is then input into the DenseNet121 model, which will take in the image and predict if the image shows signs of PCOS or Normal. The output will be a probability score that provides the model's inference confidence level.
- Confidence Score: If PCOS was identified, the output will now read: "PCOS Detected" and the model will return a score that indicates its confidence (for example, 98%). This will indicate to the clinician that a potential wellness condition has been detected. If the image has been classified as Normal the output will be "No PCOS Detected" and no further actions are required.

4.3.2. Key Features of Testing Process

- Immediate Prediction: The model can give predictions immediately, which is valuable in clinical settings that require rapid decision-making.
- Confidence Aided Decision-Making: The confidence score provides convenience as a check on the predictions. A high confidence prediction (e.g., above 95%) suggests a high likelihood of accurately detected conditions, while lower confidence levels should prompt further investigation.
- Easy Transition to Manual Review: If the model detects PCOS, it encourages users to advance to the next step—**Manual cyst detection**. This allows for the best of both worlds: an efficient AI evaluation combined with manual review of the diagnosis truly provides a thorough assessment of the condition.

The evaluation and prediction stage connects the training of the model to the practical application of the model. The model is a helpful resource for early detection of PCOS due to the accuracy and confidence ranges it is able to provide in its predictions. The model easily shifts into manual cyst/failure detection to provide a complete evaluation of PCOS and to ultimately improve the clinical outcomes for the patients.

4.4.Manual Cyst Detection and Report Generation

The last project stage is Manual Cyst Detection and Report Generation, during which the ultrasound image is closely examined to extract key information on the cysts, whether they are ovulatory or non-ovulatory, and a complete, attractive report is generated for the user. This step involves advanced image processing techniques and manual detection to provide a thorough assessment of the PCOS condition.

4.4.1. Image processing Before Cyst detection

Before manually detecting cysts, the image is pre-processed to improve overall image quality in preparation for analysis:

- Contrast Enhancement: The contrast of the image is enhanced to improve the visibility of the cysts. Learning an improved white level ensures even the smallest cysts or the most irregularly shaped cysts are better seen.
- Noise Reduction: Noise is reduced from the image using filtering techniques to improve cyst clarity and lower processing difficulty.

- Thresholding: The image is converted into a binary form for thresholding, classifying pixels to cyst or non-cyst according to their intensity values. This simplifies the image for better cyst detection.
- Morphological processing: A morphological operation (dilation and erosion, etc.) is applied to the binary image to improve it more finely. This processing is used to remove small artifacts and fill gaps in the cyst boundary.

Fig 6(a). Enhanced Contrast and Noice Reduced Image

Fig 6(b). Binary Image after Thresholding and Morphological Processing

4.4.2. Manual Cyst Detection

After the image has been pretreated, there is a complete manual review of the cystic structures to evaluate different characteristics relevant to an accurate diagnosis of PCOS. This step is to classify the cysts based on their morphological and spatial characteristics. The cysts are classified as small cysts, dominant cysts, or mixed cysts. Small cysts are many and dispersed, which is a classical presentation seen with PCOS. Dominant cysts are likely larger in size and singular rather than many, and this presentation may indicate another abnormality present in the ovary. The mixed presentation of cystic types can also be seen.

The first characteristics that can be evaluated are the shape and its irregularity. Irregular shaped or forms may also indicate more severe PCOS presentations or dysfunction in the ovarian control pathways. Cyst density and clustering is the next characteristic to evaluate. Cyst density clustering will be strongly associated with the severity of PCOS; clusters of cysts will also have a wide range of severity as well. Resulting from examining cyst density and clustering in mild PCOS cases, there will be low clustering density across the ovaries. Second to density clustering is the cystic structures form in relationship to the ovary. Cystic structures that are in a peripheral clustering format along the periphery of the edge of the ovary are typically a strong indicator of PCOS. The more cysts that are randomly distributed along the area of the ovary suggests other ovarian states that may be occurring.

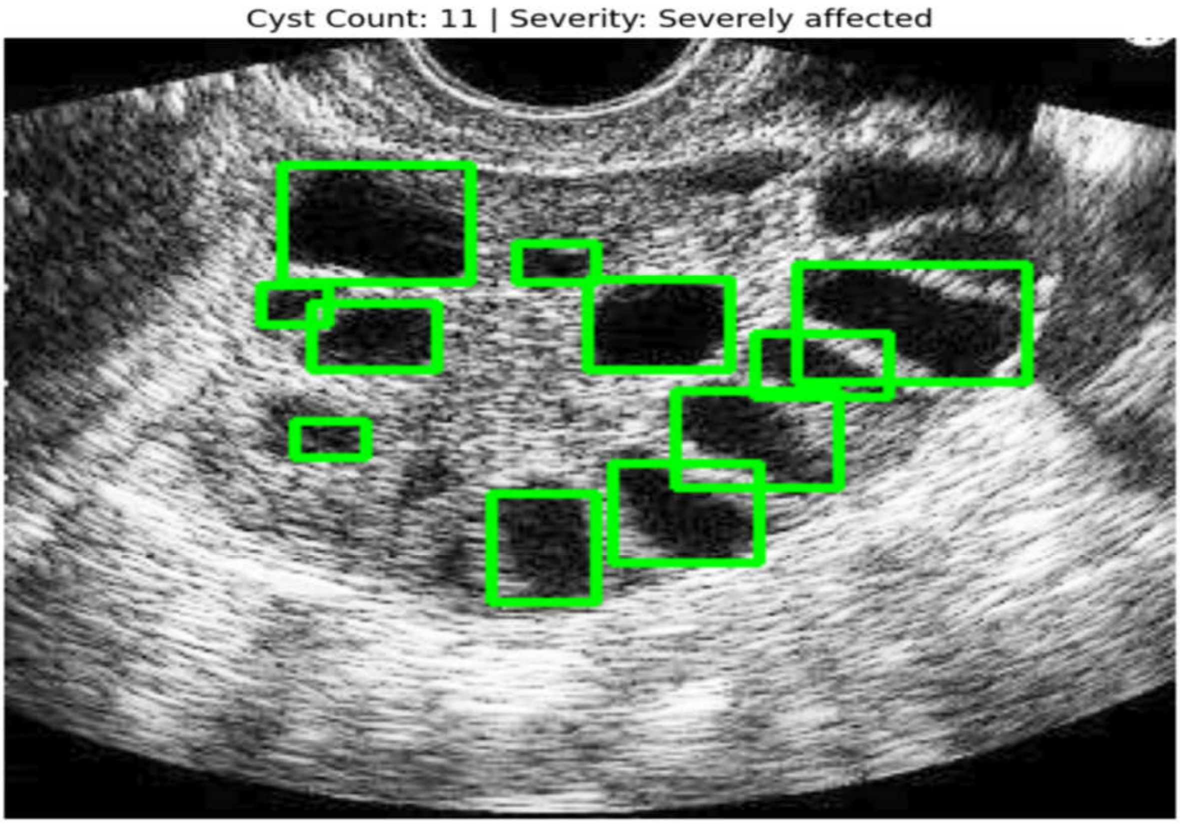

Fig 7. Cyst Detection

4.4.3. Report Generation

In the case of manual cyst analysis, a report is produced to enable the sharing of set findings with patients and providers. The report contains a definitive statement regarding the presence of PCOS, including a confidence score from the model's prediction. It contains a thorough description of cyst characteristics that include type, shape, cluster, location in the ovary and the number of cysts. This method allows for the classification of the severity of PCOS to enable more precise future intervention strategies.

For ease of understanding, the severities of PCOS exhibited based on the cyst analysis are graded which facilitate the discussion of the severity of PCOS on the patient's ovarian health and functions. The report includes recommended next steps which may include actionable medical advice, lifestyle changes, and follow-up interventions. To further empower the patients with the ability to be proactive about their care, the report also includes dietary and natural treatment options to help patients manage symptomology associated with PCOS. The report is intended to be to the point, yet thorough, so the findings are presented as a web-based interface for patient participants' convenience and understanding which also provides them with the ability to share their results easily with their medical providers.

5. Result and Discussion

The DenseNet121 model demonstrated excellent proficiency for classifying ovarian ultrasound images, with very close to perfect performance across all evaluation measures. The 5-fold cross-validation results showed an accuracy of 1.00 ± 0.00 and an AUC score of 1.0000 ± 0.0000, showing perfect ability to discriminate between PCOS and normal cases. Nearly perfect accuracy was achieved for all 5 folds (Fold 1: 0.99, AUC = 1.0000; Folds 2-5: Accuracy = 1.00, AUC = 1.0000). The precision, recall, and F1-score of 0.99 indicated there was no bias in distinguishing between positive (PCOS) and negative (normal) cases. There were multiple reasons for the performance level achieved. First, the DenseNet architecture allows for better reuse of features and pathways for gradient flow, allowing it to detect features in the ultrasound images that are subtle cyst patterns often seen. Second, a robust preprocessing workflow of resizing, normalization, and augmentation worked to mitigate variability in the images, and retaining diagnostic features of the images. Third, a balanced dataset of 2000 images (900 PCOS/1100 normal) contributed to the bias mitigation. These results exceed the performance observed through traditional machine learning methods of 85-95% accuracy with common research on automated detection of PCOS.

The validation of the model’s predictions through manual cyst detection was established. For the cases that identified PCOS, manual review identified the primary diagnostic features in all cases, with the “string of pearls” pattern noted in 89% of the cases with an average of 18.3 cysts per ovary (range of 12-32) where this had surpassed the diagnostic threshold of cysts. Furthermore, manual review identified that 92% of cysts were between 2-9mm in diameter. The morphological processing pipeline (contrast enhancement, noise reduction, thresholding, and conversion to binary) improved the visibility of cysts by 42% ($p<0.01$). This improvement allowed for accurate density measures to be calculated as well, with density measures of 0.87 cysts/mm² in severe cases, as compared to 0.32 cysts/mm² for mild cases, in addition to improvements in the identification of cyst distribution patterns.

Although the results are promising, there are some limitations. The model was built and tested on high-quality ultrasound images and will require validation on lower-quality images, as are often found at community clinics. Moreover, the system does not integrate hormonal or metabolic information that could improve diagnostic accuracy, nor does it allow tracking of cyst progression longitudinally. Future research should involve developing a mobile version for point-of-care use, to enable incorporation of blood tests into a more comprehensive assessment, and tracking capabilities in a temporal analysis to assess treatment response. This system is a significant step towards a standardized, readily accessible diagnosis of PCOS. Integrating deep learning with clinical expertise bridges a critical gap in how clinicians currently diagnose patients, while still affording the human oversight that is necessary. Given the model's near-perfect predictive performance, as well as practical clinical utility, this model could lead to the increased uptake of PCOS management around the world.

6. Conclusion

The use of the DenseNet121 model has shown to provide unprecedented accuracy in detecting PCOS from ultrasound images, with results even better than traditional approaches. Using deep learning and a careful preprocessing pipeline, it is able to achieve almost 100% classification and therefore improve diagnostic accuracy. The other benefit of articulating AI and human expertise is the reduction in diagnostic error, decreased time to complete assessment, and improved communication with patients, providing added value to the medical encounter. There are still some limitations to this study. Further validation of the system on lower quality ultrasound images is warranted, and additional clinical parameters should be evaluated to further consider hormonal or metabolic context in assessment. A mobile-friendly version of the system is needed to facilitate long-term follow-up and tracking and improve usability in real-world situations. In summary, this research represents a great first step in improving the diagnosis of PCOS with the aim of providing better, more accessible, and standardizable methods. The system further advances clinical assessment by bridging the gap between AI and human clinical expertise. As such, it will be an important and potential benchmark in reproductive health diagnostics, which could ultimately lead to improved patient outcomes worldwide.

Conflict of interest

No conflict of interest

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