PCOSense: A Multimodal AI Framework for PCOS (PMOS) Prediction using Clinical Data and Ultrasound Images

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ABSTRACT
Polycystic Ovary Syndrome (PCOS) is one of the most common hormonal disorders seen in women of reproductive age. Recently, PCOS has been renamed as Polyendocrine Metabolic Ovarian Syndrome (PMOS). In this research, a multimodal AI framework called PCOSense is proposed that can predict PCOS using clinical data and ovarian ultrasound images. For clinical prediction, a hybrid machine learning algorithm was applied. To classify ultrasound images for PCOS diagnosis, a deep learning algorithm that was built on MobileNetV2 with an attention and residual learning scheme was implemented. To enhance the accuracy level of the diagnosis, the probability outputs from both models were fused at the decision level to make a final prediction. According to the experimental results, it can be seen that the performance of the classifier for PCOS classification from ultrasound image is high. Moreover, a web application was designed based on the Streamlit framework to predict PCOS in real time using clinical variables and ultrasound images. This shows the practical usefulness of the proposed framework for intelligent healthcare support.

Keywords
Polycystic Ovarian Syndrome (PCOS), Multimodal Framework, Artificial Intelligence (AI), Machine Learning (ML), PMOS, Deep Learning (DL), Ultrasound Images, Fusion, Prediction

1. INTRODUCTION
One of the most common hormonal diseases that affect women during their reproductive years is Polycystic Ovary Syndrome (PCOS), which has now been renamed to Polyendocrine Metabolic Ovary Syndrome (PMOS) [1]. Those who have it usually suffer from symptoms such as irregular periods, hormone imbalance, difficulty in conceiving, as well as obesity, acne and insulin resistance [2]. Early diagnosis of PCOS is very important as delayed detection can lead to long-term problems such as type 2 diabetes, cardiovascular problems and reproductive complications [3]. Traditionally, diagnosis of PCOS is based on physical assessment, hormonal analysis, and ultrasound imaging, all performed around the Rotterdam criteria [27]. However, because of how heterogenous PCOS is, and because symptoms don't look the same in everyone, the diagnosis can become confusing, slow, and more or less dependent on how an expert reads the findings.

In recent times, ML and DL techniques have been applied in healthcare and disease diagnoses [6]. Many researchers have used machine learning algorithms such as Random Forest, Logistic Regression, Support Vector Machine, and Naïve Bayes for PCOS prediction using clinical plus hormonal data [15]. Similarly, various researches have investigated ultrasound image analysis using CNNs and transfer learning techniques to identify PCOS [14]. These intelligent approaches are helpful in reducing manual efforts, improving the prediction accuracy and assisting in the early diagnosis of PCOS [30].

The initial stage of this research established a combined machine learning system which used clinical information together with pathological data to predict PCOS cases [35]. The model combined three classifiers which included Gaussian Naïve Bayes and Logistic Regression and Random Forest through a weighted soft voting system to produce successful clinical diagnosis results [25] [26].The clinical model delivered accurate predictions but it failed to identify the essential visual elements which appear in ovarian ultrasound images [27] [28]. The current research builds upon the earlier work by using DL approach for ultrasound image classification [26] [28].

In this study, a deep learning algorithm is proposed for diagnosing PCOS based on ultrasound images .The model operates on MobileNetV2 architecture which includes Residual Blocks together with Squeeze-and-Excitation (SE) Attention and Spatial Attention mechanisms to boost its ability to extract features and its classification results [31] [33]. The research aims to enhance ultrasound-based PCOS prediction accuracy through automated ovarian feature detection in ultrasound images which also reduces the number of false negatives [21]. The research project functions as its second phase which aims to create a multimodal PCOS prediction system that will merge ultrasound image results with clinical data for improved diagnosis accuracy [31].

The specific objectives of the study are:

- To preprocess and analyze ovarian ultrasound images for PCOS detection.
- To develop a hybrid deep learning model using MobileNetV2, Residual Learning, and Attention Mechanisms for ultrasound image classification.
- To improve the accuracy of classification and to reduce false negative predictions in PCOS detection.
- To compare the performance of the proposed model with the existing deep learning architectures.
- To establish a foundation for multimodal fusion of clinical and ultrasound data for intelligent diagnosis of PCOS.

2. LITERATURE REVIEW
This section presents an overview of the literature work on the prediction and diagnosis of Polycystic Ovary Syndrome (PCOS) using Machine Learning (ML) and Deep Learning (DL) along with multi-modal fusion methodologies. Researchers have developed more accurate and reliable ways

to diagnose PCOS by combining clinical data, hormonal parameters, lifestyle factors, and ultrasound images.

2.1 vMachine Learning Approaches for PCOS Prediction

A number of machine learning algorithms have been successfully utilized for PCOS prediction using clinical, hormonal, and lifestyle information [7]. Some common machine learning algorithms include random forest, logistic regression, SVM (support vector machine), naive bayes, and decision tree [8][10]. Variables like body mass index (BMI), menstrual patterns, hormones, insulin resistance, weight gain, and follicles count are used in machine learning-based predictions [17]. It has been shown that ensemble and hybrid ML models are better than single algorithms, as they combine the power of several classifiers [11] [25].

A number of studies achieved high accuracy on clinical datasets. Yamini et al. [7] reported that Random Forest had 90% accuracy, while Rahman et al. [8] reported that Random Forest and AdaBoost models had 94% accuracy. Zad et al. [9] applied electronic health records to predict PCOS and reported good ROC-AUC performance with Logistic Regression and Random Forest. These models achieved good results, but most of them were based solely on structured clinical data and could not capture important visual features in ovarian ultrasound images [27] [28].

2.2 Deep Learning Approaches Using Ultrasound Images

To overcome the limitations of clinical-only prediction systems, many researchers started using Deep Learning (DL) techniques for ultrasound image analysis [13] [20]. Models such as CNN and transfer learning models like VGG16, ResNet, MobileNet, and EfficientNet have been widely used for automatic feature extraction from ultrasound scans [4] [29]. These models help in identifying important ovarian features such as follicle distribution, ovarian texture, and cyst patterns without manual feature engineering [14] [30].

Several studies achieved very high accuracy using deep learning techniques. Suha and Islam [13] used ensemble techniques with transfer learning and obtained a 99.89% accuracy in the detection of PCOS using ultrasound. Galagan et al. [20] used CNN models on more than 3,800 ultrasound images and obtained an accuracy of 99.7%. Hoque et al. [29] further improved the performance by using hybrid CNN-Transformer architectures. While deep learning methods showed promising results for image classification, several studies considered the ultrasound images only and overlooked significant clinical and hormonal information related to PCOS [27].

2.3 Multimodal Fusion Methods for PCOS Detection

Since the diagnosis of PCOS requires both clinical manifestations and ultrasound results, researchers began to develop multimodal fusion systems that combine clinical data and ultrasound image analysis [27] [28]. These systems seek to improve the reliability of the diagnosis by combining information from different sources. Recent studies [31] investigated different fusion techniques, such as feature-level fusion, decision-level fusion, and cross-attention fusion.

Sakthivel et al. [12] proposed a multimodal system by combining ultrasound image features extracted with ResNet-50 with clinical attributes such as BMI, menstrual cycle irregularities and lifestyle habits. Similarly, Alamoudi et al. [27] proposed a deep learning-based fusion system for integrating ultrasound imaging and clinical information. Lakshmi et al. presented a multimodal deep learning framework using cross-attention and Grad-CAM to achieve an explainable multimodal solution. These studies showed that multimodal approaches generally provide better prediction performance and more reliable diagnosis compared to standalone ML or DL models [27] [31].

2.4 Research Gaps Identified from Literature

From the reviewed literature, it was observed that many machine learning models focused only on clinical and hormonal data while ignoring important ovarian morphology present in ultrasound images [27]. On the other hand, several deep learning approaches concentrated only on the ultrasound image classification without considering clinical symptoms and hormonal factors associated with PCOS [18] [28]. Because of this, many systems fail to provide a complete and reliable diagnosis.

Another important issue identified in previous studies is false negative prediction, which is critical in medical diagnosis because undetected PCOS cases may delay treatment and increase long-term complications [20] [21]. Many existing deep learning models also suffer from lack of interpretability and high computational complexity [31]. Finally, some studies used limited or non-diverse data sets, which may limit model generalisation to real-world medical data [15]. Therefore, a better and efficient hybrid system is needed that combines the traits of both machine and deep learning while improving accuracy, reducing false negatives and supporting future multimodal PCOS diagnosis.

3. METHODOLOGY

The proposed methodology is to detect Polycystic Ovary Syndrome (PCOS) using ovarian ultrasound images with the aid of deep learning techniques. Ultrasound images are collected, preprocessed, and used to train a deep learning model for classifying images into PCOS and Normal categories in this work. A transfer learning approach based on MobileNetV2 and additional feature enhancement techniques is used to improve prediction performance. The proposed model is assessed by several performance metrics such as accuracy, precision, recall, F1-score, and ROC-AUC.

3.1 Dataset

The dataset of ultrasound images used in this study was collected from public online resources for PCOS detection. The data set is consisting of ultrasound images of ovaries which are classified into two classes PCOS and Normal. The images are separated into training and testing folders for training and testing the model. The PCOS class includes ultrasound images with polycystic ovarian patterns and the Normal class includes images without PCOS-related abnormalities.

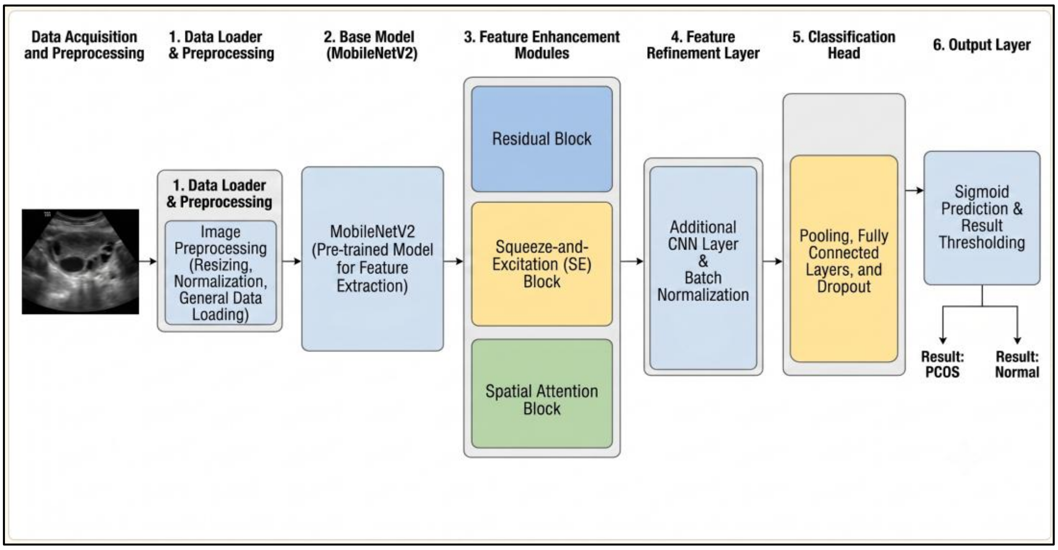
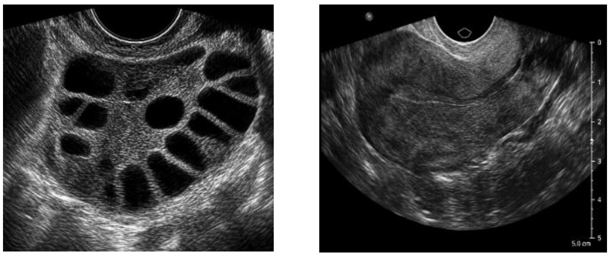


Fig 1: System architecture of deep learning model based on ultrasound image

Table 1. Distribution of Ovarian Ultrasound Image Dataset

Class	Description	Total Images
NORMAL	Non-PCOS ovaries	1142
PCOS	Affected ovaries with PCOS	844
Total		**1986**

The collected dataset is used for training and evaluation of deep learning model for ultrasound based PCOS classification. Training the model requires preprocessing and augmentation as medical image datasets are usually small and have variability in image quality. The dataset contains crucial visual information regarding ovarian morphology, follicle structures and cyst patterns, which allows the model to learn meaningful features for accurate PCOS detection.



(a) An infection ultrasound image

(b) Ultrasound image without infection

Fig 2: Ultrasound images of PCOS with and without infection

3.2 Image Preprocessing and Data Augmentation

The first step prior to training the deep learning network is the pre-processing of the ultrasound images which helps enhance the quality of the image and learn the data efficiently. All the ultrasound images are resized to 224 x 224 pixels such that the same size of input data can be used according to the MobileNetV2 architecture. Normalisation of images is done by rescaling the pixel value to the range [0,1] with rescale factor as 1/255. This normalisation assists in speeding up the process of convergence during training.

Medical image dataset is usually small and there could be differences in orientation and image quality. Techniques such as data augmentation are adopted in order to enhance the variability in the dataset while avoiding overfitting. In this work, the training images are augmented with rotation, zoom and horizontal flip. These transformations enable the model to learn robust features and improve its generalisation ability on unseen ultrasound images. To monitor the model performance and prevent overfitting, a validation split is employed during training.

3.3 Custom Feature Augmentation Module

In order to improve the performance of the suggested deep learning network, some feature enhancement blocks have been added to the network architecture, such as Squeeze-and-Excitation block, Spatial Attention block, and Residual Block. The addition of these blocks has been done to make the network concentrate on the significant features related to ovaries.

3.3.1 Squeeze-and-Excitation (SE) Block

The Squeeze-and-Excitation (SE) block helps the model in understanding the significant feature channels. The first step in SE involves squeezing the input feature map using the global average pooling. It then learns the significance of each channel with the help of dense layers. Significant features get more weight while less significant features get lower weights. Thus, the model will be able to give more attention to relevant ovarian features regarding PCOS.

3.3.2 Spatial Attention Module

The Spatial Attention block assists in bringing the necessary attention to the most important parts of the ultrasound image. Not only it brings attention to feature maps but also helps to find out which part of the image is more important to focus on. Through the application of maximum and average pooling, it helps to draw attention to structures like follicles and ovaries.

3.3.3 Residual Block

The residual block helps the model to learn complex features as well as maintain the essential information passed through the previous layers. It has shortcuts that allow the input features to be passed directly to the later layers, thus ensuring the model does not face issues such as vanishing gradients. The model becomes stable, thus learning the complex ovarian patterns for PCOS diagnosis.

These feature enhancement blocks collectively help in enhancing the learning capability of the proposed model by highlighting the essential features and suppressing unnecessary features within the ultrasound images. This combined approach of using an attention mechanism along with residual learning helps in achieving higher accuracy rates, stability of the model, and detecting ovarian patterns associated with PCOS.

3.4 Transfer learning based model (MobileNetV2)

The deep learning network used for classifying ultrasound images is MobileNetV2. This is a lightweight and efficient CNN which was pre-trained on the ImageNet data set. This is because it had learned some important general features of an image like edges, textures, and shapes from ImageNet data set and such learned features can be readily utilised in analysing medical images. Pre-trained models prove extremely useful when there is insufficient training data available for the task at hand.

The highest classification layers from the base architecture are stripped away and replaced with custom binary classification layers to suit the detection of PCOS. The first layer of the CNN is frozen so that the learned features are preserved; the following layers are then fine-tuned using ultrasound images to learn the patterns of ovaries that indicate PCOS. Transfer learning helps improve the classification process by saving time and avoiding the overfitting of the ultrasound images data.

3.5 Proposed Deep Learning Architecture

The images obtained through the ovarian ultrasound test are examined by considering the features that characterize PCOS using the deep learning model presented here. In this study, the architecture used to analyze the images involves transfer learning, which implies the use of MobileNetV2 pretrained on another large data set. In other words, transfer learning will allow the model to acquire features from medical images, including edge detection, texture and shape recognition. It is important to note that all images used for training have been resized to 224x224 pixels.

To improve feature extraction, additional feature enhancement components are integrated on top of the base model. These include Residual Blocks, Squeeze-and-Excitation (SE) Attention, and Spatial Attention mechanisms. The Residual Block enables the model learn more complex representations without losing important information and the attention mechanisms help the network focus on significant ovarian regions and important feature channels present in ultrasound images. These components help the model to better recognize the PCOS-related ovarian patterns such as follicles and cystic structures.

Following the attention and residual layers, another convolution layer containing 64 filters with kernel size 3 × 3 is applied to further enhance the features. The use of ReLU activation will help in introducing non-linearity in the network. Batch normalisation plays an important role by making the training process smoother and faster. These convolution layers make the neural network understand the spatial features present in images and differentiate between PCOS and Normal.

In the next step, after feature extraction, the global average pooling method is used to reduce dimensionality and extract important high-level features. The important features thus extracted are fed to the dense layers where they undergo classification. To prevent overfitting in the model, the dropout layer is used. Finally, the sigmoid activation function is used in the output layer to classify the ultrasound images into one of the two classes, that is, PCOS or normal.

3.6 Model Training and Evaluation

Various metrics of performance evaluation are adopted to measure the performance of the deep learning approach. These metrics measure the efficiency of the model in terms of its classifying capabilities for classifying PCOS and Normal ultrasound images. The process of evaluation plays a vital role in the evaluation of the proposed framework.

Accuracy was measured as the total percentage of ultrasound scans that were correctly identified. Precision measures the proportion of positive images of PCOS that the model predicts, whereas Recall gives an indication of how successful the model is in predicting PCOS. F1 score is the harmonic mean of Precision and Recall.

Moreover, ROC-AUC test is conducted for checking the classification ability of the model at various threshold levels besides these measures. Furthermore, a Confusion Matrix is used to check the results of True Positive, True Negative, False Positive, and False Negative. The false negative class is of significant importance since undetected PCOS may result in a late diagnosis of the disease.

Furthermore, the performance of the developed framework is analyzed through comparative testing against different pre-existing deep learning frameworks like MobileNetV2, VGG16, ResNet, and EfficientNet.

The objective of such analysis is to measure the efficiency and efficacy of the developed framework for detecting PCOS through ultrasound imaging.

3.7 Decision-Level Fusion for Multimodal PCOS Prediction

In this work, a decision-level fusion strategy was applied to integrate the prediction probability values generated from the clinical machine learning model and the deep learning model using the ultrasound image. The clinical model predicts the probability of PCOS according to the patient's clinical and pathological features, and the ultrasound model predicts the probability of PCOS according to the ovarian ultrasound images. The system is able to give a more reliable and accurate prediction by combining the outputs of both models than using a single model solely.

The final prediction probability is calculated using weighted averaging, where slightly higher importance is given to the ultrasound model because ultrasound images contain important ovarian morphological patterns related to PCOS. The final fusion equation used in this work is:

Final Probability = (0.6 × Ultrasound Probability) + (0.4 × Clinical Probability)

If the final probability exceeds the predefined threshold value, the case is classified as PCOS; otherwise, it is classified as Normal. The integration of clinical and ultrasound derived information in this multimodal fusion method improves overall diagnostic performance and decreases false negative predictions.

4. RESULTS AND IMPLEMENTATION

The proposed deep learning model for detection of PCOS using ovarian ultrasound images was tested on the test dataset. The model has been trained based on the MobileNetV2 architecture with residual learning and attention mechanisms for better feature extraction. To analyze the generalization ability and classification performance of the model for PCOS and Normal cases, the model was evaluated on unseen ultrasound images.

4.1 Performance Metrics

The performance of the proposed deep learning model was analyzed using various classification metrics like precision, recall, precision, and F1-score. The use of these metrics is essential for evaluating the effectiveness of the proposed model in classifying PCOS and non-PCOS cases using ultrasound images.

Table 2: Ultrasound Deep Learning Model Performance Measures

Metric	**Value(%)**
Accuracy	99.75%
Precision	100.00%
Recall	99.41%
F1-Score	99.70%

The proposed model was able to attain an accuracy of 99.75% with good overall classification performance for both the PCOS and non-PCOS cases. The precision value of 100% indicates that all the predicted PCOS images were correctly classified without any false positive predictions. This is important in medical diagnosis because this will reduce the chances that healthy individuals will be wrongly diagnosed as patients with PCOS.

The recall value of 99.41% indicates that the model predicted almost all the actual PCOS cases with minimum number of missed predictions. The F1-score of 99.70% reflects a good trade-off between precision and recall, confirming the robustness and reliability of the proposed architecture. The model achieved high performance by integrating transfer learning, residual learning, and attention mechanisms, which improved feature.

Confusion Matrix Analysis of Ultrasound Deep Learning Model

The confusion matrix gives an elaborate insight into how well the developed deep learning model classifies PCOS patients and non-PCOS patients through the illustration of the distribution of correct and incorrect classifications for both PCOS and non-PCOS categories.

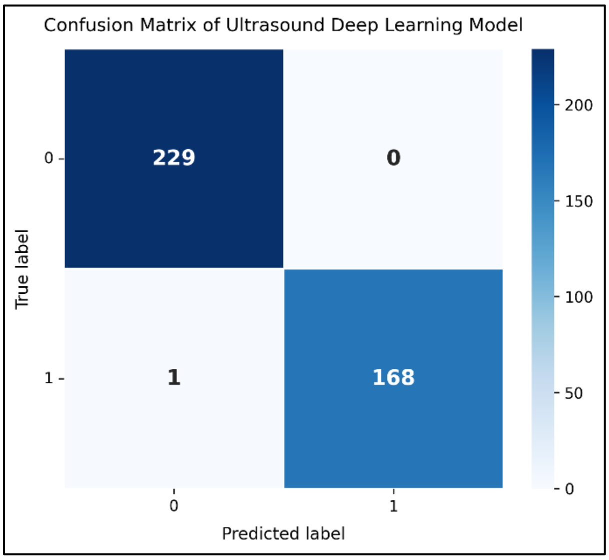


Fig 3: Confusion Matrix of Ultrasound Deep Learning Model

From the confusion matrix above, the developed model accurately classified 229 non-PCOS samples (True Negatives) and 168 PCOS samples (True Positives). It did not generate any false positives, meaning that it did not misclassify healthy samples as PCOS. Furthermore, there was only one instance of a false negative, where a PCOS image was mistakenly classified as a non-PCOS image.

The results reveal that the proposed model has a very good capability of classification with very small prediction errors. There are no false positives, i.e. the predictions for healthy individuals are reliable, and the very low number of false negatives proves the high effectiveness of the model in identifying true PCOS cases. Adding attention mechanisms together with residual learning improved feature extraction and reduced misclassification in the analysis of ultrasound images.

4.2 ROC Curve and AUC Analysis

The ability of the suggested deep learning model to classify with various thresholds is analyzed with the help of the Receiver Operating Characteristic (ROC) curve. ROC is plotted using True Positive Rate vs False Positive Rate in order to determine the capability of the model to distinguish between PCOS and non-PCOS.

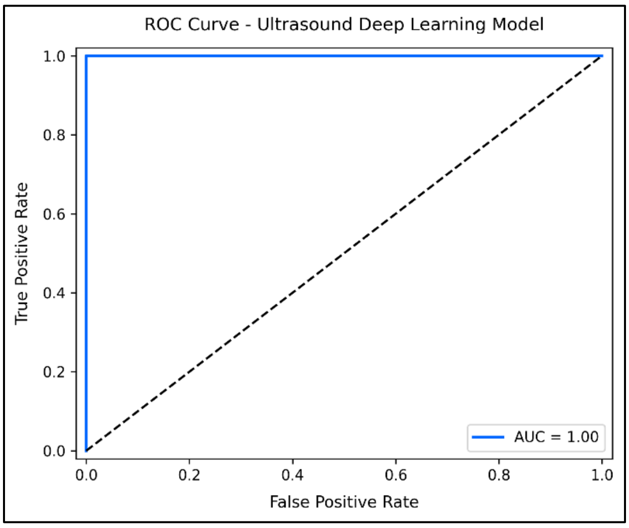


Fig 4: ROC Curve of Ultrasound Deep Learning Model

The proposed ultrasound-based deep learning model achieved a ROC curve with an Area Under the Curve (AUC) of 1.00, which is indicative of excellent classification performance. The curve is close to the top left corner of the graph, implying high sensitivity and a very low false positive rate. It indicates that the model is capable of distinguishing PCOS and Normal ultrasound images with very minimal overlapping.

The high score of the AUC also validates the effectiveness and efficiency of the proposed framework in detecting PCOS using ultrasound images. The integration of transfer learning, attention learning, and residual learning techniques proved effective in obtaining good results.

4.3 Comparative Analysis with Existing Deep Learning Models

The performance of the proposed architecture was evaluated by comparing it with several existing deep learning models such as MobileNetV2, ResNet50, EfficientNet, and VGG16.

Table 3: Comparative Analysis of Deep Learning Models

Model	Accuracy
MobileNetV2	98.74%
ResNet50	81%
EfficientNet	57.54%
VGG16	99.50%
Proposed Model	**99.75%**

From the experimental result, it can be seen that the proposed model obtained the best accuracy score of 99.75%. While VGG16 is another model that also had outstanding accuracy performance with 99.50% accuracy rate, the proposed model had better results with higher recall values and lesser numbers of false negatives. MobileNetV2 got 98.74% accuracy, but the performances of ResNet50 and EfficientNet on the ultrasound image data were relatively poor compared to others.

The better performance of the proposed model is mainly due to the use of Residual Blocks, Squeeze-and-Excitation (SE) Attention, and Spatial Attention mechanisms along with MobileNetV2. These components helped the model focus on important ovarian features and regions present in ultrasound images, which improved the model's ability to identify PCOS patterns more accurately.

4.5 Ablation Study

An ablation study was performed to identify the individual contribution of each block within the entire deep learning model. In order to perform an analysis of this kind, five variants of the model were evaluated, with all of them trained and tested under identical conditions by employing the ultrasound dataset:

- **MobileNetV2 (Baseline):** Basic MobileNetV2 architecture without additional blocks.
- **MobileNetV2 + Residual:** Base architecture of the model combined with a Residual Block (128 filters).
- **MobileNetV2 + SE Attention:** Base architecture of the model combined with an SE Attention channel.
- **MobileNetV2 + Spatial Attention:** Base architecture of the model combined with a Spatial Attention module.
- **Proposed Model (Full Architecture):** Architecture combining all mentioned above.

Table 4 summarizes the comparative performance across all five configurations.

Table 4: Ablation Study Performance Comparison

Model Configuration	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
MobileNetV2 (Baseline)	91.21%	100.00%	79.29 %	88.45 %
MobileNetV2 + Residual	98.49%	100.00%	96.45 %	98.19 %
MobileNetV2 + SE Attention	97.49%	100.00%	94.08 %	96.95 %
MobileNetV2 + Spatial Attention	91.96%	100.00%	81.07 %	89.54 %
Proposed Model	99.75%	100.00%	99.41 %	99.70 %

4.5.1 The Importance of Residual Learning

The inclusion of the Residual Block into the MobileNetV2 base network had by far the most significant impact on performance. Accuracy was raised to 98.49% from 91.21% while the recall rate also saw a marked improvement from 79.29% to 96.45%. It can be seen that the shortcuts play an important part in preserving features in deep feature extraction.

4.5.2 Role of SE Channel Attention

Adding the SE Attention mechanism also showed a significant improvement in comparison to the base model with accuracy and recall values of 97.49% and 94.08%, respectively. The functioning of the SE mechanism involves assigning weights to feature channels according to their importance and eliminating unimportant noise.

4.5.3 Role of Spatial Attention

The Spatial Attention module slightly improved upon the baseline, bringing the accuracy score to 91.96%, while the recall rose to 81.07%. This module ensures that the neural network can concentrate its attention on meaningful parts of the image, for example, ovarian follicles.

4.5.4 Synergy Effect of All Modules Together

When all the three modules (Residual Block, SE Attention, and Spatial Attention) were combined together into one unified module, the best results were obtained in all the measures. The unified model demonstrated an outstanding overall accuracy of 99.75%, a precision of 100.00%, a recall of 99.41%, and an F1-score of 99.70%. The enormous improvement in the value of recall, which is 99.41%, is particularly noteworthy as it indicates that the combination of these feature enhancement modules helped in reducing false negatives.

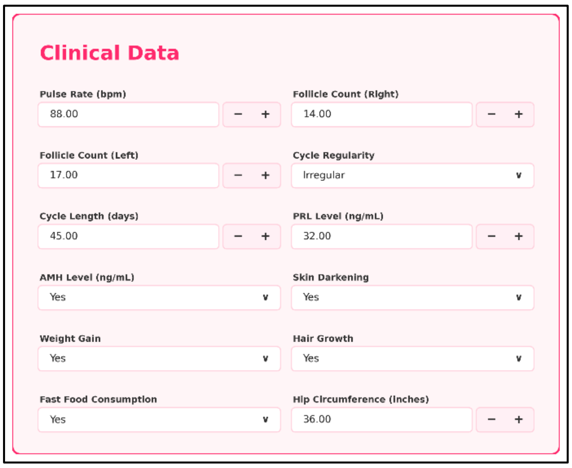
4.6 Streamlit-Based Real-Time PCOS Prediction System

To demonstrate the practical implementation of the proposed system, a web application based on Streamlit for real-time PCOS prediction was created. In the designed application, a user is able to provide clinical features and ultrasound images of ovaries through an interactive interface. The provided ultrasound images will be evaluated using the proposed deep learning-based approach, while the clinical features will be analyzed using a previously proposed machine learning model. The predicted probabilities from both approaches will then be fused by the proposed fusion scheme at the decision level to obtain the final PCOS diagnosis result.

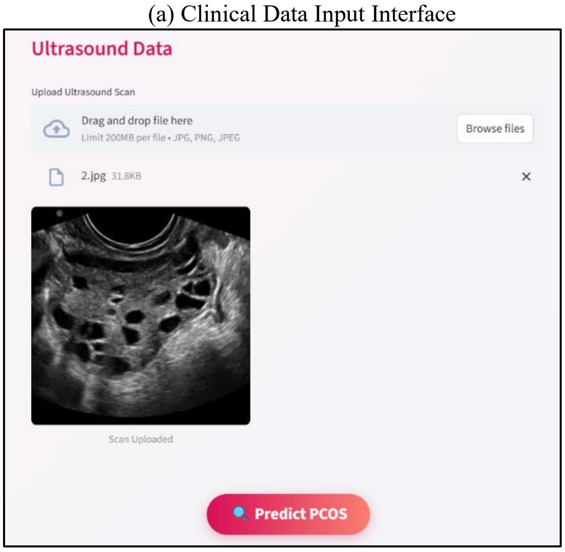
4.6.1 PCOS Case Prediction

This section shows the prediction result for a sample PCOS case using the developed Streamlit application. The user is required to provide clinical data as well as upload an ultrasonic image of a normal ovary via the application interface. The two models, which include the machine learning model and the deep learning model, are then individually evaluated to come up with the prediction outcome.

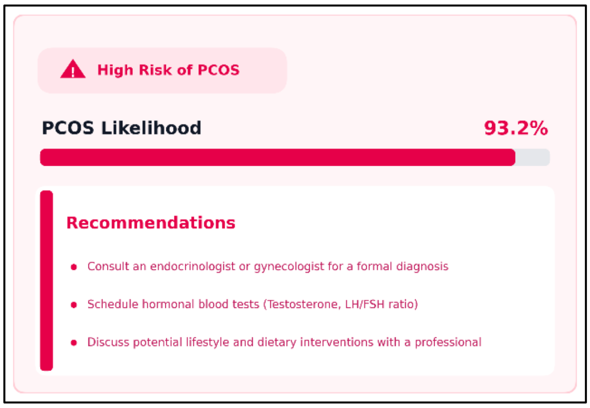
The probability outcomes for both the models are fused using the decision-level fusion method to get the final likelihood score of the prediction. The system was able to classify the sample case as PCOS with high prediction probability. This proves that the proposed multimodal framework is effective for real-time PCOS detection.



(a) Clinical Data Input Interface



(b) Ultrasound Image Upload Interface



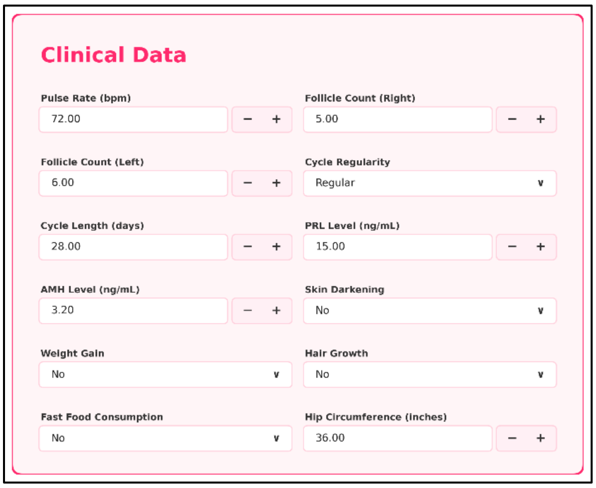
(c) Final PCOS Prediction Result with Recommendation System

Fig 5: Streamlit-Based Multimodal PCOS Prediction System

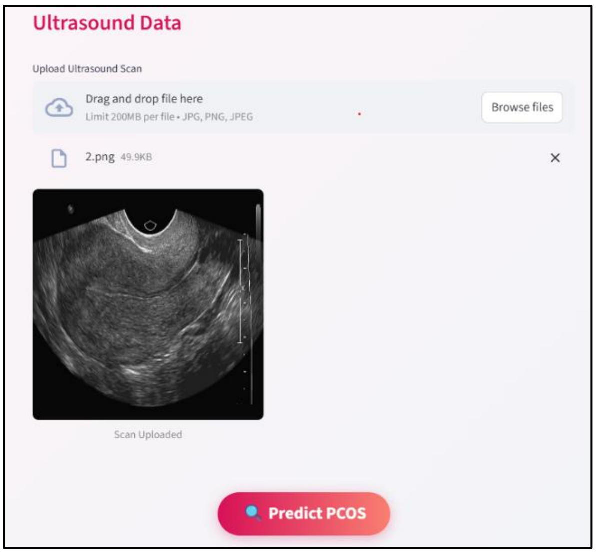
4.6.2 Non-PCOS Case Prediction

This section presents the prediction result for a sample non-PCOS case using the developed Streamlit application.The user is required to provide clinical data as well as upload an ultrasonic image of a normal ovary via the application interface. The two models, which include the machine learning model and the deep learning model, are then individually evaluated to come up with the prediction outcome.

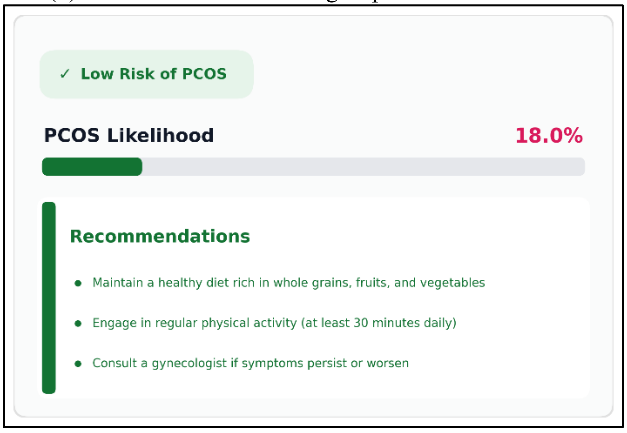
The probability outcomes for both the models are fused using the decision-level fusion method to get the final likelihood score of the prediction. The system was able to correctly classify the non-PCOS case, proving its effectiveness and applicability.



(a) Clinical Data Input Interface



(b) Normal Ultrasound Image Upload Interface



(c) Final Non-PCOS Prediction Result with Recommendation System

Fig 6: Streamlit-Based Multimodal Non-PCOS Prediction System

5. DISCUSSION

The outcomes generated by using the suggested deep learning architecture indicate that the system is very efficient in identifying PCOS from ovarian ultrasounds. The proposed deep learning algorithm had a very high rate of accuracy, precision, recall and F1 score, indicating that the system is very effective in predicting whether a patient suffers from PCOS or not. Very low false negative values were generated, and this factor is very crucial because if a patient is not diagnosed, then the diagnosis will be delayed.

Good performance of the proposed architecture is mainly due to the combination of transfer learning, residual learning and attention mechanisms. MobileNetV2 was effective in efficiently extracting important image features, and the Residual Block helped to retain important information during the training process. Also, the Squeeze-and-Excitation (SE) and Spatial Attention mechanisms empowered the model to focus on important ovarian regions and follicle patterns in ultrasound images. These methods enhanced feature extraction and enabled the model to recognise patterns related to PCOS more accurately.

The developed application based on Streamlit also showed the practical implementation of the proposed system for real-time prediction of PCOS. The system provides a better and complete prediction method through the association of clinical information and ultrasound image analysis with the decision level fusion. The proposed framework showed promising results. However, the study was limited by the size of the available ultrasound dataset. Larger datasets and more advanced explainability techniques can be used in future to further improve the reliability and practical usability of the system in healthcare environments.

6. CONCLUSION

In the current study, a deep learning framework for the detection of Polycystic Ovary Syndrome (PCOS) through the use of ovarian ultrasound images is created. In this study, the proposed architecture used MobileNetV2 as its base model, incorporating Residual blocks, SE Attention, and Spatial Attention techniques to extract features better. The model was highly accurate, demonstrating strong results in its accuracy, precision, recall, and F1-Score. The model displayed its capability to classify PCOS and non-PCOS images accurately.

The proposed architecture also proved to outperform other existing deep learning architectures such as MobileNetV2, ResNet50, EfficientNet, and VGG16. The use of techniques such as transfer learning, residual learning and attention was key in directing the attention of the algorithm to the essential features of the ovaries and in enabling the detection of patterns associated with PCOS. As the previously created machine learning clinical model and the novel ultrasound deep learning model performed well, another multi-modal decision-level fusion approach was designed using both the clinical and ultrasound models.

A web application was developed to predict PCOS in real time using clinical data and ultrasound images. The proposed framework provides a simple yet effective interface for smart detection of PCOS and healthcare services. Promising results were obtained using the proposed system, however, future improvements may include using bigger and diversified datasets, improving model explainability, and utilising cloud infrastructure for implementation.

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