LiteSkipNet-1.0: A Novel Architecture for Early Detection of Polycystic Ovary Syndrome

Abstract— **Polycystic Ovary Syndrome (PCOS) is one of the most prevalent endocrine anomalies among women. It is a major cause of infertility in females; primarily due to anovulation, where the ovary fails to release the egg regularly. Although ultrasound imaging is a frequently used method for PCOS detection, the effectiveness of its results depends on expert knowledge, leading to inconsistency in results. This study proposes a novel lightweight Convolutional Neural Network (CNN)-based architecture specifically designed for automatic PCOS detection using ultrasound images of the ovary. In contrast to traditional approaches that depend on large pre-trained models such as MobileNetV2, DenseNet121, and ResNet50, the suggested architecture achieved superior performance with fewer parameters. The experimental outcomes indicate that the suggested CNN model achieved a superior accuracy of 97%, outperforming existing pre-trained models while maintaining computational efficiency. These results highlight the proposed approach's potential as a reliable and scalable diagnostic tool, reducing dependency on expert interpretation and enabling deployment in resource-limited environments. This study aimed to offer a promising solution for healthcare professionals and fertility experts to enhance early identification and intervention for PCOS**.

1. Introduction:

Polycystic Ovary Syndrome (PCOS) is one of the most significant hormonal disorders affecting women, especially in their reproductive years. Around 12%-21% of women worldwide in their pre-menopausal stage are impacted by PCOS [1]. PCOS patients face challenging indications such as absent or irregular menstrual periods, elevated androgen levels, and the production of various small cysts within the ovaries. PCOS is the primary contributor to infertility among women and is associated with numerous metabolic and psychological disorders [2]. Infertility can arise from various causes, including the abnormal increase in the number and size of follicles during the ovulation phase, which is often recognized as an early sign of PCOS [3]. The production of multiple cysts leads to infertility in about 70% of affected women [4]. PCOS patients often have to deal with thyroid problems, severe hair fall, type 2 diabetes, acne, thyroid issues, rapid weight gain, depression, excessive hair growth on the body, and sexual dissatisfaction [5][6]. These physical issues impact the quality of life, making routine work more challenging for the patients [7]. More importantly, such women are most likely to suffer from insulin resistance and are thus at a high risk of developing cardiovascular diseases [8]. Recent research studies also indicate that PCOS is one of the major causes of ovarian cancer [9]. Since the development of PCOS is associated with genetics and geographic locations, other factors like infections and unhealthy nutrition also complicate the situation [10].

Several traditional approaches such as hormonal tests, clinical examination, and ultrasound imaging can be implemented to diagnose PCOS [11]. Among these approaches, one of the most effective and reliable methods for detecting PCOS is ultrasound scanning [12]. The e proficiency of healthcare professionals in interpreting the results plays a critical. However, due to the shortage of radiologists in least-developed countries, many women with PCOS remain undiagnosed and untreated [13]. Additionally, the medical interpretation could be complicated and time-consuming due to significant image noise, leading to a less accurate diagnosis [14]. This justifies the urgent need for trustworthy and effective diagnostic tools that provide clinical experts with the assistance they need to identify several disorders. The advancements in the field of machine learning and deep learning have produced remarkable improvements in medical imaging. These techniques have improved image analysis, resulting in enhanced accuracy and reliability in healthcare. Deep learning methods are most widely used in healthcare, specifically for disease diagnosis [15]. Among these methods, CNNs are most widely used for image classification and segmentation due to their ability to efficiently diagnose several diseases [16].

- **Research Objectives**

This research proposes a novel CNN-based deep learning framework for the detection of PCOS by using ultrasound images of the ovaries. The proposed approach has the following objectives:

- Enhance the diagnostic accuracy of PCOS detection through a lightweight and efficient model designed to leverage domain-specific features.
- Minimize computational requirements, enabling deployment in resource-constrained environments such as clinics and mobile platforms.

By fulfilling these objectives, this research can potentially lead to early diagnosis of PCOS, ultimately enhancing the quality of life for affected women.

To establish a performance benchmark and facilitate a comparison with the proposed custom architecture, this study first implemented three pre-trained models—MobileNetV2, DenseNet121, and ResNet50—on a dataset specific to PCOS detection. These models were chosen for their effectiveness in a wide range of image classification tasks, allowing for the application of transfer learning to optimize accuracy. The results obtained from these pre-trained models provided critical insights into the strengths and limitations of existing architectures for PCOS detection. Subsequently, the proposed CNN model was developed to address the identified challenges, introducing novel features and optimizations specifically tailored to the nuances of PCOS diagnosis.

This study is organized as follows: The "Related Work" section reviews the previously employed techniques for PCOS detection, and the methodology adopted for implementing pre-trained models proposed model for PCOS detection is discussed in the "Methods and Materials" section; "Results and Discussion" section represents results analysis with comparative findings and discussion; finally, "Conclusion" section includes the summary of the key findings leading to conclude the research with future directions.

2. Related Work:

Physicians most frequently diagnose PCOS by analyzing ultrasound images of the ovaries, looking for the presence of multiple follicular cysts to confirm the condition [17]. Researchers have been developing computer-assisted techniques for identifying follicles and diagnosing PCOS. These methods offer significant benefits, including faster image processing, reduced diagnostic errors, and less reliance on human interpretation.

Many researchers focused on developing machine learning models that employ image processing methods to identify and classify follicles as either damaged or undamaged. Gopalakrishnan et al.[18] applied various image processing techniques such as noise reduction, thresholding, Canny edge detection, and image enhancement to detect follicles in images. The Scale-Invariant Feature Transform Method was employed for feature extraction and then these features were utilized in classification tasks through machine learning algorithms like Support Vector Machine (SVM), Naive Bayes (NB), and decision trees. Their findings indicated that SVM gained the highest accuracy of 94.40%. Deepika et al [19] used various machine learning methods to identify PCOS from ultrasound images. The approach started with highlighting follicle details through image preprocessing. Techniques including histogram equalization, and binarization were used to improve the visibility of these images. Then, machine learning algorithms such as NN-LVQ, K-Nearest Neighbour (KNN) using Euclidean distance, and SVM with an RBF kernel were applied for classification. The SVM-RBF kernel delivered the best results, achieving 82% accuracy. Inan et al.[20] first employed Square methods for selecting the features and then tested these features with certain machine learning algorithms, including Random Forest (RF), KNN, NB, SVM, Adaptive Boosting, XGBoost, Ensemble, and Multi-Layer Perceptron. The results showed that XGBoost was the leading performer, achieving an accuracy of 95.83%. Makhdoomi et al.[21] explored various Machine learning techniques for the detection of PCOS through ultrasound images. They implemented algorithms such as KNN, RF, and CNN, alongside segmentation methods like Ostu threshholding and feature extraction techniques such as Gabor wavelet analysis. They claimed to achieve the highest accuracy of 97% among these methods. Dutta et al.[22] utilized the Synthetic Minority Oversampling Technique (SMOTE) and five ML techniques, namely logistic regression (LR), RF, Decision Tree (DT), SVM, and KNN, to automate PCOS detection. They claimed that the proposed LR beat other algorithms in terms of critically classifying datasets. Bhardwaj et al.[23] utilized Pearson correlation to get the most significant features and implemented various algorithms like multi-layer perceptron, SVM, XG boost, and RF classifier for optimization of the model. They achieved an accuracy level of 93% with an SVM model. Hassan et al. [24] investigated several machine learning algorithms, including NB, SVM, Classification and Regression Trees (CART), and LR, for classifying PCOS datasets. Their results highlighted that RF achieved the best accuracy at 96%.

Deep learning techniques have become well-known in medical imaging for their high accuracy and efficiency in detecting and interpreting complex data. They offer significant advantages over traditional machine learning methods by eliminating the need for manual image processing and feature extraction [25]. Cahyono et al.[26] developed a six-layer CNN model for classifying PCOS and non-PCOS images, automating feature extraction. They achieved their best F1-Score of 76.36% after experimenting with different dropout rates, learning rates, and the softmax activation function. Vikas et al.[27] created a deep learning method using a three-layer CNN architecture, enhancing the model's performance through data augmentation. Their highest accuracy was achieved with the VGG16 model, which was fine-tuned for specific tasks through transfer learning. Dewi et al.[28] outlined a system to detect PCOS by including the Gabor Wavelet strategy (GWS) to extract features] and CNN for classification. Initially, the images were preprocessed by utilizing various methods that include data cleaning, morphology, image binarization, gray-scaling, inverted images, etc. After that, segmentation was carried out to partition the data into meaningful sections for further analysis. Then, GWS was implemented for feature extraction, and lastly, CNN was applied. CNN obtained an optimized accuracy of 80.84%. Bhosale et al.[29] proposed a method for detecting PCOS utilizing an LLR classifier. Their approach focuses on the automated quality assessment of PCOS data through a Deep Convolutional Neural Network (DCCN). Additionally, they introduced a deep learning framework that, in conjunction with the Inception model, achieved an accuracy of 84.81% in identifying PCOM from ultrasound images. Alamoudi et al.[30] proposed a novel deep learning fusion approach aimed at improving the diagnostic accuracy of PCOS. They integrated ultrasound imaging with clinical features and implemented CNN architecture, including VGG19, MobileNet, and InceptionV3, for feature extraction from images. They presented that combined features from both clinical and imaging data significantly enhance diagnostic accuracy, achieving an accuracy of 92%. Sayma et al.[31] employed a hybrid approach, combining deep learning with ensemble stacking machine learning models. In their method, feature extraction from ultrasound images was done by using deep learning techniques, then these features were fed into the ensemble stacking models for classification. Sumathi et al.[32] applied detailed image enhancement and segmentation techniques followed by feature extraction using the Gray Level Co-Occurrence Matrix (GLCM). For classification, they utilized multiple algorithms, including Support Vector Machine (SVM), DarkNet-19, AlexNet, and SqueezeNet, to gain optimal accuracy.

3. Methods and Materials:

This section explains the methodology adopted for the implementation of three pre-trained deep learning models along with our proposed CNN model. Firstly, models including MobileNetV2, DenseNet121, and ResNet50 were employed for efficient PCOS detection using ultrasound ovarian images. The approach consists of four steps: I) dataset collection and preprocessing, II) designing model architecture, III) proposed model, and IV) performance analysis. The architecture of these models is shown in Figure 1. The approach began with the collection and pre-processing of the dataset. The dataset went through extensive pre-processing to make it thoroughly ready for the training. Three pre-trained models namely MobileNetV2, DenseNet121, and ResNet50 were selected based on their architecture to execute on the clean dataset. These models were fine-tuned to maximize the accuracy and efficiency in detecting the disease. The activities performed in each step are explained below.

I. Dataset collection and Preprocessing:

This study utilizes ovarian ultrasound images obtained from Figshare's repository. This dataset was specifically created to support research for developing automated PCOS detection models. There were 5,000 images in the dataset, with 2,858 labeled as PCOS and 2,142 labeled as non-PCOS. An image-preprocessing approach was implemented to initially clean the dataset. Python packages such as OS and PILLOW were used for thorough cleaning, effectively identifying and removing corrupt files from the dataset to ensure data integrity. The images were resized to 224x224 pixels to match the input size required by DenseNet121 and MobileNetV2. Data augmentation techniques, including width and height shifts (up to 20%), geometric transformations like rotations (up to 40 degrees), zoom (0.2), shear (0.2), and horizontal flipping, were employed to enhance data variability and reduce overfitting. For the evaluation of the model performance, the dataset was split into an 80:20 ratio, where 80% of the data was used for training the model and the remaining 20% for testing purposes.

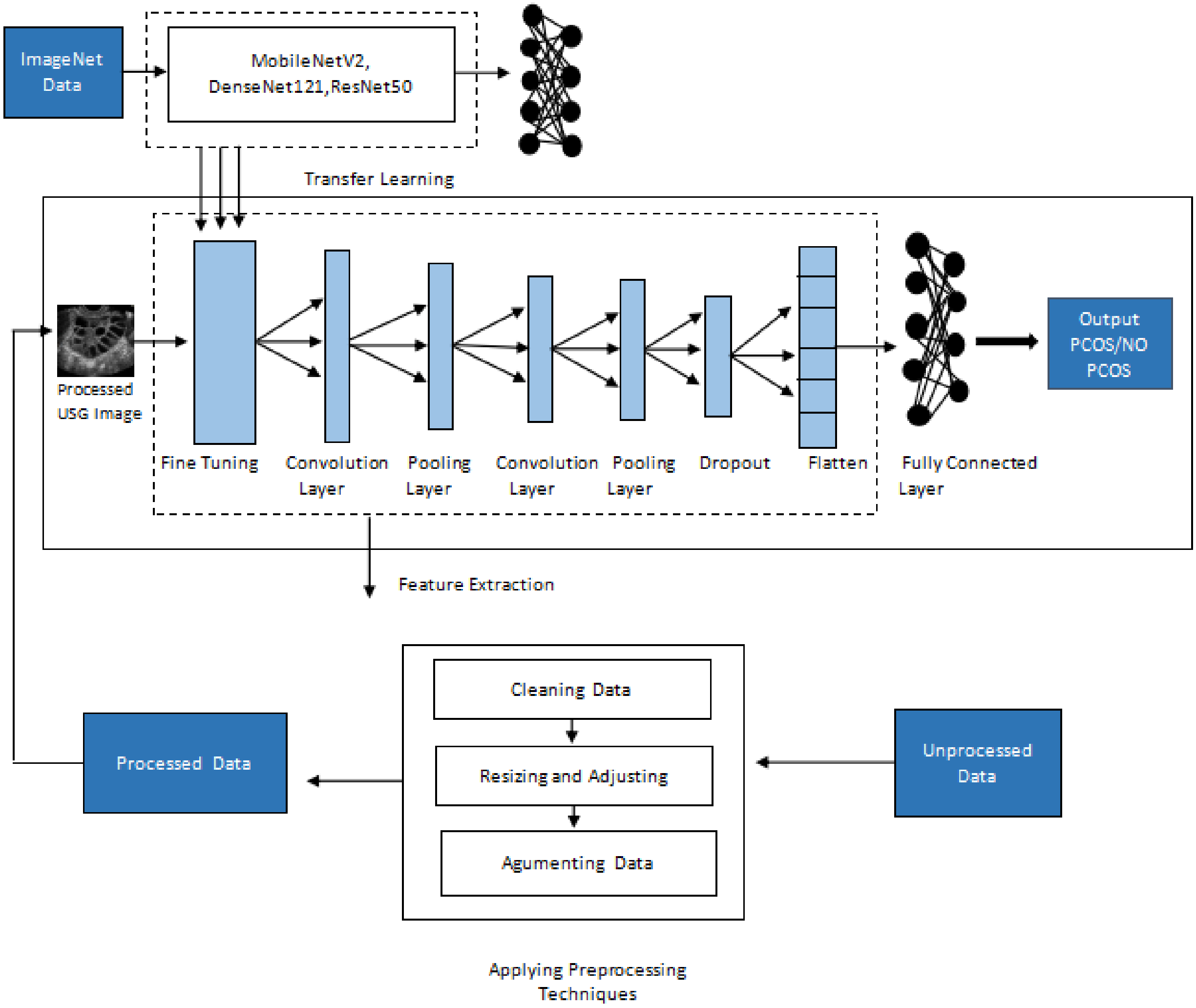


Figure 1: Architecture of Implemented Pre-trained Models

II. Designing model Architecture:

After applying data preprocessing techniques, a CNN-based architecture was utilized for the classification task. Specifically, three pre-trained models were implemented, namely MobileNetv2, DenseNet12, and ResNet50. All these models were significantly fine-tuned to adjust pre-trained weights to enhance the model's performance. This approach leveraged the strengths of each model while maintaining consistency.

The architecture of the CNN models used in this study is shown in Figure 1. In this architecture, a structured sequence of layers including convolution layers, pooling layers, dropout layer, and flattening layer is used to extract essential features from images. These layers convert the raw ultrasound images into meaningful features, which are crucial for facilitating the model to differentiate between PCOS and non-PCOS cases. The extracted features consist of the crucial patterns and characteristics of the images, which are then used in the classification step for precise predictions. The summary of each layer is given as follows:

- **Fine Tuning Layer:**

This is the first layer of this architecture that implements transfer learning with fine-tuning, a process that increases performance on target domains by leveraging pre-trained models. This research implemented MobileNetV2 and DenseNet121, eliminating their fully connected layers for transfer learning. Certain layers in each model were unfrozen to optimize their performance on the dataset. A description of pre-trained models is given in Table 1.

Table 1: Description of Pre-trained Models

Model	Layers	Parameters (million)	Accuracy %
MobileNetV2	53	3.4	90.1 on ImageNet Data [33].
DenseNet121	121	8.1	92.3 on ImageNet Data [34].
ResNet50	50	25.6	92.1 on ImageNet Data [35]

- **Convolution layer**:

This layer is a key component of CNNs, containing a set of filters that are typically smaller than the input image. These filters slide across the images to detect patterns such as textures, edges, and shapes that are recognized by the convolution layer. In this CNN architecture, the padding was set to same, uniformly pads the input images with zeros to maintain consistent output size with zeros. The stride of 1 was utilized to ensure output dimensions match the input. To determine the probability of the classification result, the sigmoid activation function was utilized, producing a result between 0 and 1.

- **Pooling Layer:**

This layer reduces the image's spatial dimensions while keeping critical information. Computational requirements of the neural network are minimized by reducing the parameters. A max-pooling operation was applied to select the maximum value from the 4x4 region of the feature space.

- **Dropout Layer:**

This layer aims to combat overfitting while accelerating the training process. It is accomplished by selectively setting a portion of input values to 0 during each training step, using a consistent dropout rate. This CNN model utilizes a dropout rate of 0.7 to guard against overfitting.

- **Flatten Layer:**

This layer converts the multi-dimensional array into a single one-dimensional array. This dimensional array represents the most important and condensed set of features obtained from the input images. This array serves as the input layer of the classification neural network, where each element is sent to an individual neuron.

- **Fully Connect Layer:**

The fully connected layer serves as the final layer in the CNN architecture and acts as the classifier for this approach. This layer functions as a feed-forward artificial neural network. Every neuron within this layer is connected to all neurons from the previous layer, resembling the traditional multi-layer perceptron neural network. This layer combines and interprets the high-level features extracted by the pooling layers and merges them into a feature vector. Subsequently, the Fully Connected Layer processes this vector to generate the ultimate classification output, utilizing activation functions to convert the outcomes into probabilities for decision-making.

- **Parameters:**

The CNN model employed binary cross-entropy as the loss function and the 'Adam' optimizer, with 'accuracy' as the primary evaluation metric. Careful tuning of hyperparameters such as learning rate, regularization (L1 or L2), number of layers, batch size, and number of epochs was performed to enhance model performance. The model was trained for 10 epochs on classification tasks, with validation data used to monitor accuracy. Then, 349 test images were used to evaluate the model's predictive accuracy.

III. Proposed Model

By evaluating various pre-trained models and their performance on the PCOS dataset, certain limitations and areas for improvement in the context of PCOS diagnosis were identified. While the pre-trained models achieved considerable accuracy, their performance was restricted by the generalized nature of their architectures, which were not specifically designed for the unique features and issues associated with PCOS data. To address these limitations, a custom deep learning architecture was developed from scratch using Py Torch. The proposed model optimized feature extraction and classification by integrating domain-relevant insights and addressing data-specific features.

- **Network Architecture**

The proposed architecture is developed to analyze PCOS ultrasound images with a primary focus on extracting critical features for accurate diagnosis. The architecture is optimized to capture multi-level feature representations, facilitating the identification of refined and complex features related to PCOS. A series of convolutional transitions, augmented by residual connections facilitate gradient flow and ensure stable training. The architecture and workflow of the proposed model are presented in the block diagram shown in Figure 2. This diagram provides a detailed visualization of the major components and operational flow within the architecture.

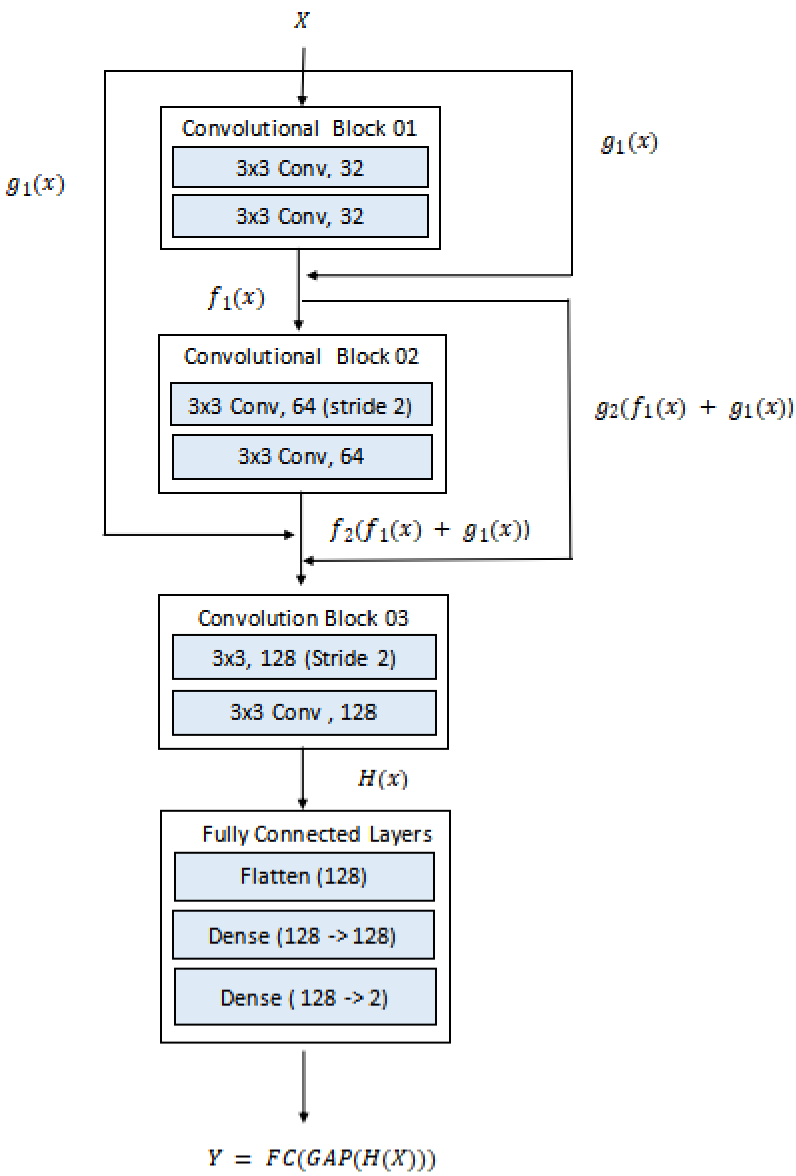


Figure 2: Proposed CNN Architecture

Let X denote the input feature map. The architecture is made up of three convolutional blocks, with each block applying a series of 3×3 convolutions, batch normalization (BN), and ReLU activations. In the first block, X passes through two consecutive 3×3 convolutions, both employing 32 filters, leading to an intermediate feature map. $f_1(X)$. To retain critical information and enable gradient flow, a skip connection $g_1(X)$ Is integrated. This skip connection takes the original input X and combines it with the output of the first block, helping to preserve crucial features from previous layers for further processing.

The second convolutional block performs downsampling through a stride-2, combined with a 3×3 convolution, which reduces the feature map dimensions while preserving essential details. After that, another 3×3 convolution utilizing 64 filters further enhances the extracted features and generates the subsequent feature map, $f_2(f_1(X) + g_1(X))$. This output is further improved through an additional skip connection, $g_2(f_1(X) + g_1(X))$, which helps to capture the complex features while preserving residual links. By maintaining these residual connections, the model ensures that critical information flows smoothly throughout the layers, optimizing the network's ability to learn efficiently. The model achieves an optimal balance between network depth and gradient flow through the combining effect of the residual pathways, enabling efficient feature learning at various scales.

In the third convolutional block, a down-sampling operation is applied using a 3×3 convolution with 128 filters. This further decreases the dimensional size while capturing more complicated patterns. This segment produces the final deep feature representation, $H(X)$, which holds essential high-level information critical for PCOS detection.

The output, $H(X)$, is sent to a Global Average Pooling (GAP) layer, which groups these features into a concise and compact format. This compressed representation is then fed into fully connected (FC) layers, allowing for task-specific training. The fully connected sections contain three dense layers, with each layer having 128 neurons. These layers include dropout layers and ReLU activations to generate the final prediction. This final step maps the extracted features to the final classification decision. The final prediction Y is obtained through:

$$Y = FC(GAP(H(X))) \qquad \text{Eq (1)}$$

The overall architecture with skip connections is represented in Eq 2:

$$H(X) = f_3(f_2(f_1(X) + g_1(X)) + g_2(f_1(X) + g_1(X) + g_1(X)) \qquad \text{Eq (2)}$$

Here:

- $f_k(X)$: The transformation in the k-th convolutional block.
- $g_k(X)$: The skip connections are added at each stage using 1 ×1 convolutions or identity mappings.
- $H(X)$: The final feature representation after passing through all convolutional blocks and skip connections.

Table 2 provides a detailed model summary of this proposed CNN architecture implemented for PCOS detection.

Table 2: Model Summary

Layer	Configuration	Output Shape
Input Layer	Input Image	(3, 128, 128)
Convolutional Block 1	3×3 Conv, 32 → ReLU → BN (×2)	(32, 128, 128)
Residual Connection 1	1×1 Conv, 3 → 32	(32, 128, 128)
Convolutional Block 2	3×3 Conv, 64 (stride=2) → ReLU → BN (×2)	(64, 64, 64)
Residual Connection 2	Identity Shortcut	(64, 64, 64)
Feature Combination	Element-wise Addition of Block	(64, 64, 64)

Convolutional Block 3	3×3 Conv,128 Filters(Stride=2)→ ReLU→ BN(×2)	(128, 32, 32)
Global Average Pooling	Adaptive Average Pooling(Output Size:1×1)	(128, 1, 1)
Flatten	Flattening Operations	(128)
Fully Connected Layer	Dense Layer (128 Units)→ ReLU→ Dropout(p=0.4)	(128)
Output Layer	Dense Layer (2 Units, Final Classification)	(2)

Table 2: Model Summary

The pseudocode of the proposed technique for PCOS detection has been shown in Algorithm.

- **Algorithm:** *Proposed CNN-Based Model for PCOS Detection*

Input:

- **USG img**: *Ovarian USG Images*

Output:

- *List res: PCOS Detected (1), PCOS Not-Detected (0)*

Steps:
1: ***for all*** *i ∈ USG img* ***do***
2: Preprocess i: Resize the input image to 128×128 and normalize pixel values.
3: Pass i through the Purposed CNN Architecture:
 a) *Conv Block 1: Two 3×3 convolutions utilizing 32 filters and skip connection.*
 b) *Conv Block 2: Downsampling using 3×3 convolutions with 64 filters and residual connection*
 c) *Conv Block 3: Further downsampling with 3×3 convolutions and 128 filters.*
4: Aggregate features using Global Average Pooling.
5: Pass the features through Dense Layers with ReLU activations and dropout regularization.
6: Compile the model with Adam optimizer, binary cross-entropy loss, and accuracy as the evaluation metric.
7: Obtain the final prediction using the Output Layer with sigmoid activation.
8: Store the result in res[i].
9: ***end for***
10: ***return*** *res*

1V. Performance analysis:

We evaluate the performance of each predictive model on the test data using various measures such as accuracy, precision, recall(sensitivity), specificity, and score. Other performance metrics are primarily derived by comparing the predicted values with the actual values in the training dataset. These metrics can be categorized into four distinct groups: True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN). These performance measures are mathematically represented in Eq 3-6.

$$\text{Accuracy} = \frac{(TP + TN)}{(TP + TN + FP + FN} \qquad \text{Eq (3)}$$

$$\text{Recall (R)} = \frac{(TP)}{(TP + FN)} \qquad \text{Eq (4)}$$

$$\text{Precision (P)} = \frac{(TP)}{(TP + FP)} \qquad \text{Eq (5)}$$

$$\text{F1 Score} = \frac{2 * (P * R)}{(P + R)} \qquad \text{Eq (6)}$$

4. Results and Discussion:

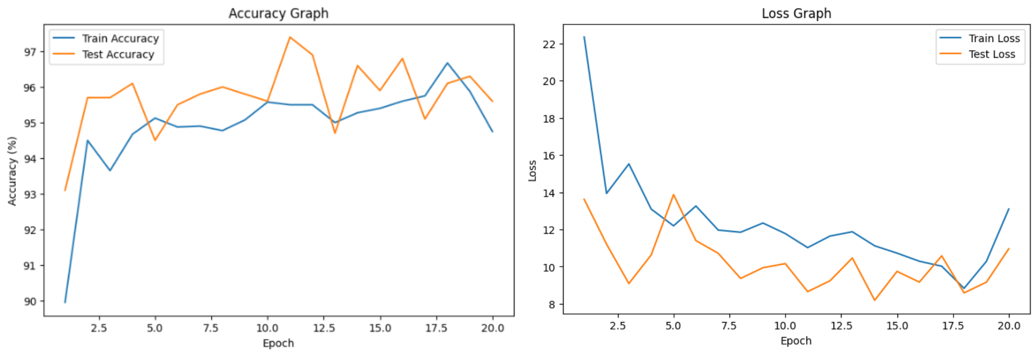
This section presents an analysis of four CNN-based models for the detection of PCOS. The first three models—MobileNetV2, DenseNet121, and ResNet50—used transfer learning by implementing pre-trained weights to improve feature extraction and classification performance. The fourth model, a custom CNN architecture, was trained from scratch to address the unique features of the PCOS dataset. The performance of all four models, including metrics like accuracy, precision, recall, and F1-score, is summarized in Table 3. This analysis highlights the comparative performance of the pre-trained and custom models in diagnosing PCOS.

DenseNet121 and ResNet50, the pre-trained models, achieved an impressive accuracy of 96%, showing their strong ability to extract features from ultrasound images for PCOS diagnosis. Both models showed reliable performance in both precision and recall, with values of 95% and 96% respectively. This emphasizes that they correctly recognize positive cases (recall) and accurately predict the occurrence of PCOS (precision) from the images. In comparison, MobileNetV2 showed a slightly lower accuracy of 95%. However, it sustained competitive performance with a precision of 95% and a recall of 94%, illustrating that although it was slightly less effective in accurately identifying PCOS, it still produced reliable outcomes for positive and negative cases. Notably, the suggested model surpassed all these pre-trained models, attaining an accuracy of 97%. It also showed superior metrics, with a precision of 97%, an F1-score of 97%, and a recall of 96%. These observations demonstrate the model's ability to capture key features relevant to PCOS detection, highlighting its improved precision in classifying ultrasound images. The proposed model's ability to outperform the larger pre-trained models highlights its capability to address the challenges of PCOS diagnosis.

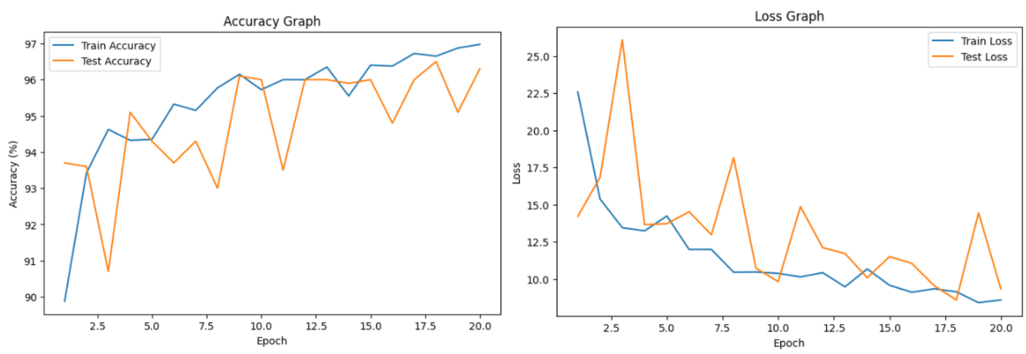
Table 3: Performance Analysis of Deep Learning Models

Deep Learning Models	Accuracy	Precision	Recall	F1-Score
CNN with MobileNetv2	0.95	0.95	0.94	0.95
CNN with DenseNet121	0.96	0.96	0.95	0.96
CNN with Resnet50	0.96	0.95	0.95	0.96
Proposed Model	0.97	0.97	0.96	0.97

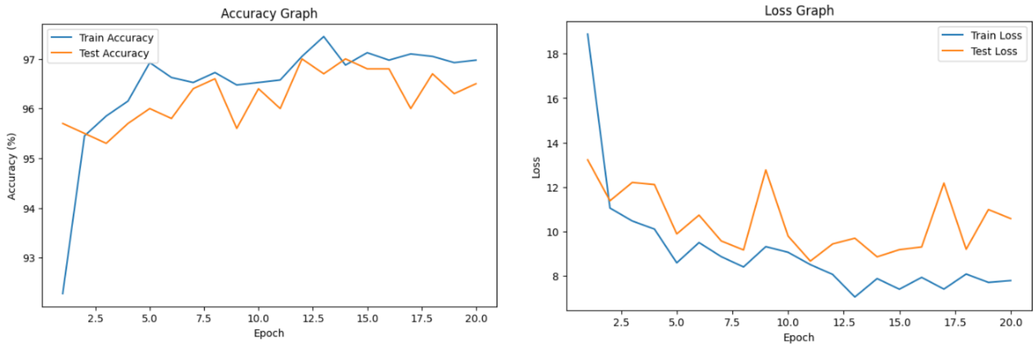
The trends of accuracy and loss for MobileNetV2, DenseNet121, ResNet50, and the proposed model over 20 epochs can be seen in Figure 4 respectively. These graphs demonstrate a clear picture of how each model learns and generalizes. In the case of MobileNetV2, the training accuracy gradually increased, reaching a maximum of 95% by the 17th epoch, accompanied by a drop in training loss. However, the testing accuracy ceased to improve and stayed below the training curve, showing minor overfitting, as seen from the elevated testing loss. DenseNet121 and ResNet50 showed similar patterns, attaining their highest accuracies of 96% around the 15th epoch. Both models maintained consistent training and testing loss curves, which highlights their stability during training. The proposed CNN model demonstrated a learning trend, achieving the highest accuracy of 97% by the 18th epoch, exceeding all previously trained models. Its loss graph indicated a notable reduction in training loss during the early epochs and sustained a lower testing loss throughout, indicating strong and efficient optimization. These findings illustrate the strength of the proposed CNN model, showcasing its superior performance with reduced overfitting compared to the pre-trained models.



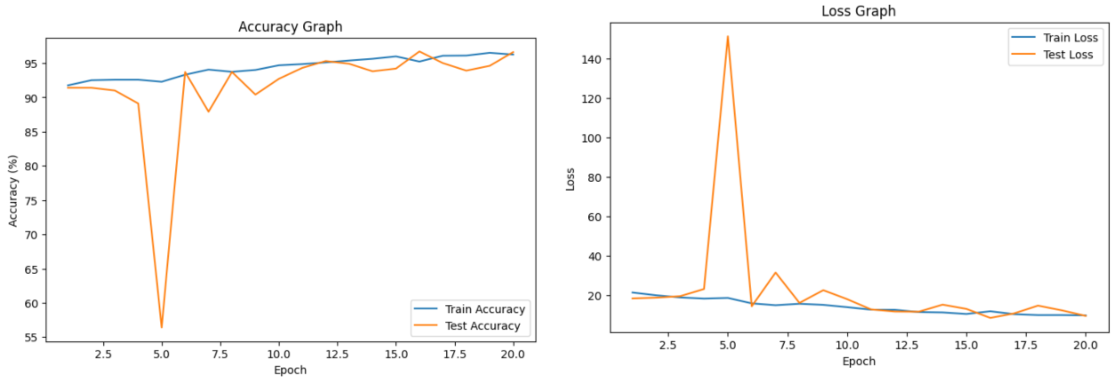
(a) CNN with MobileNetV2



(b) CNN with DenseNet121



(c) CNN with ResNet50



(d) Proposed Model

Figure 4: Accuracy and loss per epoch for implemented models (a) CNN with MobileNetV2 (b) CNN with DenseNet121 (c) CNN with ResNet50 (d) Proposed Model.

The suggested model represents significant progress in achieving a balance between performance and computational efficiency, particularly for PCOS detection tasks. In contrast to conventional deep learning networks, such as ResNet50, which mainly rely on local residual connections within single convolutional layers, our proposed design features a novel skip connection that extends across several stages of the network. This novel multi-step skip connection improves gradient flow, encourages better feature reuse, and facilitates efficient multi-scale feature integration**.** In terms of accuracy, our proposed model surpassed well-known pre-trained models, including MobileNetV2, DenseNet121, and ResNet50, in PCOS detection tasks. The added skip connection not only helps the model learn features more effectively across different stages but also allows it to maintain high performance across various scales without unnecessary repetition.

The importance of the proposed approach can be determined by comparing it with other models. Models like ResNet50 achieve high accuracy by utilizing a vast number of parameters (around 25 million), while the proposed architecture delivers optimal accuracy with only 300k parameters. This decrease in parameters not only lightens the architecture but also enhances its adaptability for use in resource-limited settings, such as mobile devices and edge platforms, where computational efficiency is critical. The enhanced capacity of the proposed model to achieve high performance with fewer parameters illustrates its capability to maintain a balance between accuracy and efficiency when compared to traditional deep learning models. The findings suggest that the proposed approach is not only appropriate for tasks that demand high accuracy but is also optimized for real-world use, making it a practical and effective solution for medical image analysis in everyday applications.

5. Conclusion and Future Work:

This study presented a compact CNN architecture designed for PCOS diagnosis using ovarian ultrasound images. The proposed framework showed better performance against pre-trained CNN models using fewer parameters to produce efficient and accurate results. The compact design together with skip connections enables the model to identify features at various scales so patients receive precise reliable diagnostic results. This work marks a considerable improvement in detecting PCOS, offering an optimized solution that balances performance and usability. By decreasing dependence on expert interpretation, the model can change diagnostic workflows and find wide applicability in real-world clinical settings, ultimately improving care for women affected by PCOS.

By integrating explainability techniques, such as saliency maps or attention mechanisms, the suggested model could be improved in the future. These methods would highlight affected areas in ultrasound images that facilitate the model's predictions, enhancing the transparency of the diagnosis process, and thus making it easier for healthcare professionals to trust. This approach can establish a connection between automated detection and clinical decision-making, offering a tool that not only produces accurate results but also clarifies its rationale. By combining accuracy with interpretability, the proposed model could become a valuable asset in clinical practice, helping to improve the diagnostic process and building greater trust in AI-based healthcare solutions.

Code Availability :

The code, implementation details, training scripts, and assessment metrics for the presented PCOS detection model can be accessed through the following link.
https://github.com/xajeel/lite-skip-bridgeNet
This repository also includes a link to the dataset used in this study, along with guidelines for downloading and preprocessing the data. Developers and researchers can get these resources to replicate the results or extend the work further.

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