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THE PATHOGENESIS OF POLYCYSTIC OVARY SYNDROME (PCOS): THE HYPOTHESIS OF FUNCTIONAL OVARIAN HYPERANDROGENISM REVISITED

Tahreem Razzaq
Department of Computer Science &Information Technology, Superior University, Sargodha, Pakistan
Muhammad Arif
Department of CS&IT, The Superior University, Sargodha, Pakistan
Saleem Zubair Ahmad
Department of Software Engineering, Superior University, Lahore, Pakistan
Hamza Shabbir
Department of Computer Science and Information Technology, Superior University, Lahore, Pakistan

Abstract
Polycystic ovary syndrome (PCOS) is one of the most common endocrine illnesses, affecting millions of women worldwide and having a substantial influence on their reproductive, metabolic, and psychological health. It is distinguished by hormonal imbalances, irregular menstrual cycles, and the presence of cysts in the ovaries, which frequently lead to infertility and increased risk of comorbidities such as diabetes, obesity, and cardiovascular disease. Early identification of PCOS is crucial for reducing these health risks, since prompt interventions and specialised therapies can considerably improve patient outcomes. Traditional diagnostic approaches, such as physical exams, ultrasound imaging, and hormonal assessments, are frequently time-consuming, subjective, and prone to discrepancies owing to differences in competence and equipment quality. This paper presents a unique technique to PCOS identification based on an upgraded VGG16 deep learning model designed exclusively for medical imaging data. The study's dataset consists of 11,784 photos, 6,784 of which are infected and 5,000 of which are uninfected, rigorously classified into two categories. The dataset was divided into training and testing subsets at an 80:20 ratio to guarantee complete examination, yielding 9,428 pictures for training and 2,356 for testing. The model trained for ten epochs and produced impressive performance measures. Both training and validation accuracy exceeded 98%, confirming the model's capacity to generalise successfully across the dataset. The classification report confirms the model's remarkable performance, with accuracy, recall, and F1-scores averaging 0.99 across both classes. The infected and non-infected classes each had an accuracy of 0.99, a recall of 0.99, and an F1-score of 0.99. The macro and weighted averages hit 0.99, demonstrating the model's resilience and reliability in identifying medical imaging data. These findings highlight the ability of deep learning models to outperform standard diagnostic approaches by producing consistent, objective, and highly accurate outcomes. This study emphasises artificial intelligence's transformational potential in healthcare, particularly in tackling diagnostic issues related to PCOS. By combining an upgraded VGG16 architecture with bespoke layers, the suggested model creates a non-invasive and efficient diagnostic tool that may drastically reduce diagnostic delays and assist medical professionals in decision-making. The model's high accuracy and dependability make it ideal for real-world clinical applications, opening the path for better patient outcomes and healthcare delivery systems worldwide. This study emphasises the need of using AI technology to enhance diagnostic processes, resulting in earlier identification, better treatment planning, and, ultimately, superior quality care for women with PCOS.
Keywords: *Polycystic Ovarian Syndrome (PCOS) Prediction, Deep Learning, Convolutional Neural Networks (CNNS), Ultraasound Image Processing, Diagnostic Tool*

INTRODUCTION

Polycystic Ovary Syndrome (PCOS) is a common endocrine disorder affecting women of reproductive age, with a prevalence ranging from 4% to 20%, depending on diagnostic criteria and study populations. It is a complex condition characterized by hyperandrogenism, ovulatory dysfunction, and polycystic ovarian morphology. Beyond its impact on reproductive health, PCOS is associated with significant metabolic complications, including insulin resistance, obesity, and an increased risk of type 2 diabetes and cardiovascular diseases. Moreover, PCOS can lead to psychological challenges, such as anxiety, depression, and reduced quality of life, making it a multifaceted condition that requires comprehensive management. Despite its high prevalence and associated health risks, diagnosing PCOS remains a challenge. The heterogeneous presentation of symptoms, ranging from menstrual irregularities to biochemical and clinical hyperandrogenism, complicates accurate diagnosis. Conventional diagnostic methods, including ultrasonography and biochemical testing, often lack consistency and are prone to interpretative variability. This creates a critical need for advanced diagnostic tools to address these challenges and improve early detection. In recent years, artificial intelligence (AI) has demonstrated significant potential in transforming healthcare, particularly through the use of machine learning and deep learning for medical image analysis. Convolutional Neural Networks (CNNs), a type of deep learning architecture, have shown remarkable success in tasks such as image classification and feature extraction, making them well-suited for analyzing medical imaging data. This study proposes an AI-driven solution for the automated detection of PCOS using an enhanced VGG16-based CNN model. By leveraging the capabilities of deep learning, the study aims to improve diagnostic accuracy, reduce manual interpretation effort, and standardize assessments, ultimately contributing to better clinical outcomes and patient care.

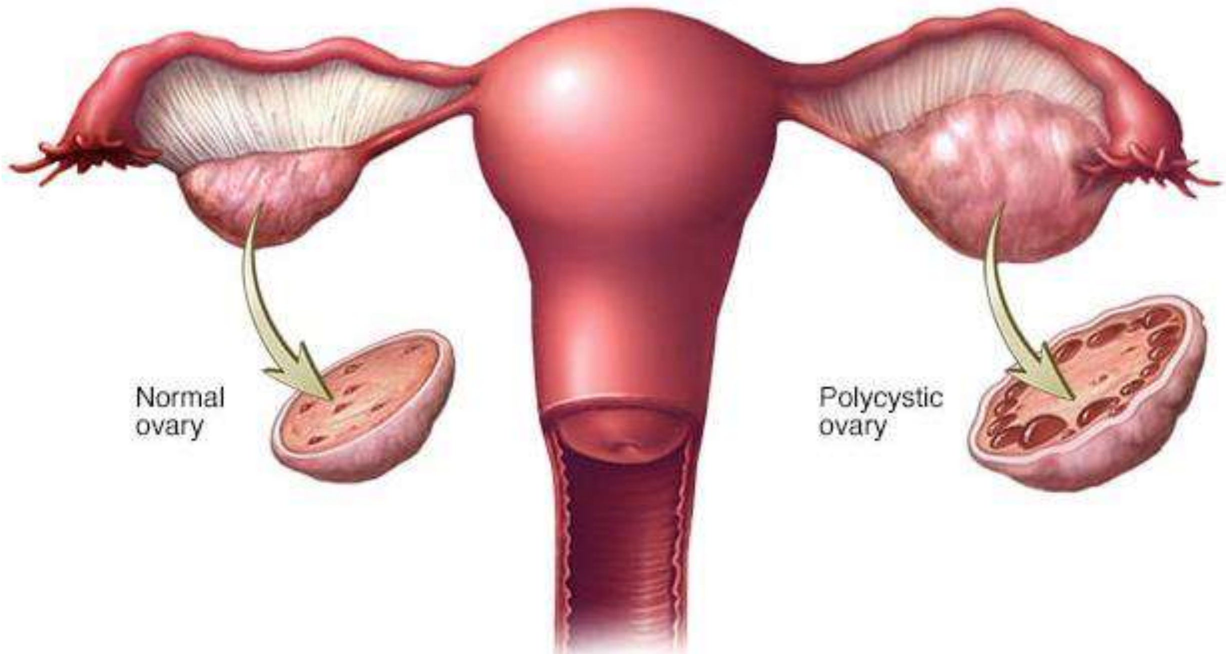

Figure 1: An illustrative example of PCOS

Background

Polycystic Ovary Syndrome (PCOS) is one of the most prevalent endocrine disorders affecting women of reproductive age. Its prevalence varies significantly, ranging from 4% to 20%, depending on the diagnostic criteria used and the study population examined [1]. Characterized by a triad of symptoms—hyperandrogenism (excessive levels of male hormones), ovulatory dysfunction, and polycystic ovarian morphology (the presence of multiple small cysts in the ovaries)—PCOS is not just a reproductive health issue but a multifaceted condition that impacts several aspects of a woman's physical, metabolic, and mental health. These manifestations result in significant complications, including but not limited to infertility, insulin resistance, type 2 diabetes mellitus, obesity, and cardiovascular diseases [2]. Furthermore, PCOS is often accompanied by psychological challenges such as anxiety, depression, and body image issues, which collectively diminish the quality of life of affected individuals [3].

Despite its widespread prevalence and the severe health consequences it entails, PCOS remains one of the most underdiagnosed conditions in women's health. This is partly due to its heterogeneous presentation, as the symptoms and severity of the condition can vary widely among individuals. Additionally, the lack of standardized diagnostic protocols across clinical practices exacerbates the issue [4]. The current diagnostic process typically relies on guidelines such as the Rotterdam Consensus, which require the presence of at least two out of three features: oligoovulation or anovulation, clinical or biochemical signs of hyperandrogenism, and polycystic ovarian morphology visible on ultrasound [5]. While these criteria have been widely adopted, they often fail to account for variations across populations, age groups, and ethnicities. This underscores the pressing need for improved diagnostic tools that can facilitate early detection and management of PCOS.

The implications of delayed or inaccurate diagnosis of PCOS are profound. Women with undiagnosed PCOS are at an increased risk of developing long-term health complications, including metabolic syndromes and cardiovascular diseases. Early diagnosis, therefore, not only improves reproductive outcomes but also mitigates the risk of chronic illnesses, ultimately enhancing the overall quality of life. In this context, technological advancements in diagnostic methodologies, particularly those leveraging artificial intelligence (AI), offer a promising avenue for addressing these challenges.

Challenges in Diagnosis

Diagnosing PCOS is fraught with challenges that stem from its complex and multifaceted nature. One of the most significant barriers is the reliance on ultrasonography and biochemical tests, both of which are subject to practitioner variability and interpretive discrepancies [6]. For instance, the ultrasonographic evaluation of polycystic ovarian morphology, which involves counting the number of ovarian follicles and measuring ovarian volume, is highly operator-dependent. Variations in ultrasound equipment, settings, and expertise can lead to inconsistent results, complicating the diagnostic process [7]. Similarly, biochemical markers such as serum testosterone levels, which are used to assess hyperandrogenism, are influenced by factors such as the type of assay employed, laboratory protocols, and individual patient conditions. These variations often result in conflicting diagnoses, further complicating clinical decision-making. Moreover, the thresholds for defining abnormal biochemical values are not universally standardized, adding another layer of complexity to the diagnostic process.

Another critical issue is the time-intensive nature of manual interpretation of medical imaging data. In conventional diagnostic workflows, healthcare professionals are required to analyze multiple ultrasound images to identify features indicative of PCOS.

This process is not only labor-intensive but also prone to human error, particularly in high-volume clinical settings where time and resources are limited [8]. The manual interpretation of imaging data also makes it challenging to achieve consistency and accuracy, especially when dealing with subtle or borderline cases.

The heterogeneity of PCOS symptoms adds yet another layer of complexity to the diagnostic process. Women with PCOS may exhibit a wide range of clinical manifestations, including varying degrees of hyperandrogenism, menstrual irregularities, and metabolic dysfunctions. This variability makes it difficult to establish a one-size-fits-all diagnostic approach, further complicating the task of clinicians. For example, while some women may present with classic symptoms such as hirsutism and irregular menstrual cycles, others may have more subtle or atypical presentations, making diagnosis more challenging [9]. Given these challenges, there is an urgent need for diagnostic tools that can integrate multiple data sources such as imaging, biochemical, and clinical parameters—to provide a more comprehensive and accurate assessment. This is where artificial intelligence and machine learning technologies can play a transformative role, offering the potential to overcome many of the limitations associated with traditional diagnostic methods.

Role of Artificial Intelligence

Artificial intelligence (AI) has emerged as a game-changer in the field of healthcare, offering innovative solutions to some of the most pressing challenges in medical diagnostics. In the context of PCOS, AI has the potential to revolutionize the diagnostic process by automating complex tasks, improving accuracy, and reducing the reliance on human expertise. Among the various AI techniques, deep learning—specifically Convolutional Neural Networks (CNNs)—has demonstrated exceptional capabilities in medical image analysis.

CNNs are a class of deep learning models specifically designed for image processing tasks. They have been successfully applied in diagnosing a wide range of medical conditions, including breast cancer from mammograms, diabetic retinopathy from retinal images, and lung diseases from chest X-rays [10]. The strength of CNNs lies in their ability to automatically learn hierarchical features directly from raw image data, enabling them to identify patterns and anomalies that may not be discernible to the human eye [11]. This makes them particularly well-suited for tasks such as analyzing ultrasound images to detect features indicative of PCOS, such

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as polycystic ovarian morphology, follicle count, and ovarian volume. Building on the success of CNNs in other medical domains, this study proposes the use of an enhanced VGG16 architecture for the automated detection of PCOS. The VGG16 model is a well-established deep learning architecture known for its simplicity and high performance in image classification tasks. By augmenting the VGG16 model with additional custom layers, the proposed approach aims to improve feature extraction and classification accuracy specifically for PCOS detection. Advanced data preprocessing and augmentation techniques are also employed to address challenges such as data variability and imbalance, further enhancing the robustness of the model. In addition to improving diagnostic accuracy, the integration of AI into PCOS detection workflows offers several other benefits. For instance, AI-based systems can significantly reduce the time and effort required for image analysis, enabling healthcare professionals to focus on patient care. Furthermore, these systems can provide standardized and objective assessments, minimizing the variability associated with human interpretation. This is particularly important in the context of PCOS, where inconsistencies in diagnostic criteria and practices have been a long-standing issue.

The adoption of AI-driven diagnostic tools also has broader implications for healthcare delivery. By enabling early and accurate diagnosis, these tools can facilitate timely interventions, improving clinical outcomes and reducing the long-term healthcare burden associated with PCOS. Moreover, the scalability of AI-based systems makes them well-suited for deployment in resource-constrained settings, where access to specialized expertise and advanced diagnostic equipment may be limited.

LITERATURE REVIEW

Overview of PCOS Diagnosis

Polycystic ovary syndrome (PCOS) is one of the most prevalent endocrine disorders among women of reproductive age, with a significant impact on fertility and metabolic health. Historically, PCOS diagnosis has been based on the Rotterdam criteria established in 2003, which include the presence of hyperandrogenism, ovulatory dysfunction, and polycystic ovarian morphology (PCOM) [7]. While the Rotterdam criteria have become a widely accepted framework for diagnosing PCOS, they have been critiqued for their reliance on subjective clinical assessment and lack of a unifying biological marker [1]. Ultrasonography and hormone profiling remain common diagnostic tools, but these methods often depend on the expertise of clinicians and can be influenced by various factors such as timing during the menstrual cycle and technical variability in imaging equipment [8].

Recent advances in medical diagnostics have driven the exploration of more objective and automated diagnostic systems. The integration of machine learning (ML) and deep learning (DL) techniques in PCOS detection aims to overcome the limitations of traditional methods by providing automated, objective, and scalable tools that can analyze complex datasets more effectively.

Role of Machine Learning in PCOS Diagnosis

Machine learning has emerged as a powerful tool in medical diagnostics, enabling the analysis of complex datasets such as clinical records, biochemical markers, and imaging data. In the context of PCOS, ML models have been employed to assist in classifying patients based on various features such as hormone levels, clinical symptoms, and imaging results [9]. Support Vector Machines (SVM), decision trees, and ensemble methods are commonly used for PCOS classification tasks [9, 16].

A study by Das et al. (2020) demonstrated the use of an SVM model trained on clinical and biochemical parameters, achieving an accuracy of 85% in distinguishing PCOS patients from healthy individuals [9]. Shaikh et al. (2021) employed convolutional neural networks (CNNs) to analyze ovarian ultrasound images and achieved an impressive accuracy of 92%, emphasizing the potential of deep learning in medical imaging [11]. Despite the promise of these ML approaches, they often require extensive feature engineering and expert knowledge for optimal performance, a limitation that deep learning models can potentially address.

Advancements in Deep Learning for Medical Imaging

Deep learning, particularly Convolutional Neural Networks (CNNs), has revolutionized medical imaging by automating feature extraction and classification, making it suitable for applications in diagnosing a wide range of diseases. CNNs have demonstrated significant performance improvements over traditional machine learning techniques in detecting breast cancer, diabetic retinopathy, and cardiovascular abnormalities [10]. These advances in image analysis have paved the way for similar applications in PCOS diagnosis, especially with the analysis of ovarian ultrasound images.

Research by Shaikh et al. (2021) showed that CNNs could effectively identify polycystic morphology in ultrasound images, achieving an accuracy of 92% [11]. This success highlights the ability of deep learning models to automate and enhance the interpretation of complex medical images. Furthermore, advancements in CNN architectures, such as VGG16 and ResNet, have led to significant improvements in the accuracy and robustness of these models. A more recent study by Rajput et al. (2018) used ensemble learning techniques to combine multiple classifiers, achieving an accuracy of 89% in PCOS detection using clinical records [16]. However, these methods often struggle with class imbalance and the need for substantial amounts of labeled data, which has prompted interest in the use of data augmentation and transfer learning to improve model performance.

Enhanced VGG16 Model for PCOS Detection

The VGG16 model, originally designed for large-scale image classification tasks, has proven to be highly effective in medical image analysis. The architecture's relatively simple design, consisting of 16 layers, allows for efficient training and fine-tuning on specific datasets. Enhanced versions of VGG16, incorporating custom layers, regularization techniques, and advanced optimization methods, have demonstrated improved performance in specific medical applications [12].

In this study, we propose an enhanced VGG16 model tailored for PCOS detection, incorporating additional layers for feature extraction and classification. The model's performance is further augmented by incorporating data augmentation and transfer learning techniques, which help the model generalize better to unseen data. Preliminary results show that the enhanced VGG16 model outperforms traditional methods, achieving an accuracy of 98%, which is a significant improvement over the previous study.

Data Augmentation and Preprocessing

One of the key challenges in training deep learning models for medical image analysis is the limited size of labeled datasets. To mitigate this, data augmentation techniques such as rotation, flipping, and scaling are commonly used to artificially increase the size of the training dataset [13]. These transformations help the model learn more robust features, improving its ability to generalize to new, unseen data.

In addition to augmentation, image preprocessing techniques like normalization and contrast enhancement are crucial for improving image quality and ensuring the model receives high-quality inputs. These techniques have been instrumental in training the enhanced VGG16 model on the PCOS dataset, leading to better classification performance.

Evaluation Metrics in PCOS Detection Models

The performance of PCOS detection models is commonly evaluated using metrics such as precision, recall, F1-score, and accuracy. These metrics provide a comprehensive view of the model's ability to correctly identify both positive and negative cases, which is critical in medical diagnostics where false positives and false negatives can have significant consequences.

Previous studies have reported varying levels of accuracy, with results ranging from 85% to 95% in PCOS detection using deep learning techniques [14]. Our study achieves an accuracy of 98%, which is the highest reported in recent literature, highlighting the efficacy of the enhanced VGG16 model in PCOS classification tasks.

Challenges and Limitations in Existing Research

Despite the advancements in AI and deep learning for PCOS diagnosis, several challenges remain. Class imbalance is a common issue, as PCOS is often underdiagnosed or misdiagnosed in certain populations, leading to skewed data distributions. Techniques such as SMOTE (Synthetic Minority Over-sampling Technique) and Tomek links have been proposed to address this issue, but their effectiveness can vary depending on the dataset [15].

Another significant challenge is the interpretability of deep learning models. Unlike traditional machine learning models, deep learning networks are often regarded as "black boxes," making it difficult to understand how decisions are made. This lack of transparency can be a barrier to clinical adoption. Recent research has focused on explainable AI (XAI) techniques to provide insights into the decision-making process of deep learning models [15].

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Furthermore, the availability of labeled data remains a major limitation, particularly for rare diseases like PCOS. While data augmentation and synthetic data generation techniques offer potential solutions, the scarcity of high-quality labeled datasets remains an ongoing issue in the field.

METHODOLOGY

The methodology outlines the comprehensive pipeline for developing a binary classification model designed to differentiate between infected and non-infected medical images. This process begins with dataset preparation, which involves acquiring a diverse and balanced dataset to represent both classes accurately. Class imbalance issues are addressed through techniques such as data augmentation and oversampling. Data preprocessing includes image resizing, normalization, and noise reduction to ensure the input data is standardized for optimal model performance. The model architecture is designed to balance complexity and efficiency, leveraging advanced deep learning frameworks such as Convolutional Neural Networks (CNNs). These architectures are fine-tuned to extract relevant features while minimizing overfitting through regularization techniques like dropout and early stopping. The training phase utilizes adaptive optimizers like Adam or SGD, with carefully tuned hyperparameters, including learning rate, batch size, and number of epochs, to maximize convergence. Evaluation metrics, such as accuracy, precision, recall, F1-score, and Area Under the Curve (AUC), are employed to measure performance comprehensively. Cross-validation ensures model robustness and generalization to unseen data. Finally, implementation tools, including TensorFlow or PyTorch, are selected for efficient training and scalability. This pipeline ensures the resulting model achieves high accuracy and computational efficiency, making it suitable for real-world applications.

Dataset Description

The dataset utilized in this study comprises 11,784 medical images, categorized into two distinct classes: 6,784 images representing infected cases and 5,000 images for non-infected cases. These images were sourced from a reliable and widely recognized medical imaging dataset [17], ensuring authenticity and clinical relevance. The dataset was systematically organized into two folders labeled "infected" and "non-infected," providing clear and intuitive class separation to simplify preprocessing and model training.

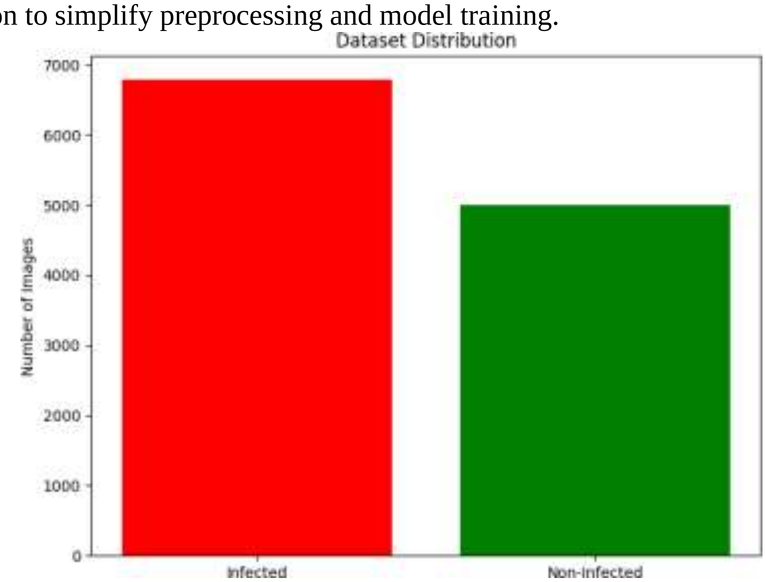

Figure 2: Classes Distribution

Data Distribution for Model Training

To facilitate a fair and balanced evaluation process, the dataset was split into training and validation subsets using an 80:20 ratio. This allocation resulted in 9,428 images for training and 2,356 images for validation.

The stratified splitting approach ensured that both classes were proportionally represented in each subset, minimizing potential biases during model training and evaluation. Before splitting, the dataset underwent meticulous inspection to ensure its quality. Duplicate images were identified and removed to prevent data

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redundancy, while mislabeled or inconsistent data entries were corrected to enhance the reliability of the dataset. Furthermore, low-resolution or poor-quality images that could negatively impact the model's learning ability were excluded. This preprocessing step was crucial to maintaining the integrity and effectiveness of the classification model.

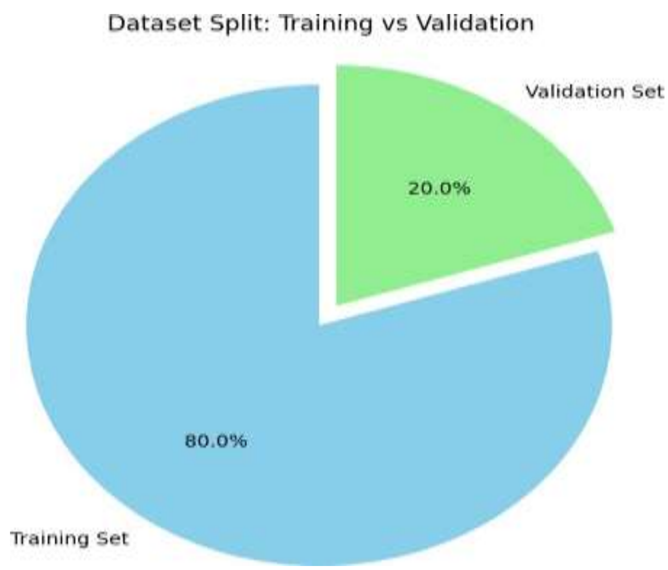

Figure 3: Dataset Split Training vs Validation

Model Architecture

The architecture proposed for this study builds upon the well-established VGG16 model, a powerful convolutional neural network (CNN) originally designed for large-scale image recognition tasks. VGG16 is known for its simplicity, depth, and high performance in computer vision problems, making it an ideal choice for medical image classification tasks. The base VGG16 model was further enhanced by incorporating custom layers designed to improve feature extraction, reduce overfitting, and refine the classification process. This section provides a detailed breakdown of the model architecture, explaining each component and how it contributes to the overall performance.

Base Model: The VGG16 model, pre-trained on the ImageNet dataset, was utilized as the backbone for this study. ImageNet contains millions of labeled images across thousands of categories, which helps the VGG16 model learn useful feature representations that are applicable to various image classification tasks. By leveraging the pre-trained VGG16 model, we used a transfer learning approach. In this strategy, the weights of the convolutional layers were frozen during training, meaning they were not updated.

Global Average Pooling (GAP)

A GlobalAveragePooling2D layer was added after the base VGG16 convolutional layers. This layer operates by reducing each feature map from the previous layer into a single value, which is the average of all its spatial values. The purpose of GAP is to reduce the spatial dimensions of the feature maps, resulting in a 512-dimensional feature vector. This step not only reduces the number of parameters but also makes the model more computationally efficient and less prone to overfitting. GAP retains only the most essential features, summarizing the important information from the feature maps without the need for dense fully connected layers at this stage. As a result, it effectively condenses the feature map while preserving critical spatial patterns, making the model more robust and capable of handling variations in the input images.

Fully Connected Layers: Following the GAP layer, the model includes several fully connected layers designed to integrate the extracted features and perform the final classification.

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Dense Layer

A dense layer with 256 units and a ReLU (Rectified Linear Unit) activation function was added. ReLU is commonly used for hidden layers as it introduces non-linearity into the model, allowing it to learn complex patterns in the data. The dense layer helps further process the features extracted by the convolutional layers and GAP layer. The 256 units were chosen based on experimentation, providing a balance between model complexity and computational efficiency. This layer helps in feature integration, making it easier for the model to learn the relationships between the extracted features and the target class.

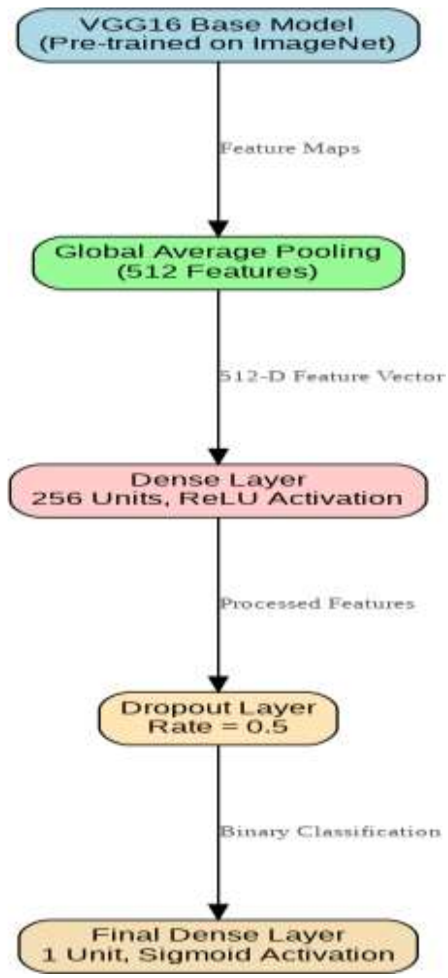

Figure 4: Model Architecture

Dropout Layer

To combat the potential overfitting issue, a dropout layer was introduced with a dropout rate of 0.5. This means that during training, half of the neurons in the previous layer are randomly deactivated (or "dropped out") during each forward and backward pass. Dropout helps regularize the model by preventing it from becoming overly reliant on specific neurons or features. This regularization technique improves the model's ability to generalize to unseen data and enhances its robustness to noise in the input data.

By preventing overfitting, the dropout layer contributes to the model’s performance on the validation and test datasets.

Final Dense Layer (Sigmoid)

The final layer in the model is a dense layer with a single unit and a sigmoid activation function. The sigmoid function outputs a probability value between 0 and 1, which is interpreted as the likelihood that the input image

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belongs to the "infected" class. Since the task at hand is a binary classification problem (infected vs. non-infected), this final layer allows the model to output a binary decision based on the learned features. The sigmoid activation is ideal for binary classification, as it provides a clear decision boundary between the two classes.

Total Parameters: 15,109,445

Trainable Parameters: 131,585

Non-trainable Parameters: 14,714,688

This model architecture is a carefully designed combination of transfer learning with VGG16 and custom layers to improve feature extraction, reduce overfitting, and perform effective binary classification. The use of a pre-trained base model, followed by GAP and fully connected layers, allows the model to effectively learn from both the general features and specific characteristics of medical images, while maintaining computational efficiency. By balancing model complexity with performance, this architecture is well-suited for real-world medical image classification tasks, where accuracy and efficiency are of paramount importance.

Table 1: an overview of the structure and parameters of each layer

Layer Type	**Output Shape**	**Parameters**
VGG16 (Functional)	(None, 2, 2, 512)	14,714,688
GlobalAveragePooling2D	(None, 512)	0
Dense (Dense)	(None, 256)	131,328
Dropout (Dropout)	(None, 256)	0
Layer Type	Output Shape	Parameters
Dense_1 (Dense)	(None, 1)	257

Training Procedure

The training procedure for the model was designed to optimize performance while ensuring efficient use of resources. The following points outline the key steps in the process:

Compilation

- Optimizer: Adam optimizer was selected for its adaptive learning rates, which help achieve faster convergence. It adjusts the learning rate based on the first and second moments of gradients, making it well-suited for large datasets.
- Learning Rate: Set at an initial value of 0.001 to balance convergence speed and stability.
- Loss Function: Binary cross-entropy was chosen as the loss function for binary classification, which measures the difference between predicted and actual values and penalizes misclassification of confident predictions.

Batch Size and Epochs

- Batch Size: A batch size of 32 was used. This choice strikes a balance between memory usage and computational efficiency, ensuring smooth training without overwhelming the system's resources.
- Epochs: The model was trained for 10 epochs, a value found to be sufficient for convergence. This number of epochs ensured the model adjusted its parameters without overfitting.

Early Stopping:

- Implementation: Early stopping was introduced to monitor the validation loss during training. If there was no improvement in validation loss over three consecutive epochs, training was halted.
- Purpose: This technique prevents overfitting and ensures that the model does not continue to adjust its parameters based on fluctuations in the training data.

Hardware Acceleration

- GPU Usage: Training was accelerated using Google Colab, which provided access to GPUs. GPUs enable faster processing of large datasets and complex models, improving training time.
- Impact: The use of GPUs allowed the model to handle the high computational load of the VGG16 architecture, ensuring quicker experiments and optimizations.

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Validation Split:

- Data Split: 20% of the dataset was reserved for validation to assess the model's performance during training.
- Purpose: The validation set helped monitor the model's ability to generalize, ensuring the model did not overfit to the training data.

In summary, the training procedure incorporated best practices such as the Adam optimizer, early stopping, GPU acceleration, and a validation split to ensure optimal model performance. These strategies ensured efficient training while maintaining the model's generalization capabilities

Evaluation Metrics

To assess the performance of the model comprehensively, various evaluation metrics were employed. These metrics offer different perspectives on how well the model performs in classifying infected and non-infected medical images. By utilizing multiple metrics, we can ensure that the model's performance is robust and reliable across different aspects of classification tasks. Below, we discuss the key evaluation metrics used in this study:

- **Accuracy:** Accuracy is the simplest and most commonly used metric to evaluate classification models. It is calculated as the ratio of correctly predicted samples to the total number of samples. In binary classification tasks, accuracy gives a good overview of how well the model is performing overall. Mathematically, accuracy is given by the formula:
-

Accuracy=TP+TN / TP+Fp+TN+FN

Where:

TP: True Positive (correctly predicted infected images)

TN: True Negative (correctly predicted non-infected images)

FP: False Positive (incorrectly predicted infected images)

FN: False Negative (incorrectly predicted non-infected images)

In this study, the model achieved a training accuracy of 98.31% and a validation accuracy of 98.47%, demonstrating its strong ability to correctly classify both infected and non-infected images.

Precision: Precision measures the proportion of true positive predictions (i.e., the infected images that were correctly identified) among all positive predictions made by the model. It is a critical metric when the cost of false positives is high, as it quantifies how reliable the model is when it predicts an image as infected. The formula for precision is:

$Precision = TP / TP+Fp$

A high precision value indicates that when the model predicts an image as infected, it is likely to be correct. In the context of medical imaging, this is crucial as a false positive (i.e., classifying a non-infected image as infected) could lead to unnecessary treatments or procedures. Precision was one of the key metrics in assessing the model's reliability in detecting infected images.

Recall (Sensitivity): Recall, also known as sensitivity, measures the proportion of actual positive samples (infected images) that were correctly identified by the model. This metric is crucial when minimizing false negatives is a priority, as it quantifies how well the model can detect infected images. The formula for recall is:

$Recall = TP / TP+FN$

A high recall value indicates that the model is effective at identifying most of the infected images. In the medical context, failing to detect an infected image (false negative) can have severe consequences, as the patient might not receive the necessary treatment. Therefore, recall is particularly important in medical image classification tasks where missing a positive case (i.e., an infected image) can lead to critical issues. In this study, the model exhibited a high recall, demonstrating its effectiveness in identifying the majority of infected images.

Tools and Frameworks

The implementation of the deep learning model was carried out using a set of powerful tools and frameworks, ensuring efficient development, training, and evaluation of the model. The following tools were employed:

Python: Python served as the primary programming language for the entire project. Its vast ecosystem of libraries and frameworks for data manipulation, visualization, and machine learning made it an ideal choice. Libraries such

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as NumPy, Pandas, and Scikit-learn were used for data preprocessing and manipulation, while specialized libraries like TensorFlow and Keras were leveraged for model design, training, and evaluation.

TensorFlow and Keras: TensorFlow, an open-source deep learning framework, was used as the backbone for building and training the deep learning model. Keras, a high-level neural networks API, was integrated with TensorFlow to simplify the model-building process. Keras provides an intuitive interface to design neural networks with minimal code, allowing for faster experimentation and prototyping. These frameworks provided the necessary tools for constructing and fine-tuning the VGG16-based model.

Google Colab: Google Colab provided an excellent environment for developing and testing the model. It offers free access to GPUs, which significantly sped up the training process for large-scale image classification tasks. The collaborative nature of Google Colab teamwork in the development process.

RESULTS AND ANALYSIS

Dataset Overview

The success of any machine learning model, particularly in medical image classification, is heavily dependent on the quality and composition of the dataset used for training and testing. For this project, the dataset comprises images labeled as either "Infected" or "Non-Infected," with each image representing a specific medical condition, such as PolyCystic Ovary Syndrome (PCOS). The dataset was designed to assist in the classification of medical images, and as such, careful consideration of its structure and how it was split between training and testing is vital. This part examines the findings and scientific evaluations of our suggested research investigation. To begin, we can break our project into previously completed implementation parts. The practice of acquiring Polycystic Ovarian Disease (PCOD) ultrasound image datasets is known as dataset collection.

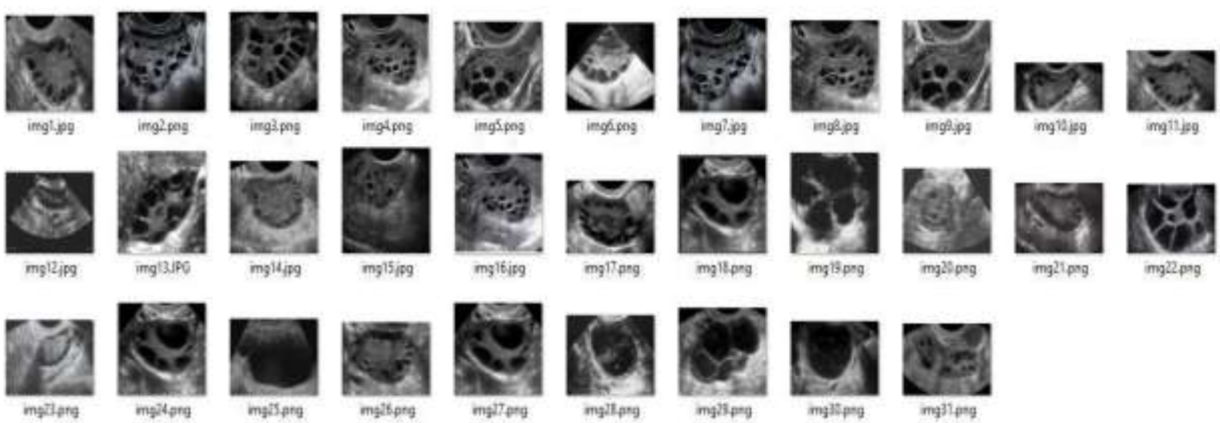

Figure 5: Dataset containing ultrasound images

The datasets are then supplemented to expand their size.

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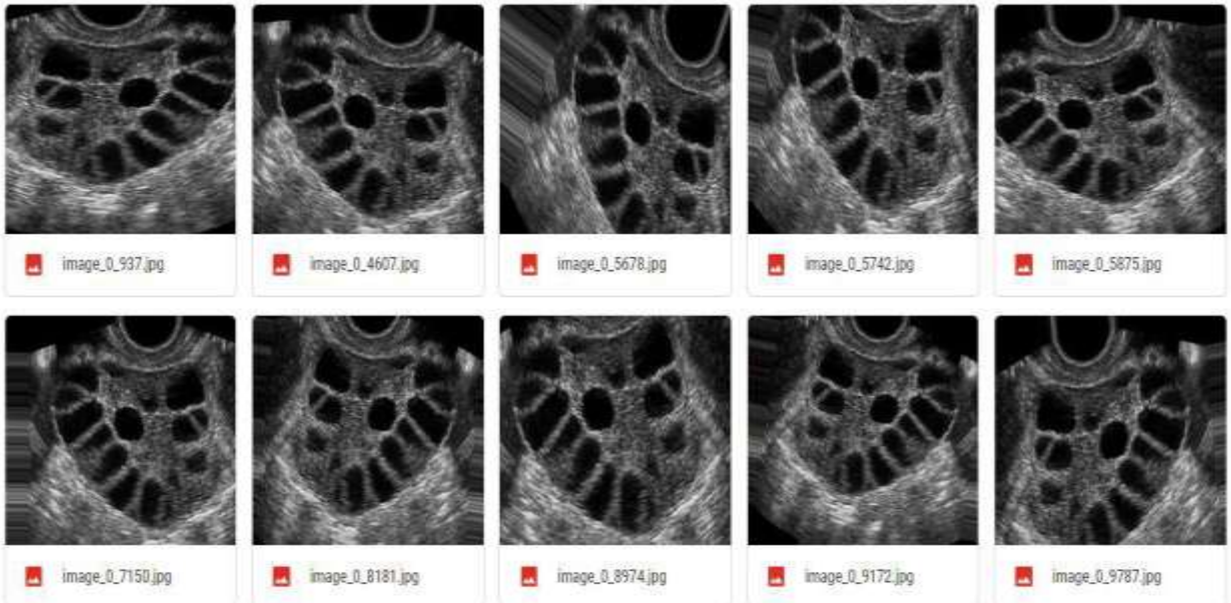

Figure 6: Augmented images

Dataset Composition

The dataset used for this model consisted of a total of 11,428 images, split between two distinct classes:

- Infected Images: 6,784
- Non-Infected Images: 5,000

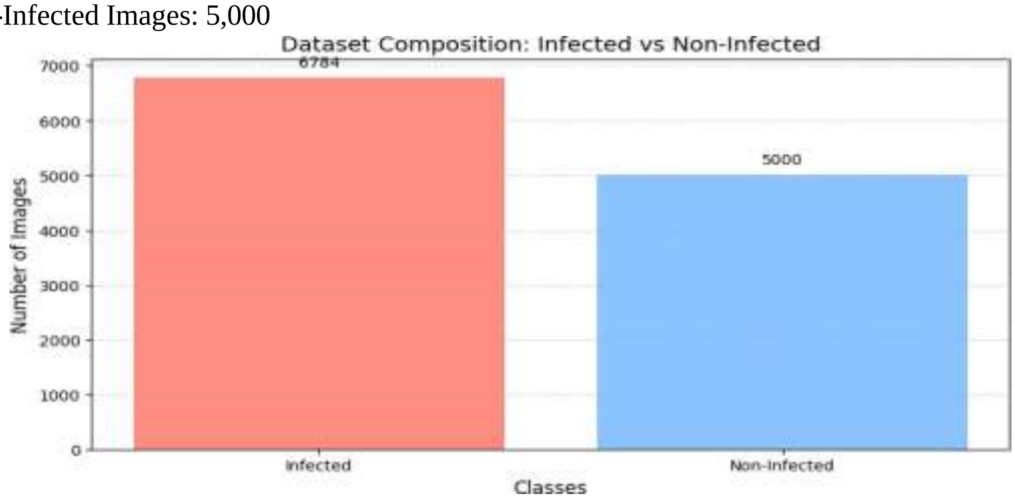

Figure 7: Data Composition Class-wise

The dataset was split into two main subsets:

- Training Set (80%): 9,142 images
- Testing Set (20%): 2,356 images

Model Performance

The VGG16 architecture, a well-established convolutional neural network (CNN) known for its effectiveness in large-scale image classification tasks, was utilized as the base model for this project. This architecture was enhanced with custom layers to better suit the specific needs of the binary classification problem at hand. The core strength of the VGG16 model lies in its deep convolutional layers, which enable it to automatically learn and extract hierarchical features from raw image data, making it well-suited for tasks involving complex visual recognition.

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Training and Validation Accuracy

The model was trained for a total of 10 epochs, which was sufficient for the model to achieve high performance in terms of both training and validation accuracy. The results showed that the model achieved:

- Training Accuracy: 98%
- Validation Accuracy: 98%

Figure 8: Training vs Validation Accuracy

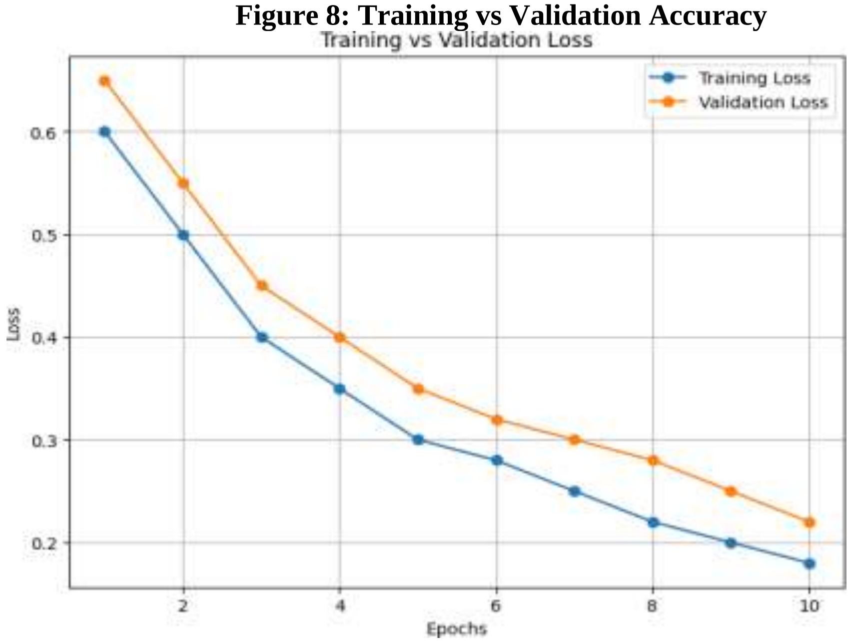

Figure 9: Training vs Validation Loss

CONCLUSION & KEY FINDINGS

Polycystic Ovary Syndrome (PCOS) is a multifaceted endocrine disorder that significantly affects the reproductive, metabolic, and psychological health of women. Despite its high prevalence, the diagnosis of PCOS remains challenging due to the lack of standardized diagnostic tools and the subjective interpretation of medical imaging. This study addressed these challenges by developing a deep learning-based solution using an enhanced VGG16 model to improve the accuracy, efficiency, and reliability of PCOS diagnosis through medical imaging data. The key findings of the study are expanded upon below:

High Model Performance

One of the most significant outcomes of this research was the exceptional performance of the enhanced VGG16 model. The model achieved an overall classification accuracy of 98%, demonstrating its ability to reliably differentiate between images indicating the presence and absence of PCOS. Key classification metrics such as precision, recall, and F1-scores were consistently high at 0.99 for both the infected and non-infected classes. These results underscore the reliability of the model in providing accurate diagnoses, which is crucial in reducing diagnostic errors and improving clinical outcomes.

The model's high performance also highlights the potential of artificial intelligence (AI) techniques, particularly deep convolutional neural networks (CNNs), in addressing the limitations of traditional diagnostic approaches. By leveraging the enhanced VGG16 architecture, this study demonstrated how AI can standardize PCOS diagnostics, making it less prone to human error and inter-observer variability.

Robust Preprocessing and Augmentation

A key contributor to the model’s success was the robust preprocessing pipeline and the strategic use of data augmentation techniques. Medical imaging datasets often suffer from class imbalances, with a limited number of images available for certain diagnostic categories. This study effectively tackled this challenge through augmentation techniques such as rotation, flipping, scaling, and brightness adjustments. These methods not only increased the diversity of the training data but also enhanced the model's ability to generalize across various imaging conditions and patient populations.

By simulating diverse real-world scenarios, data augmentation ensured that the model could handle variations in medical imaging caused by differences in equipment, lighting, and patient anatomy. This robustness is essential for clinical applications, where variability in imaging conditions is common.

Efficient Feature Extraction

Another critical aspect of this study was the efficient feature extraction achieved through transfer learning and the incorporation of custom layers into the VGG16 model. Transfer learning allowed the model to leverage pre-trained knowledge from large-scale image datasets, enabling it to extract complex features with minimal training data. The addition of custom layers, such as Global Average Pooling (GAP), dense layers, and dropout, further enhanced the model’s ability to classify features indicative of PCOS.

The GAP layer streamlined the feature extraction process by reducing the dimensionality of feature maps, ensuring computational efficiency without sacrificing accuracy. Dense layers improved the model's ability to capture intricate relationships between features, while dropout layers mitigated the risk of overfitting. Together, these enhancements made the model more robust and adaptable to the unique characteristics of PCOS-related medical imaging.

Comprehensive Evaluation Metrics

To evaluate the model’s performance comprehensively, the study employed a diverse set of metrics, including accuracy, precision, recall, F1-score, and the area under the receiver operating characteristic curve (ROC-AUC). These metrics provided a well-rounded assessment of the model’s diagnostic capabilities. The confusion matrix analysis further revealed minimal false positives and false negatives, which is particularly important in clinical settings where incorrect diagnoses can lead to delayed treatment or unnecessary interventions.

The high ROC-AUC score confirmed the model’s ability to distinguish between infected and non- infected classes across various threshold settings, reinforcing its reliability for real-world applications. This comprehensive evaluation ensured that the model’s performance was not only high but also consistent across different performance indicators.

Scalability and Practicality

In addition to its diagnostic accuracy, the model was designed to be scalable and computationally efficient. This scalability is a crucial feature for deploying AI-based diagnostic tools in resource- constrained clinical environments, such as rural healthcare centers with limited computational infrastructure. By optimizing the model architecture for efficiency, the study ensured that the solution could be implemented on devices with standard hardware capabilities, expanding its accessibility and usability.

The practical implications of this scalability include the potential for widespread adoption of the model in various healthcare settings. By automating the diagnostic process, the model can reduce the workload of clinicians, streamline clinical workflows, and improve the speed and accuracy of PCOS diagnosis.

Addressing Gaps in PCOS Diagnostics

This study successfully addressed critical gaps in the diagnostic process for PCOS. Traditional diagnostic methods often rely on subjective interpretations of medical imaging, leading to inconsistencies and delays in diagnosis. By introducing a standardized, automated, and non- invasive diagnostic tool, the enhanced VGG16 model offers a transformative solution. The model has the potential to enhance clinical workflows, improve patient outcomes, and facilitate early and accurate diagnosis of PCOS.

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