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ORIGINAL

Automated Detection of Polycystic Ovary Syndrome Using Convolutional Neural Networks on Ultrasound Images

Detección automatizada del síndrome de ovario poliquístico mediante redes neuronales convolucionales en imágenes de ultrasonido

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ABSTRACT

Polycystic Ovary Syndrome (PCOS) is a prevalent endocrine disorder affecting millions of women worldwide, yet it remains frequently underdiagnosed due to symptom variability and limited diagnostic resources. This paper presents a Convolutional Neural Network (CNN)-based system for automated PCOS detection from ultrasound images. The model leverages deep learning for accurate feature extraction and classification, aiming to support clinicians and improve diagnostic accessibility. Experimental results demonstrate high accuracy, underscoring the potential of AI-driven solutions in advancing women's healthcare. Beyond accuracy, the system offers scalability, reduced diagnostic time, and potential integration into telemedicine platforms, highlighting its role in bridging healthcare gaps and enabling earlier intervention.

Keywords: Polycystic Ovary Syndrome; Convolution Neural Network; Women Health; AI driven Solution; Diagnostics; Healthcare.

RESUMEN

El síndrome de ovario poliquístico (SOP) es un trastorno endocrino prevalente que afecta a millones de mujeres en todo el mundo, pero que sigue estando infradiagnosticado debido a la variabilidad de los síntomas y a los limitados recursos diagnósticos. Este artículo presenta un sistema basado en una red neuronal convolucional (CNN) para la detección automatizada del SOP a partir de imágenes de ultrasonido. El modelo aprovecha el aprendizaje profundo para la extracción y clasificación precisas de características, con el objetivo de ayudar a los médicos y mejorar la accesibilidad del diagnóstico. Los resultados experimentales demuestran una alta precisión, lo que subraya el potencial de las soluciones basadas en la inteligencia artificial para mejorar la atención sanitaria de las mujeres. Más allá de la precisión, el sistema ofrece escalabilidad, reducción del tiempo de diagnóstico y posibilidad de integración en plataformas de telemedicina, lo que destaca su papel a la hora de salvar las diferencias en la atención sanitaria y permitir una intervención más temprana.

Palabras clave: Síndrome de Ovario Poliquístico; Red Neuronal Convolucional; Salud de la Mujer; Solución Basada en la Inteligencia Artificial; Diagnóstico; Atención Sanitaria.

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INTRODUCTION

Polycystic Ovary Syndrome (PCOS) endocrine disorder affecting 5–10 % of women of reproductive age, characterized by symptoms such as irregular menstruation, hyperandrogenism, infertility, and metabolic disturbances. The diagnosis of PCOS is particularly challenging due to its heterogeneous presentation, requiring a combination of clinical, biochemical, and imaging criteria. Traditionally, clinicians rely on the Rotterdam Criteria, which mandates the presence of at least two out of three findings: oligo/anovulation, clinical or biochemical hyperandrogenism, and polycystic ovarian morphology on ultrasound. However, conventional diagnosis is limited by the subjectivity of ultrasound interpretation, variability in image quality, and dependence on specialist expertise. Manual assessment of ovarian ultrasound images can lead to inconsistent results, delayed diagnosis, and increased patient burden, especially in resource-limited settings.[1,2,3,4,5,6,7,8]

To address these challenges, recent advancements have focused on leveraging artificial intelligence (AI) and deep learning, particularly Convolutional Neural Networks (CNNs), for automated PCOS detection from ultrasound images. These AI-driven systems preprocess and standardize images, extract relevant features, and classify cases as PCOS or non-PCOS with high accuracy. The present system described in this paper utilizes a custom CNN model trained on a diverse dataset of ovarian ultrasound images, providing a user-friendly interface for image upload, real-time prediction, and tailored health recommendations. This approach aims to deliver accessible, objective, and reliable PCOS diagnostics, supporting clinicians and empowering patients with actionable insights.

As awareness of PCOS continues to grow, so does the need for diagnostic approaches that are not only accurate but also empathetic and inclusive. Many women experience frustration and anxiety due to delayed or missed diagnoses, often undergoing multiple tests before receiving clarity. By integrating AI into diagnostic workflows, we can ease this journey making detection faster, more consistent, and less dependent on subjective interpretation. Importantly, such technology can bridge gaps in healthcare access,[9,10,11] especially for women in remote or underserved regions. When designed with care and usability in mind, these tools can empower individuals with knowledge about their health, offering support that feels both personal and reliable.

Related work

Polycystic Ovary Syndrome (PCOS) is one of the most common endocrine disorders affecting women of reproductive age. Numerous studies have explored the application of Convolutional Neural Networks (CNNs) and related deep learning models for improving PCOS diagnosis via ultrasound imaging.

This paper has introduced a CNN-based classification framework utilizing AlexNet for accurate PCOS detection from ultrasonic images. The model emphasized feature extraction and reliable pattern recognition, showcasing improved diagnostic sustainability and automation in healthcare.[12]

The authors have developed a CNN-driven image descriptor focused on blob detection and image segmentation of transvaginal ultrasound scans. Their work highlighted the importance of edge detection and morphological pattern identification to enhance PCOS classification, contributing significantly to pediatric diagnostics and non-invasive screening.[13]

The authors have implemented a lightweight MobileNet architecture for analyzing ultrasound images. This approach balanced computational efficiency with high classification performance. The study emphasized how AI-assisted ultrasonography could reduce manual interpretation dependency and boost clinical confidence.[14]

The authors have developed an advanced PCOS detection by incorporating transformer-based models and pretrained CNNs. By integrating attention mechanisms, their method significantly improved detection accuracy and training efficiency, demonstrating the benefit of hybrid deep learning systems in medical imaging.[15]

The researchers have combined ResNet and Gaussian Naive Bayes (GNB) for comprehensive ultrasound image analysis. Employing watershed segmentation and feature extraction, their model showcased high diagnostic reliability. The study also leveraged data augmentation to address dataset limitations and enhance generalizability.[16]

The researchers have conducted a comparative study using CNN, Support Vector Machines (SVM), and K-Nearest Neighbors (KNN). While CNN achieved superior accuracy, the integration of multiple algorithms was found beneficial for difficult or edge-case diagnoses. Their research supports the development of precision medicine models by combining data-driven and image-based techniques.[17]

METHOD

The proposed system is an end-to-end CNN-based diagnostic tool for PCOS detection from ultrasound images.

This architecture aims to offer a quick, accessible, and AI-powered screening tool for PCOS, especially valuable in remote or undeserved areas where expert analysis may be unavailable. This AI-driven system offers an accessible, efficient, and user-friendly approach for early PCOS detection using ovary ultrasound images and deep learning. Following process shows the workflow of the proposed work as shown in the architecture (figure 1).

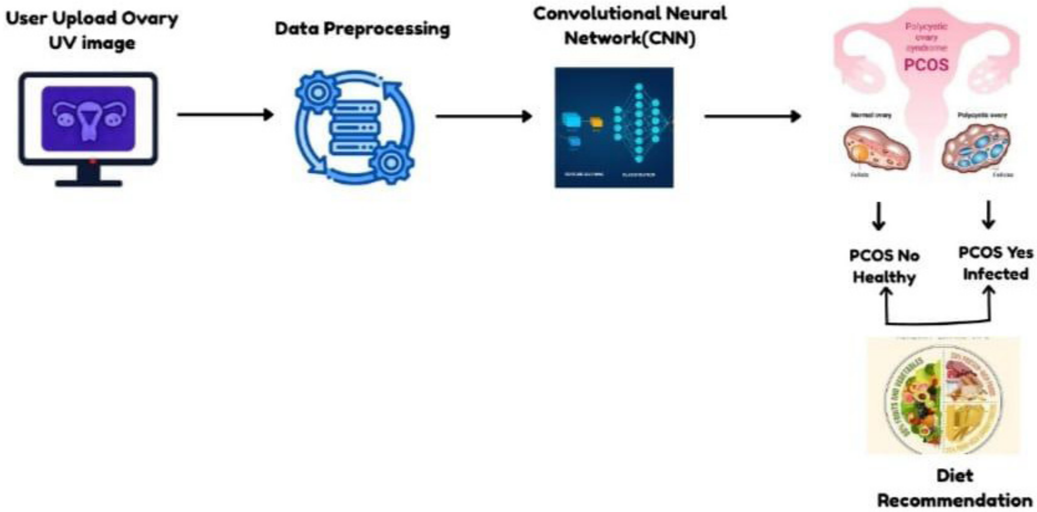

Figure 1. System Architecture for PCOS Detection Using Convolutional Neural Network (CNN) on Ovary UV Images

User Upload

When a user uploads an ultrasound image of their ovaries to the system, the process starts. These ultrasonography pictures, which are typically taken during standard pelvic exams, are essential for identifying the ovaries' structural features. A "string of pearls" appearance, an increase in ovarian volume, or the presence of numerous immature follicles are some of the visual indicators that PCOS frequently presents with. The system is made more accessible and user-friendly by removing the need for manual interpretation at the outset by enabling users or clinicians to upload these images directly.

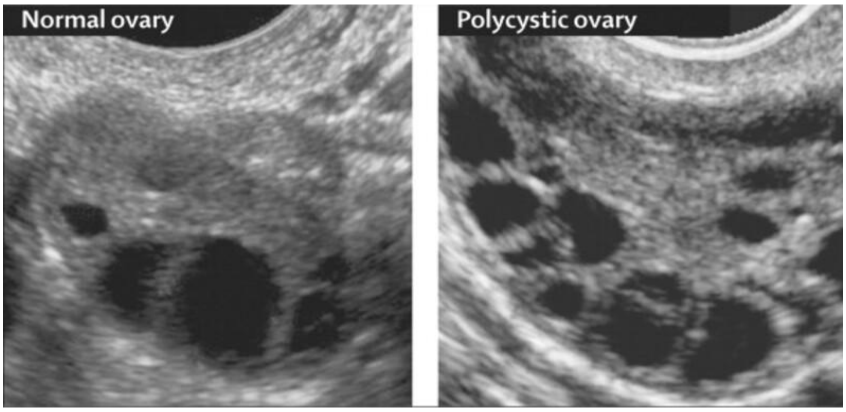

Figure 2. Image of Normal & Polycystic ovary

A dataset of 5000 ultrasound pictures of ovaries, including both normal and polycystic cases, was sourced from Kaggle for this investigation. As shown in the figure 2, A small number of follicles, usually less than ten, with consistent size and regular distribution throughout the ovarian tissue are normally visible in normal ovarian ultrasound pictures. The presence of several tiny, fluid-filled cysts (often more than 12 follicles) throughout the ovary's periphery, on the other hand, is what distinguishes polycystic ovary pictures. Furthermore, polycystic ovaries frequently have changed echotexture and enlarged ovarian volume, which are distinguishing visual indicators. During training, the CNN model learns to extract and categorize discriminative features from these morphological differences.

Data Preprocessing

The ultrasound image goes through a few preprocessing stages after uploading to guarantee that the deep learning model analyzes it effectively. First, noise reduction is used to remove background artifacts and ultrasound speckle noise that might mask significant ovarian features. The CNN then resizes the images to a predetermined resolution, guaranteeing consistency and uniformity throughout the dataset. By bringing pixel intensity values into line with a common scale, normalization enables the model to concentrate on significant feature differences rather than lighting variations. To improve robustness and generalization, the dataset is artificially expanded using data augmentation techniques like flipping, rotation, zooming, and contrast adjustment. In more complex applications, segmentation can also be used to separate the ovary from the surrounding pelvic structures, increasing the precision of the diagnosis. All these preprocessing procedures work together to ensure that all images, regardless of their origin or quality, are converted into reliable, high-quality inputs that can be used for CNN-based classification.

CNN Classification

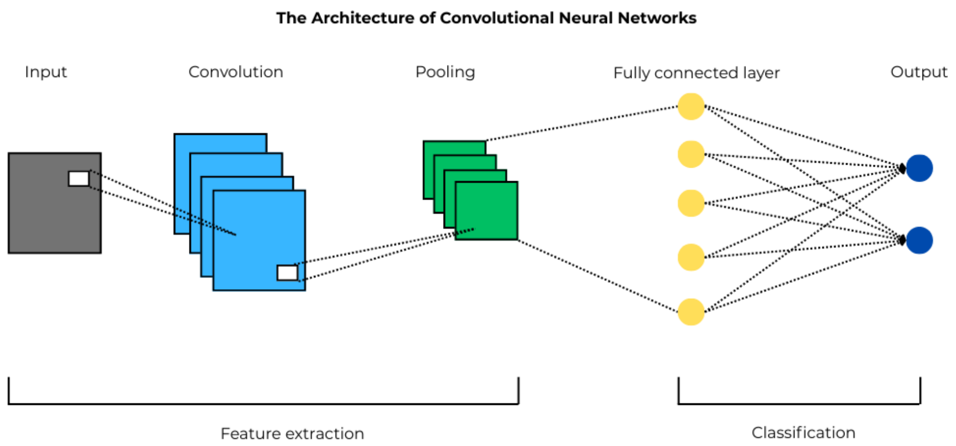

Figure 3. The Architecture of CNN

As shown in the figure 3, A Convolutional Neural Network (CNN), a kind of deep learning architecture is particularly useful for medical imaging tasks. CNN follows the following processes like Feature Extraction- To identify local patterns like cyst structures, follicle distribution, and textural variations, convolutional layers apply a number of filters to the image.Pooling- Increases computation efficiency by reducing dimensionality while maintaining the most important spatial features.Deep Feature Learning- From basic shapes to intricate ovarian patterns, stacked layers gradually pick up abstract features and Classification Layer-To predict the ovarian condition, a fully connected layer combines learned features.

PCOS Detection

A clear and useful diagnostic recommendation is provided by the CNN's binary classification result:

- PCOS No (Healthy): there are no abnormal enlargements or cystic features in the ovary.
- PCOS Yes (Infected): the ovary exhibits characteristic signs of PCOS, like enlarged volume or numerous peripheral follicles.

To provide a more comprehensive clinical picture in subsequent iterations, this binary output might be extended into a multi-class classification system (such as mild, moderate, and severe PCOS).

Visual Feedback

In addition to the prediction, the system offers visual feedback to enhance interpretability. These could include labeled diagrams that provide a side-by-side comparison between a polycystic ovary and a healthy ovary with annotations of important features like "multiple follicles detected," heatmaps or saliency maps (via Grad-CAM) that highlight the areas of the ultrasound that influence the model's decision, and an overlay on the original image where suspected cysts are directly marked. By making the results more transparent and clinically meaningful, these visual explanations not only improve comprehension for patients and clinicians but also foster confidence in AI-driven diagnostics.

Optional Diet Recommendation

The system incorporates a wellness recommendation module in addition to detection. It offers straightforward, non-prescriptive dietary recommendations to support reproductive health based on the diagnosis. For Healthy Users-To maintain ovarian health, it is recommended to eat balanced meals that contain enough proteins, vitamins, and water. General dietary and lifestyle guidelines for PCOS users include consuming fewer processed sugars, eating more fiber-rich foods, eating meals with a low glycemic index, and getting regular exercise. This feature is intended to give users, particularly those in areas with limited access to healthcare, easily accessible, preventive advice. It provides users with useful lifestyle strategies, but it does not take the place of medical advice.

RESULTS AND DISCUSSION

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Model Summary:

Model: "sequential"
```

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 126, 126, 32)	896
max_pooling2d (MaxPooling2D)	(None, 63, 63, 32)	0
conv2d_1 (Conv2D)	(None, 61, 61, 64)	18,496
max_pooling2d_1 (MaxPooling2D)	(None, 30, 30, 64)	0
conv2d_2 (Conv2D)	(None, 28, 28, 128)	73,856
max_pooling2d_2 (MaxPooling2D)	(None, 14, 14, 128)	0
flatten (Flatten)	(None, 25088)	0
dense (Dense)	(None, 128)	3,211,392
dropout (Dropout)	(None, 128)	0
dense_1 (Dense)	(None, 1)	129

```
 Total params: 3,304,771 (12.61 MB)
 Trainable params: 3,304,769 (12.61 MB)
 Non-trainable params: 0 (0.00 B)
 Optimizer params: 2 (12.00 B)
None

Expected Input Shape: (None, 128, 128, 3)
Processed Image Shape: (1, 224, 224, 3)
```

Figure 4. Model building summary

The custom CNN model achieved an accuracy of 97 % in detecting ovarian morphological features consistent with PCOS on the test dataset. This demonstrates the model's capability to reliably identify PCOS from ultrasound images, validating the effectiveness of deep learning in medical image analysis. This CNN model processes ovary ultrasound images of size 128×128×3 to detect PCOS. It consists of three convolutional layers with max pooling, followed by a flatten layer and two dense layers for classification. A dropout layer is included to prevent overfitting. The model has approximately 3,3 million trainable parameters ashown in the figure 4.

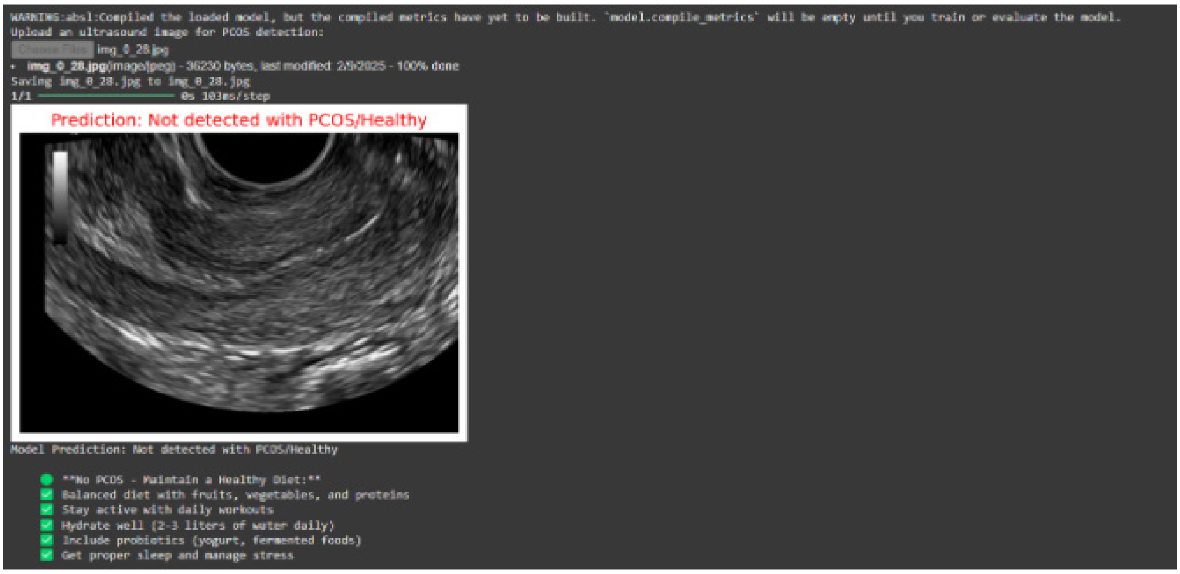

Figure 5. classification of image as healthy (non PCOS case)

The developed CNN model successfully classified ovary ultrasound images into PCOS and Non-PCOS (Healthy) categories. In the first test case, the model predicted "Not detected with PCOS/Healthy", supported by the absence of multiple enlarged follicles and consistent with normal ovarian morphology. In the second case, the model accurately detected "Detected with PCOS", indicated by the presence of multiple peripheral follicles and increased stromal density.as shown in the figure 5 and 6.

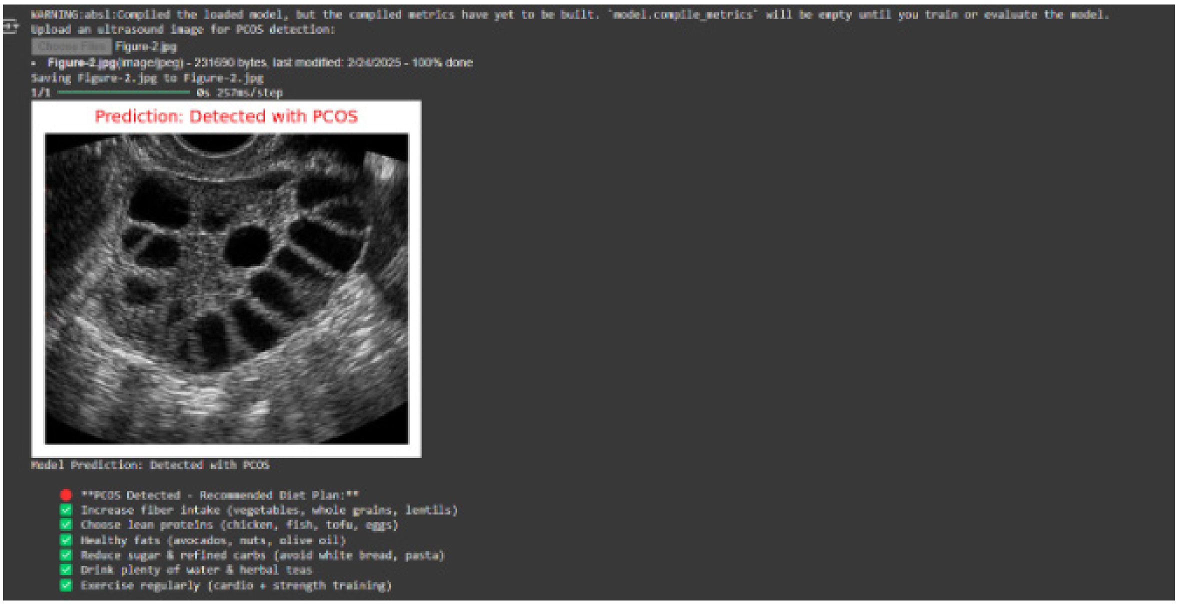

Figure 6. classification of image as PCOS (PCOS case)

The predictions were accompanied by personalized lifestyle and dietary recommendations based on the classification, emphasizing a human-centered approach to healthcare. The model demonstrates strong visual diagnostic capabilities, aligning its outputs with typical clinical features of PCOS visible in ultrasound scans. These results validate the model's ability to assist in early, non-invasive PCOS screening and patient-specific guidance, potentially enhancing clinical decision-making and patient well-being.

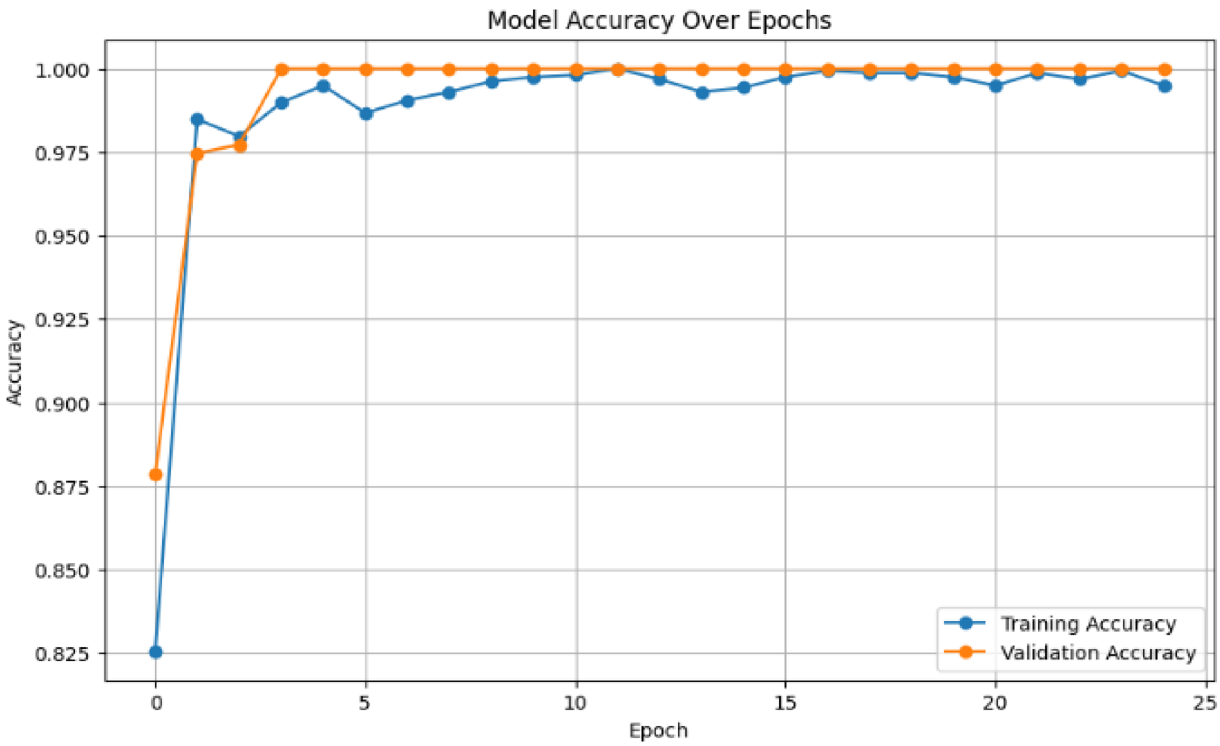

Figure 7. Model accuracy plot

As shown in figure 7 & 8, both training and validation accuracy rapidly increase and stabilize above 97 % within the first few epochs, indicating fast convergence and high model performance. The close alignment between training and validation accuracy suggests the model generalizes well without significant overfitting. The graph illustrates a rapid decline in both training and validation loss during the initial epochs, stabilizing near zero as training progresses. This indicates effective model learning with minimal overfitting and strong generalization to unseen data.

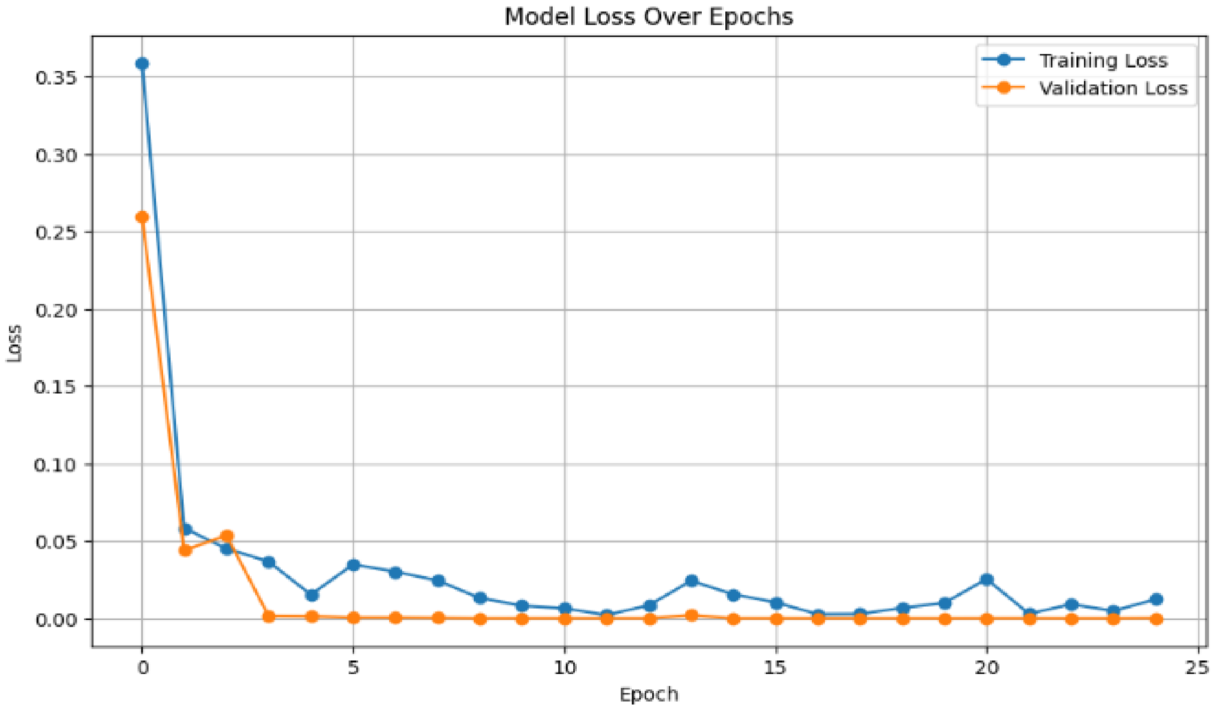

Figure 8. Model loss plot

CONCLUSIONS

The efficiency of a Convolutional Neural Network (CNN)-based system for the automated identification of Polycystic Ovary Syndrome (PCOS) from ultrasound images is demonstrated in this work. With the use of preprocessing methods, strong feature extraction, and classification, the suggested model demonstrated its potential as a trustworthy diagnostic support tool by achieving an astounding 97 % accuracy. Heatmaps and annotated overlays are examples of visual feedback mechanisms that are integrated to improve interpretability and boost trust in AI-driven medical imaging. Furthermore, the system's function is expanded beyond detection with the addition of optional dietary recommendations, supporting user-centered health management. Overall, this study highlights how deep learning holds promise for improving reproductive healthcare, especially in underserved or remote areas where access to professional diagnosis may be restricted. Future studies might concentrate on growing the dataset, improving multi-class classification for PCOS severity levels, and incorporating this system into clinical workflows in real time.

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