# PCOS DETECTION AND EXPLAINABLE AI

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**In**

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# DECLARATION

We hereby declare that reported in the B. Tech Minor Project-2 entitled " **PCOS Detection Tool: Deep Learning and Explainable AI** " submitted at **Jaypee Institute of Information Technology, Noida**, India is our own work, to the best of our knowledge and belief, it contains no material previously published or written by another person nor material which has been accepted for the award of any other degree or diploma of the university or other institute of higher learning, except where due acknowledgment has been made in the text.

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This is to certify that the work titled " **PCOS Detection Tool: Deep Learning and Explainable AI** " submitted by "**Prateek Kumar, Vedant Singh Chauhan and Shivam Singh**" in partial fulfillment for the Bachelor of Technology in Computer Science of Jaypee Institute of Information Technology, Noida has been carried out under my supervision. This work has not been submitted partially or wholly to any other University or Institute for the award of this or any other degree or diploma.

Signature :

**Dr. Kavita Pandey**

**ASSISTANT PROFESSOR**

Date :

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This study has not only deepened our understanding of the subject but has also opened up new avenues of knowledge. We are confident that the insights gained will continue to benefit us in our future endeavours.

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# SUMMARY


The PCOS Detection System is an AI-driven application designed to assist in diagnosing Polycystic Ovary Syndrome (PCOS) using ultrasound images. Leveraging the efficiency of the MobileNet deep learning model, the system achieves high accuracy in identifying PCOS features. By integrating Grad-CAM, an explainable AI tool, the system provides heatmaps highlighting critical areas of the ultrasound images that influenced its predictions, ensuring transparency and interpretability for healthcare professionals. The application is built on Python, utilizing frameworks like TensorFlow/Keras for model development, Flask for web deployment, and libraries like NumPy, Pandas, and Matplotlib for data handling and visualization.

The system features a user-friendly web interface that enables clinicians to upload ultrasound images, view predictions (PCOS or no PCOS), and access Grad-CAM heatmaps overlaid on the images. It incorporates preprocessing techniques such as image resizing, normalization, and augmentation to standardize the dataset and improve model robustness. Despite its promising results, challenges like handling ambiguous images, refining Grad-CAM outputs, and improving scalability were identified. Future improvements include expanding to multi-disease detection, integrating with Electronic Health Records (EHR), and optimizing system performance for real-world clinical use. This project highlights the potential of AI in healthcare by combining accuracy, interpretability, and usability.



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# CHAPTER 1

# INTRODUCTION

## 1.1 GENERAL INTRODUCTION

Polycystic Ovary Syndrome (PCOS) is a hormonal disorder that significantly affects women of reproductive age, leading to complications such as irregular menstrual cycles, infertility, and metabolic issues like insulin resistance. Early diagnosis is crucial for effective management, yet traditional diagnostic methods, including clinical evaluations, hormonal tests, and imaging, are time-consuming and prone to subjectivity. To address this challenge, we developed an AI-based tool that leverages deep learning for automated and efficient PCOS detection using medical images, specifically ultrasound scans. The system is designed to assist healthcare professionals in providing faster and more accurate diagnoses.

At the heart of the system is a fine-tuned MobileNet model, a lightweight convolutional neural network (CNN) known for its efficiency and strong performance on image classification tasks. This pretrained model, originally trained on ImageNet, was adapted to classify ultrasound images as PCOS-positive or negative. The dataset, sourced from Kaggle, underwent preprocessing steps including resizing, normalization, and augmentation to improve model accuracy and generalization. MobileNet's small size makes it ideal for deployment in environments with limited computational resources, ensuring practical usability in real-world clinical settings. Transfer learning techniques were applied to fine-tune the model on the specific task of PCOS detection, resulting in an accurate and efficient diagnostic system.

To ensure the system's predictions are transparent and interpretable, we integrated Grad-CAM (Gradient-weighted Class Activation Mapping). This explainability technique generates heatmaps over the input ultrasound images, highlighting regions most critical to the model's predictions. For instance, Grad-CAM identifies and emphasizes cyst-like structures within the ovaries, making it easier for healthcare professionals to understand why the model classified an image as PCOS-positive or negative. This feature addresses the common issue of AI systems being perceived as "black-box" models and fosters trust in the system by allowing clinicians to validate its predictions visually.

The complete solution is packaged into a user-friendly web application developed using Flask, enabling seamless interaction for medical practitioners. The web interface allows users to upload ultrasound images, after which the model processes the data and generates predictions along with

Grad-CAM visualizations. This design ensures that healthcare professionals can quickly access both diagnostic results and interpretable heatmaps through a single, intuitive platform. By combining deep learning, explainable AI, and practical deployment, the tool not only automates PCOS detection but also ensures transparency and accessibility, paving the way for improved diagnostic workflows and better patient outcomes.

## 1.2 PROBLEM STATEMENT

The diagnosis of Polycystic Ovary Syndrome (PCOS) through ultrasound imaging presents a significant challenge due to the complexity of interpreting medical images and the need for accuracy in predictions. While Convolutional Neural Networks (CNNs) are highly effective at image classification tasks, their black-box nature makes it difficult for healthcare professionals to trust the model's decision-making process, especially when diagnosing sensitive conditions like PCOS. Clinicians need not only accurate results but also clear explanations to understand how and why a model made a certain prediction, ensuring that AI-driven tools are practical and trustworthy in clinical settings.

To overcome this challenge, we integrated Explainable AI (XAI) techniques into our CNN-based PCOS detection system. Specifically, we used Grad-CAM (Gradient-weighted Class Activation Mapping), a method that generates heatmaps to highlight the areas in the ultrasound images most influential to the model's decision. Grad-CAM enhances transparency by providing visual explanations, showing the regions, such as cysts or abnormal ovarian features, that contributed to the model's classification. This combination of high accuracy from the CNN model and interpretability through Grad-CAM ensures that the system is not only effective in detecting PCOS but also offers valuable insights that healthcare professionals can trust.

## 1.3 SIGNIFICANCE OF THE PROBLEM

The significance and novelty of this project lie in its integration of Explainable Artificial Intelligence (XAI) with a convolutional neural network (CNN) for detecting Polycystic Ovary Syndrome (PCOS) from ultrasound images—an area where XAI has been underutilized. Traditional PCOS diagnostic methods, such as ultrasound and clinical tests, are resource-intensive and often not accessible in low-resource settings, causing delays in diagnosis. While deep learning models have shown promise in medical image analysis, their "black-box" nature makes it difficult for clinicians to trust their predictions. This project addresses this gap by incorporating Grad-CAM, an XAI technique that generates heatmaps, allowing healthcare professionals to visually understand which areas of the image influenced the model's decision, thus increasing trust in the system's predictions.

By combining CNNs for accurate PCOS detection with the transparency offered by Grad-CAM, this project not only improves early detection but also sets a precedent for the use of explainable AI in medical applications. The integration of explainability ensures that the AI model is not just an automated tool but a valuable, interpretable aid in clinical decision-making. This novel approach promotes the adoption of AI in healthcare by addressing both diagnostic accuracy and the crucial need for transparency, paving the way for more interpretable and reliable AI solutions in medical diagnostics.

## 1.4 EMPIRICAL STUDY

The empirical study of this project explores the application of deep learning, particularly a fine-tuned pretrained MobileNet model, for detecting Polycystic Ovary Syndrome (PCOS) from ultrasound images. PCOS is a complex hormonal disorder often diagnosed through clinical evaluations and imaging, but these methods can be time-consuming and prone to subjectivity. In this project, a deep learning model is leveraged to automate the detection of PCOS, improving both accuracy and efficiency. MobileNet, known for its lightweight architecture and efficient performance, was selected to classify ultrasound images, making it suitable for deployment in real-world clinical environments where computational resources may be limited. The study examines how the model was trained on a labeled dataset of ultrasound images, fine-tuned to detect features indicative of PCOS, such as ovarian cysts or abnormal follicular structures.

A major challenge in the application of AI in healthcare is the lack of interpretability in many deep learning models, which are often considered "black-box" systems. To address this, the study incorporates Explainable Artificial Intelligence (XAI) techniques, specifically Grad-CAM (Gradient-weighted Class Activation Mapping), to provide transparency and visual explanations for the model's predictions. Grad-CAM generates heatmaps that highlight the areas in an image most influential in the model's decision-making process, allowing clinicians to understand which features in the ultrasound image led to the diagnosis of PCOS. This level of interpretability is crucial for gaining the trust of healthcare professionals, who require transparency in AI-driven tools, especially when making critical medical decisions.

The study also focuses on the practical implementation of the model and its integration into a user-friendly web application using Flask. This web application enables healthcare professionals, such as radiologists or gynecologists, to upload ultrasound images, receive instant PCOS predictions, and view the Grad-CAM heatmaps overlaid on the images. The system's ability to generate real-time predictions with accompanying visual explanations makes it not only accurate but also practical and accessible for clinical use. The Flask web interface ensures that the solution is easily deployable, facilitating its adoption in medical environments where accessibility and ease of use are key considerations.

Overall, this empirical study validates the efficacy of combining deep learning with XAI for automated PCOS detection in ultrasound images. By integrating a powerful CNN model with the interpretability provided by Grad-CAM, the project demonstrates how explainable AI can improve diagnostic accuracy while ensuring that healthcare professionals can trust and understand the model's decisions. The success of this approach highlights the potential for AI technologies to revolutionize medical diagnostics, offering clinicians a transparent and efficient tool for PCOS detection, ultimately leading to faster, more reliable diagnoses and better patient outcomes.

## 1.5 BRIEF DESCRIPTION OF SOLUTION APPROACH

The solution approach for PCOS detection in this project revolves around leveraging deep learning techniques, specifically using a pretrained MobileNet model, alongside Grad-CAM for explainability, and Flask for web deployment. The first step in the approach involves working with a labeled dataset of ultrasound images, which is used to train the model. The dataset is divided into two categories: PCOS-positive and PCOS-negative. To prepare the images for model input, several preprocessing steps are undertaken. The images are resized to a standard dimension compatible with the MobileNet model, and normalization is performed to scale the pixel values to a range of 0–1. To further improve the model's ability to generalize, data augmentation techniques such as flipping, rotation, and zooming are applied, enhancing the diversity of the dataset and preventing overfitting.

The core of the model is the MobileNet architecture, a lightweight convolutional neural network (CNN) that was originally trained on the ImageNet dataset. MobileNet is well-suited for image classification tasks that require low computational resources while maintaining good performance, making it ideal for medical image classification in environments with limited resources. In this project, the MobileNet model is fine-tuned specifically for PCOS detection using the prepared ultrasound dataset. This fine-tuning process ensures that the model adapts to the unique features present in medical images, leading to accurate and reliable classification of PCOS.

To address the challenge of model interpretability, Grad-CAM (Gradient-weighted Class Activation Mapping) is applied. Grad-CAM is an explainable AI technique that generates heatmaps to highlight the areas of an image that most significantly influence the model's decision. This capability is particularly important in the healthcare domain, where clinicians need to understand and trust the model's predictions. By providing visual explanations of why certain areas of the image were important for the model's classification, Grad-CAM helps build confidence in the AI model's diagnostic capabilities, making it more accessible and trustworthy for medical professionals.

Finally, the trained MobileNet model and the Grad-CAM explanation are deployed through a web application built using Flask, a lightweight Python web framework. This web app allows healthcare professionals, such as doctors and radiologists, to upload ultrasound images and receive predictions about whether the image indicates PCOS. The web interface is designed to be simple and intuitive, allowing users to interact with the system with ease. Once a prediction is made, the app overlays the Grad-CAM heatmap onto the image, providing both the predicted classification and a visual representation of the model's focus areas. This combination of deep learning, explainability, and a user-friendly interface ensures that the tool is both accurate and accessible for use in clinical settings.

## 1.6 COMPARISION OF EXISTING APPROACHES TO THE PROBLEM FRAMED

**Comparison of Existing Approaches to PCOS Detection**

In the context of PCOS (Polycystic Ovary Syndrome) detection, there are various existing approaches that employ machine learning, deep learning, and image processing techniques. Below is a comparison of these existing methods with the approach used in our project, which involves fine-tuning a pretrained MobileNet model, utilizing Grad-CAM for explainability, and deploying the system via a Flask web application.

| Aspects | Traditional Approach | Proposed Approach |
|---|---|---|
| Traditional PCOS Diagnosis Methods | - Relies on clinical evaluation and tests (ultrasound, blood tests, physical examination). | - Utilizes deep learning (MobileNet) for automated detection of PCOS from ultrasound images. |
| | - Provides a holistic view by combining multiple criteria. | - Enhances speed and accuracy of diagnosis. |
| Machine Learning (ML)-Based Approaches | - Utilizes models like Support Vector Machines, Decision Trees, etc., on extracted features. | - Machine learning models offer automation in diagnosis. |
| | - Requires manual feature engineering. | - Improved accuracy but still relies on manual feature extraction. |
| Deep Learning-Based Approaches (CNNs) | - Not typically used in traditional methods for medical image classification. | - Uses Convolutional Neural Networks (CNNs) for end-to-end learning. |
| | - Relies on feature extraction by human experts. | - Eliminates manual feature extraction and provides high accuracy in medical image classification. |
| Explainable AI Approaches (e.g., Grad-CAM, LIME, SHAP) | - Traditional approaches are not inherently explainable. | - Incorporates Grad-CAM for explainability. |
| | - Diagnosis is often subjective, especially with ultrasound images. | - Visualizes which areas of the ultrasound influenced the decision, improving trust in AI-based diagnosis. |

**Table 1:** Existing approaches vs Proposed approach

## Our Approach

The approach used in this project involves fine-tuning a pretrained MobileNet model to detect PCOS from ultrasound images, applying Grad-CAM for explainability, and deploying the entire system through a Flask web application. MobileNet, a lightweight and efficient Convolutional Neural Network (CNN), is well-suited for deployment in real-world medical settings, especially where computational resources are limited. The model is fine-tuned on a specific PCOS dataset, allowing it to learn relevant features while benefiting from the generalization power of the pretrained model, which was initially trained on ImageNet. Grad-CAM is integrated into the model to provide interpretability, generating visual heatmaps that highlight the regions of the image that most influenced the model's decision. This feature improves transparency and trust, crucial for clinical adoption of AI-driven tools.

The use of Flask enables seamless web deployment, allowing healthcare professionals to upload ultrasound images and receive real-time predictions, along with clear visual explanations via the Grad-CAM heatmaps. This end-to-end deployment ensures that the model’s predictions are both accurate and interpretable. However, the approach does have some disadvantages. Fine-tuning the model requires high-quality labeled data and significant computational resources. Additionally, the model’s generalization to new or unseen data, particularly images from different ultrasound machines or settings, may be limited unless trained on a larger and more diverse dataset. Lastly, while the web interface is designed to be user-friendly, ensuring smooth integration and real-time functionality within clinical environments may require additional steps.

# CHAPTER 2

# LITERATURE SURVEY

## Literature Survey Summary

In our literature survey, we reviewed a total of **12-15 papers** mentioned in Table 2 belo focused on the prediction of multiple diseases using Deep Learning **(DL)** models, with a particular emphasis on those that integrated Explainable AI **(XAI)** techniques. These papers provided insights into the effectiveness of DL in disease prediction and the importance of explainability in enhancing the trust and transparency of AI models in healthcare.

| Disease | Year | Objective | Data Sets | ML Models Used | Evaluation Metrics | XAI Models Used |
|---|---|---|---|---|---|---|
| HIV [1] | 2021 | Analyze Dry Eye Disease in HIV patients using XAI and ML models | Case-control study on HIV patients | Clustering, Logistic Regression, Decision Trees, Neural Networks | Precision, Recall, Accuracy, Gini Importance, VI | LIME, Shapley, ICE |
| Cardiovascular [2] | 2022 | XAI framework for predicting cardiovascular diseases | Dataset with 303 instances, 14 attributes | SVM, AdaBoost, KNN, Bagging, LR, Naive Bayes | AUC, ROC, Sensitivity, Specificity, F1-Score | SHAP, LIME |
| Allergy [3] | 2021 | Framework for allergy diagnosis | Intradermal skin test of 878 patients (India) | Decision Tree, SVM, Random Forest | Accuracy, Sensitivity | Post-hoc Explainability |
| Asthma [4] | 2023 | Identify causes of chronic cough in asthmatic patients | Cohort from NCT04796844 trial | Logic Learning Machine | Accuracy, F1-Score, PPV, NPV, TPR, TNR | Rule-based if-then rules |
| Liver [5] | 2023 | Classify liver disease using deep learning and XAI | Indian Patient Liver Dataset | Deep Learning (Keras-Tensorflow) | Accuracy, Precision, Recall, F-Measure | SHAP |
| Monkeypox [6] | 2023 | Detect Monkeypox from skin lesion images using XAI and deep learning | Images from Kaggle (Monkeypox, Measles, etc.) | ResNet-18, ResNet-50, ResNet-101, SqueezeNet | Accuracy, Precision, Recall, F1-Score | LIME |
| Breast Cancer [7] | 2023 | Develop a clinical decision support for breast cancer prevention | Public data of Indonesian women | XGBoost, Logistic Regression, Random Forest, SVM | Accuracy, Precision, Recall | SHAP |
| Diabetes [8] | 2023 | Apply XAI techniques in diabetes prediction | Diabetes dataset (768 rows, 9 columns) | KNN, Naive Bayes, SVM, Decision Tree, Random Forest, LR | F1 Score, Accuracy, Precision, Recall, ROC AUC, Time Taken | SHAP, LIME |
| PCOS [9] | 2023 | Predict PCOS using demographic and clinical features | Kaggle PCOS dataset | RF, ADB, GB, XGB, CATB, PODBoost | Accuracy, Error-Rate, ROC-AUC, Recall, Precision, F1-Score | LIME |
| PCOS [10] | 2023 | Early detection of PCOS using optimized feature selection and XAI | PCOS dataset from Kaggle (541 instances) | Logistic Regression, RF, DT, Naive Bayes, SVM, KNN, XGBoost, AdaBoost, Stacking | Accuracy, Precision, Recall, F1-Score, AUC | Local and Global Explainability |
| Thyroid [11] | 2023 | Predict hypothyroidism and hyperthyroidism using XAI and ML | UCI Machine Learning Repository | Decision Tree, Random Forest, Gradient Boosting, Naive Bayes, KNN, LR, SVM | Accuracy, Precision, Recall, F1-Score | SHAP, LIME |

**Table 2**: Disease Selection Analysis

After analyzing these papers, we shifted our focus to **PCOS (Polycystic Ovary Syndrome)** and reviewed **5-7 papers** mentioned in Table 3 below, specifically addressing the use of DL for PCOS prediction. While there were studies that used DL models for PCOS detection, we identified a **research gap**: XAI techniques were not implemented to explain the predictions of these models. This lack of interpretability in PCOS-related DL models led to reduced trust from healthcare professionals, which hindered their adoption in clinical settings.

| Author | Year | Objective (in short) | Data Sets | ML Models Used | Evaluation Metrics | XAI Models Used |
|---|---|---|---|---|---|---|
| Khanna et. al [12] | 2023 | Detect PCOS using AI with ML and DL classifiers, and propose an automated screening system. | 541 patients from Kerala, India, with 43 attributes. | Logistic Regression, Decision Trees, Random Forest, SVM, Naïve Bayes, KNN, etc. | Accuracy, precision, recall, F1-score, AUC-ROC score, and precision-recall curve. | SHAP, LIME, ELI5, Qlattice, and feature importance with Random Forest. |
| Moral et. al [13] | 2024 | Develop an explainable AI model for early detection of PCOS using machine learning techniques. | PCOS dataset from Kaggle (541 records, 43 attributes) | Logistic Regression, Naive Bayes, Random Forest, Gradient Boosting, etc. | Accuracy, Error-Rate, ROC-AUC Score, Recall, Precision, and F1-Score. | Local Interpretable Model-Agnostic Explanations (LIME). |
| Elmannai et. al [14] | 2023 | Develop a machine learning model for early detection of PCOS using optimized feature selection and XAI. | PCOS dataset from Kaggle (541 instances, 41 attributes) | Logistic Regression (LR), Random Forest (RF), Naive Bayes (NB), etc. | Accuracy (ACC), Precision (PRE), Recall (REC), F1 Score (F1), and ROC-AUC Curve. | Local and global explainability techniques to ensure model trust. |
| Çiçek et. al [15] | 2021 | Extract patient-based explanations of important features in PCOS risk using LIME. | "Polycystic ovary syndrome" dataset from Kaggle | Random Forest (RF) | Accuracy, Sensitivity, Specificity, Positive Predictive Value, Balanced Accuracy. | Local Interpretable Model-Agnostic Explanations (LIME). |
| ÖZMEN et. al [16] | 2023 | Determine the best method for follicle detection using ovarian ultrasound images. | Ultrasound images of 54 patients (14 PCOS, 40 control). | Convolutional Neural Network (CNN) and SqueezeNet | Mean Square Error (MSE), Peak Signal-to-Noise Ratio (PSNR), accuracy, etc. | None |
| Umapathy et. al [17] | 2024 | Develop an automated system for detecting PCOS using deep learning techniques. | Two datasets with ultrasound images (100 normal, 100 PCOS) | Random Forest, k-star, MobileNet, ResNet152V2, etc. | Classification accuracy, sensitivity, specificity, and AUC. | None |
| Alamoudi et. al [18] | 2023 | Develop a computer-aided diagnosis model for diagnosing PCOS using a deep learning fusion approach. | Ovary ultrasound images and clinical data from 285 patients | VGG-16, VGG-19, InceptionV3, DenseNet121, DenseNet201, etc. | Accuracy, precision, F1-score, recall (sensitivity), specificity. | None |
| Suha et. al [19] | 2022 | Propose an extended machine learning classification technique for PCOS prediction. | 594 ovary ultrasound (USG) images. | CNN with transfer learning (VGGNet16), XGBoost stacking model | Accuracy, Precision, Sensitivity, F1 Score, Execution Time, AUC-ROC Curve. | None |

**Table 3:** PCOS papers Analysis and Trends

To fill this gap, our project aimed to develop a DL-based system for PCOS detection, incorporating Grad-CAM, an explainability technique, to visually demonstrate how the model makes its predictions. By integrating XAI with PCOS detection, we aim to provide a more transparent, understandable, and trustworthy solution for clinicians, which is critical for the clinical adoption of AI-based diagnostic tools.

# CHAPTER 3

# REQUIREMENT ANALYSIS AND SOLUTION APPROACH

## 3.1 Overall Description of the Project

The project focuses on developing an AI-powered solution for detecting Polycystic Ovary Syndrome (PCOS) using a pretrained MobileNet deep learning model. PCOS is a common hormonal disorder that affects women, and its early detection can help manage symptoms and reduce long-term health risks. The solution aims to automate the detection of PCOS from medical images, particularly ultrasound scans, while also integrating explainability through Grad-CAM, a popular technique in Explainable AI (XAI).

The project begins with data collection and preprocessing. The dataset for PCOS detection consists of ultrasound images sourced from Kaggle, a well-known platform for publicly sharing datasets. These images were preprocessed to ensure compatibility with the MobileNet model. This preprocessing step involved resizing the images to a standard dimension, normalizing the pixel values to a range of 0–1 to enhance model stability, and applying data augmentation techniques like flipping, rotation, and zooming to artificially expand the dataset. This helped improve the generalization ability of the model by creating a more diverse training set. Additionally, proper dataset splitting was performed to create balanced training, validation, and testing sets, ensuring that the model would generalize well to unseen data.

For the core of the detection process, a pretrained MobileNet model was utilized. MobileNet is a lightweight deep learning model known for its efficiency and speed, making it an ideal choice for real-time clinical use, especially on devices with limited computational resources. The model was fine-tuned for the specific task of PCOS detection using ultrasound images. The use of a pretrained model allowed for faster training and ensured the model could leverage the generalization power of features previously learned from ImageNet, improving its accuracy in classifying PCOS.

To address the challenge of model interpretability, Grad-CAM (Gradient-weighted Class Activation Mapping) was integrated into the system. Grad-CAM generates heatmaps that visualize the regions of the medical image most relevant to the model's decision-making process. These heatmaps provide valuable insights into which areas of the ultrasound scan the model focused on to make its prediction, enhancing transparency and helping healthcare professionals understand why the model made a particular prediction. This step is crucial for building trust in AI-based diagnostic tools and increasing their adoption in clinical settings.

Finally, the trained model and Grad-CAM visualizations were deployed as a web application using Flask, a lightweight Python web framework. The web interface allows medical professionals such as doctors and radiologists to upload ultrasound images for real-time PCOS predictions. After the model makes a prediction, the application overlays the Grad-CAM heatmap on the input image, providing both the prediction (PCOS or not) and a visual explanation of the model's decision. The user-friendly interface ensures that healthcare practitioners can easily interact with the system, making it practical and accessible for use in clinical environments.

By combining deep learning with explainable AI and deploying the solution through a web interface, this project aims to offer an automated, transparent, and accessible tool for diagnosing PCOS. The integration of Grad-CAM ensures that clinicians can use the AI model confidently, not as a "black-box" system but as a supplementary tool in their decision-making process. This solution has the potential to improve diagnostic accuracy, reduce the workload of healthcare professionals, and provide faster, more reliable results for patients. The project's objectives include automating the detection of PCOS from ultrasound images, incorporating explainability to make AI predictions understandable, and deploying the solution as a web application to make it easily accessible in clinical settings.

## 3.2 Requirement Analysis

### Functional Requirements

These are the core features that the system must perform to meet the end-user needs and achieve the desired functionality.

### Data Selection

The system begins by selecting an appropriate dataset of ultrasound images for PCOS detection. The dataset must consist of labeled images that are categorized into two classes: PCOS-positive and PCOS-negative. These images will be sourced from trusted repositories such as Kaggle, ensuring that the data is of high quality and diverse enough to train the model effectively. The dataset should be balanced to avoid bias, ensuring equal representation of both classes.

### Preprocessing

The system begins with preprocessing of ultrasound images to ensure compatibility with the MobileNet model. The images are resized to a standard dimension that fits the MobileNet architecture. Additionally, pixel values are normalized to a range of 0–1 to improve model training stability. To further enhance the model's generalization ability, data augmentation techniques such as flipping, rotation, and zooming are applied to artificially expand the dataset. Proper dataset splitting is performed to create balanced training, validation, and testing sets, ensuring that the model learns effectively across different image types and conditions.

### PCOS Detection Model

The system accepts ultrasound image files, such as JPEG or PNG formats, as input for PCOS detection. Using the pretrained MobileNet deep learning model, the system processes the uploaded image to determine whether the image shows signs of PCOS (Yes/No). The model outputs a prediction, indicating the presence or absence of PCOS. Along with the prediction, the system also provides a confidence score that reflects the probability of the prediction being accurate (e.g., 95%).

### Explainability with Grad-CAM

Once the model generates a prediction, the system employs Grad-CAM (Gradient-weighted Class Activation Mapping) to produce a heatmap. This heatmap highlights the areas of the ultrasound image that are most responsible for the model's decision. The heatmap is then overlaid on the original ultrasound image, offering a visual explanation of the model's decision-making process. This feature is designed to help healthcare professionals interpret the model's predictions with more confidence, providing clarity on why the model identified certain features in the image.

### Web Application for Interaction

The system is accessed through a web interface built with Flask, which allows users such as doctors and radiologists to upload ultrasound images, view predictions, and understand the model's decisions through the Grad-CAM heatmap. Once an image is uploaded, the system provides real-time feedback, displaying both the model's prediction and the corresponding Grad-CAM heatmap. Additionally, users are given the option to download both the original image with the Grad-CAM overlay and the model's prediction for their records.

**Non-Functional Requirements**

These are the quality attributes that the system should meet in terms of performance, security, scalability, and usability.

**Performance Requirements**

The system should be optimized to process ultrasound images, perform predictions, and generate Grad-CAM heatmaps within a time frame of 5-10 seconds. This ensures a fast and efficient user experience. The system must also be scalable to handle multiple simultaneous users, particularly in a clinical environment where healthcare professionals may need to access the system concurrently. To ensure that real-time predictions are delivered smoothly, the system must be designed with low latency, providing quick feedback to users without noticeable delays.

**Accuracy and Reliability**

The prediction accuracy of the model is a critical requirement. The system must achieve a high level of accuracy, ideally above 90%, for detecting PCOS based on the ultrasound image dataset. This ensures that healthcare professionals can trust the system’s predictions in clinical settings. Additionally, the system should provide reliable results across different ultrasound image datasets, demonstrating consistent performance regardless of variations in the images.

**Usability**

The system's web interface should be user-friendly and intuitive, allowing healthcare professionals to easily navigate the platform without requiring extensive training. Clear documentation should be provided to guide users, including instructions on how to upload images, interpret the predictions, and understand the Grad-CAM heatmaps.

**Overall Solution Approach**

The solution approach aims to develop a web-based system for detecting Polycystic Ovary Syndrome (PCOS) using deep learning, particularly leveraging a pretrained MobileNet model. The system not only performs PCOS detection but also integrates Explainable AI (XAI) using Grad-CAM to provide visual explanations of the model's predictions.

The overall system includes the following major components:

## Data Collection & Preprossesing

Initially, a dataset folder containing ultrasound images is gathered as shown in Fig 1, which includes both PCOS-positive and PCOS-negative samples.

| Name | Date modified | Type | Size |
|---|---|---|---|
| infected | 15-11-2024 13:31 | File folder | |
| notinfected | 15-11-2024 13:31 | File folder | |

**Fig 1**: Original Dataset

The dataset is then split into three separate folders for training, validation, and testing as shown in Fig 3 with a ratio of 70:15:15 to ensure a balanced distribution across all sets.

| | | |
|---|---|---|
| test | 15-11-2024 13:31 | File folder |
| train | 16-11-2024 15:33 | File folder |
| val | 15-11-2024 13:31 | File folder |

**Fig 3:** Dataset after Split

```
def datafolder(path,split):        #split the origional dataset folder and move images from there to the new folders
    if not os.path.exists("./"+path):
        os.mkdir("./"+path)

        for dir in os.listdir(ROOT_DIR):
            os.makedirs("./"+path+"/"+dir)
            for img in np.random.choice(a=os.listdir(os.path.join(ROOT_DIR,dir)),
                                        size=(math.floor(split * number_of_images[dir])-5),replace=False):

                O = os.path.join(ROOT_DIR,dir,img)
                D = os.path.join("./"+path,dir)
                shutil.copy(O,D)
                os.remove(O)

    else:
        print("Folder already exist")

datafolder("train",0.7)         # divide the dataset into train, test, validate

datafolder("test",0.15)

datafolder("val",0.15)
```

**Fig 4:** Code for Splitting Dataset

Then Preprocessing is applied to the images to prepare them for model input. This involves resizing the images to fit the MobileNet model's input size and normalizing the pixel values to a range of 0–1 for improved model training. To ensure that the model generalizes well, data augmentation techniques like flipping, rotation, and zooming are applied whose code reference is shown below in Fig 4.

```python
from keras.preprocessing.image import ImageDataGenerator    # augmenting image data and performing pre-processing in real-time
from keras.applications.mobilenet import preprocess_input

def preprocessingImage1(path):       # preprocessing images in batches of 32,zooming,shearing,resizing. for TRAINING
  image_data = ImageDataGenerator(zoom_range=0.2,shear_range=0.2,preprocessing_function= preprocess_input,horizontal_flip=True)
  image = image_data.flow_from_directory(directory=path,target_size=(224,224),batch_size=32,class_mode='binary')
  return image

def preprocessionfImage2(path):      # for TESTING, VALIDATION
  # """
  # Input :path
  # Output : preprocessed Image
  # """
  image_data  = ImageDataGenerator(preprocessing_function= preprocess_input )
  image = image_data.flow_from_directory(directory=path,target_size=(224,224),batch_size=32,class_mode='binary')
  return image
```

**Fig 4:** Data Preprocessing functions

### Model Training

The pretrained MobileNet model is fine-tuned for PCOS detection. Fine-tuning is performed by training the model on the ultrasound images from the training dataset as shown in Fig 5. The model's weights are updated during this phase to better adapt to the task of distinguishing between PCOS-positive and PCOS-negative images.

```
base_model = MobileNet(input_shape=(224,224,3),include_top=False)    # Base Model

for layer in base_model.layers:
  layer.trainable = False

x= Flatten()(base_model.output)
x= Dense(units=1,activation='sigmoid')(x)

model = Model(base_model.input,x)

model.compile(optimizer='rmsprop',loss=keras.losses.binary_crossentropy,metrics=['accuracy'])

from keras.callbacks import ModelCheckpoint,EarlyStopping

mc = ModelCheckpoint(filepath="bestmodel.h5",monitor='val_accuracy',verbose=1,save_best_only=True)
#Early stopping
es = EarlyStopping(monitor="val_accuracy",min_delta=0.01,patience=5,verbose=1)
cb = [mc,es]
#training the model
hist = model.fit_generator(train_data,
                           steps_per_epoch=10,
                           epochs=30,
                           validation_data=val_data,
                           validation_steps=16,
                          callbacks=cb)

model = load_model("D:/Minor/PCOS1/bestmodel.h5")
```

**Fig 5:** Model Creation and Training

**Explainability**

Grad-CAM (Gradient-weighted Class Activation Mapping) is used to generate heatmaps that explain the decision-making process of the model. Once the model predicts the presence or absence of PCOS, Grad-CAM highlights the regions in the ultrasound image that most influenced the model's decision. This visual explanation helps healthcare professionals understand and trust the model's predictions.

```
def find_target_layer(self):
    # attempt to find the final convolutional layer with 4D output
    for layer in reversed(self.model.layers):
        if len(layer.output.shape) == 4:
            return layer.name

    raise ValueError("Could not find 4D layer. Cannot apply GradCAM.")
```

**Fig 6:** Target layer Computation

```python
def compute_heatmap(self, image, eps=1e-8):
    # create a new model with output both,feature map and final prediction
    gradModel = Model(inputs=[self.model.inputs], outputs= [self.model.get_layer(self.layerName).output, self.model.output])
    with tf.GradientTape() as tape:
        inputs = tf.cast(image, tf.float32)
        (convOutputs, predictions) = gradModel(inputs)
        loss = predictions[:, self.classIdx]
    grads = tape.gradient(loss, convOutputs)
    # compute the guided gradients
    castConvOutputs = tf.cast(convOutputs > 0, "float32")
    castGrads = tf.cast(grads > 0, "float32")
    guidedGrads = castConvOutputs * castGrads * grads
    convOutputs = convOutputs[0]
    guidedGrads = guidedGrads[0]
    weights = tf.reduce_mean(guidedGrads, axis=(0, 1))
    cam = tf.reduce_sum(tf.multiply(weights, convOutputs), axis=-1)
    (w, h) = (image.shape[2], image.shape[1])
    heatmap = cv2.resize(cam.numpy(), (w, h))
    numer = heatmap - np.min(heatmap)
    denom = (heatmap.max() - heatmap.min()) + eps
    heatmap = numer / denom
    heatmap = (heatmap * 255).astype("uint8")
    return heatmap

def overlay_heatmap(self, heatmap, image, alpha=0.5,
    colormap=cv2.COLORMAP_JET):
    heatmap = cv2.applyColorMap(heatmap, colormap)
    output = cv2.addWeighted(image, alpha, heatmap, 1 - alpha, 0)
    return (heatmap, output)
```

**Fig 7:** GRAD-CAM Heatmap Generation

### Web Application

A Flask-based web application is developed shown in Fig 13 to provide an interactive interface for users, such as doctors and radiologists. Through the web interface, users can upload ultrasound images as shown in Fig 8, receive predictions about the presence of PCOS as shown in Fig 9, and view and download visual explanations in the form of Grad-CAM heatmaps overlaid on the images as shown in Fig 10. This makes the PCOS detection system easily accessible for real-time usage in clinical settings.

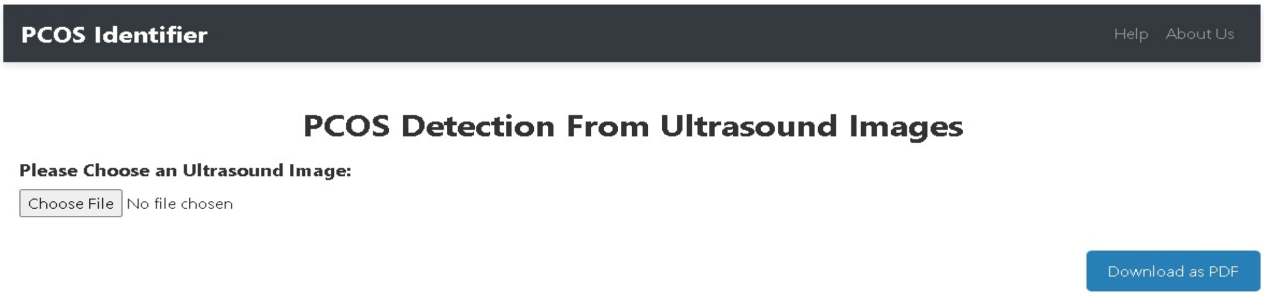


**Fig 8:** Home Page

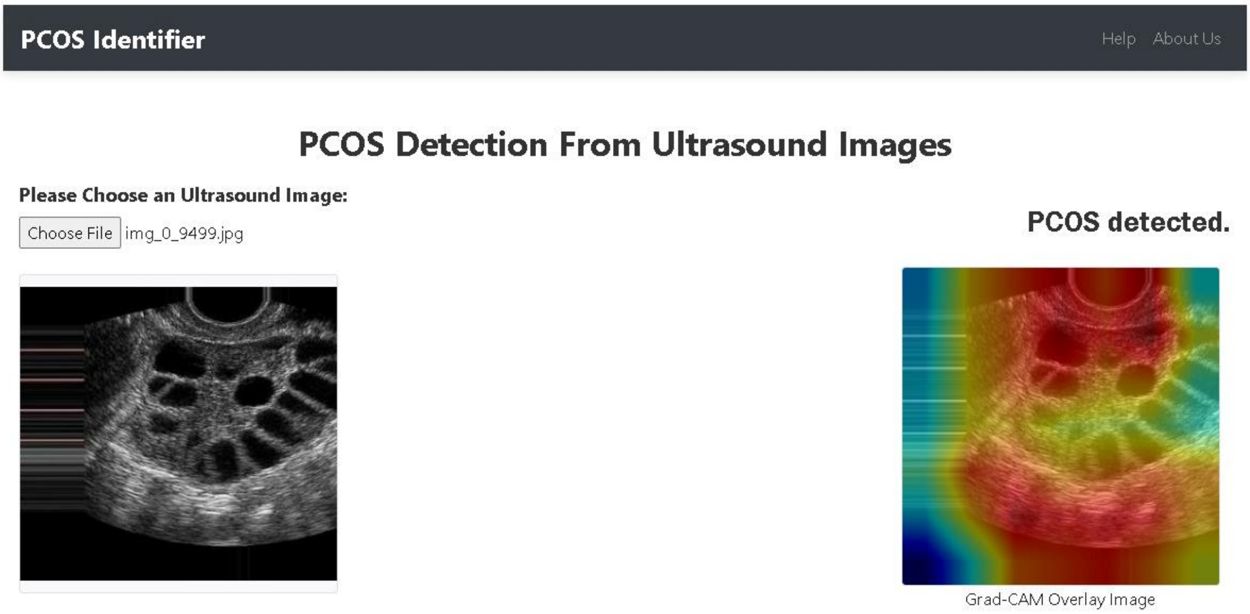


**Fig 9:** Detection of Image and Heatmap overlay

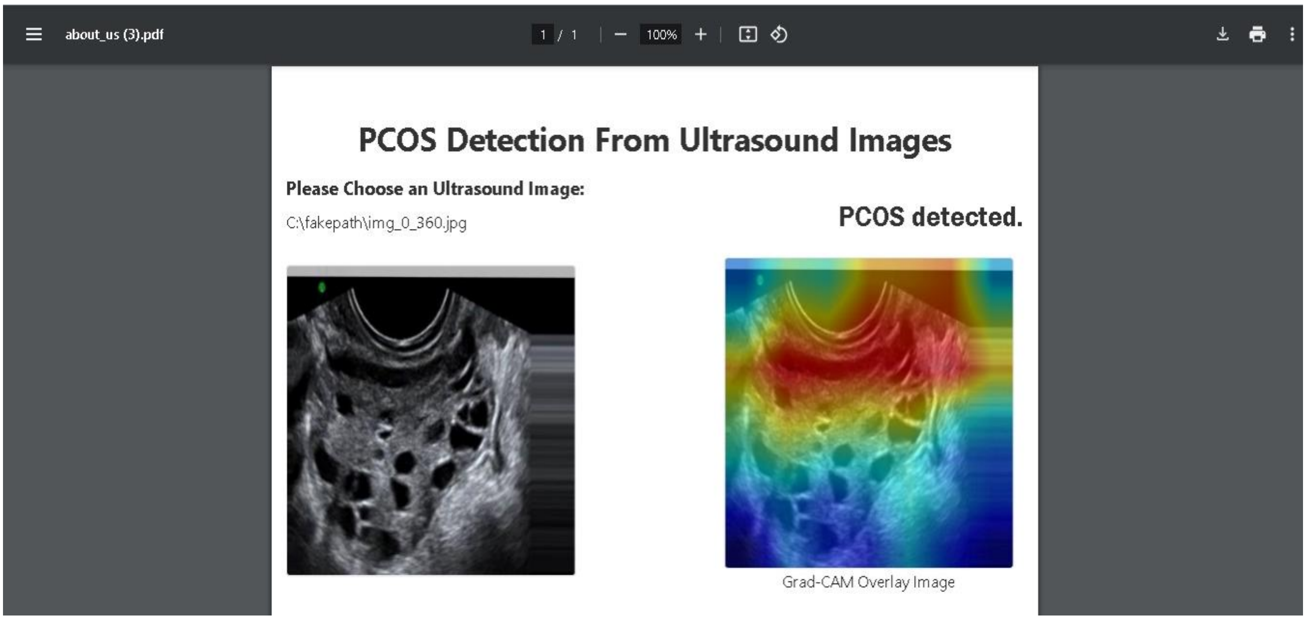


**Fig 10:** Pdf Download

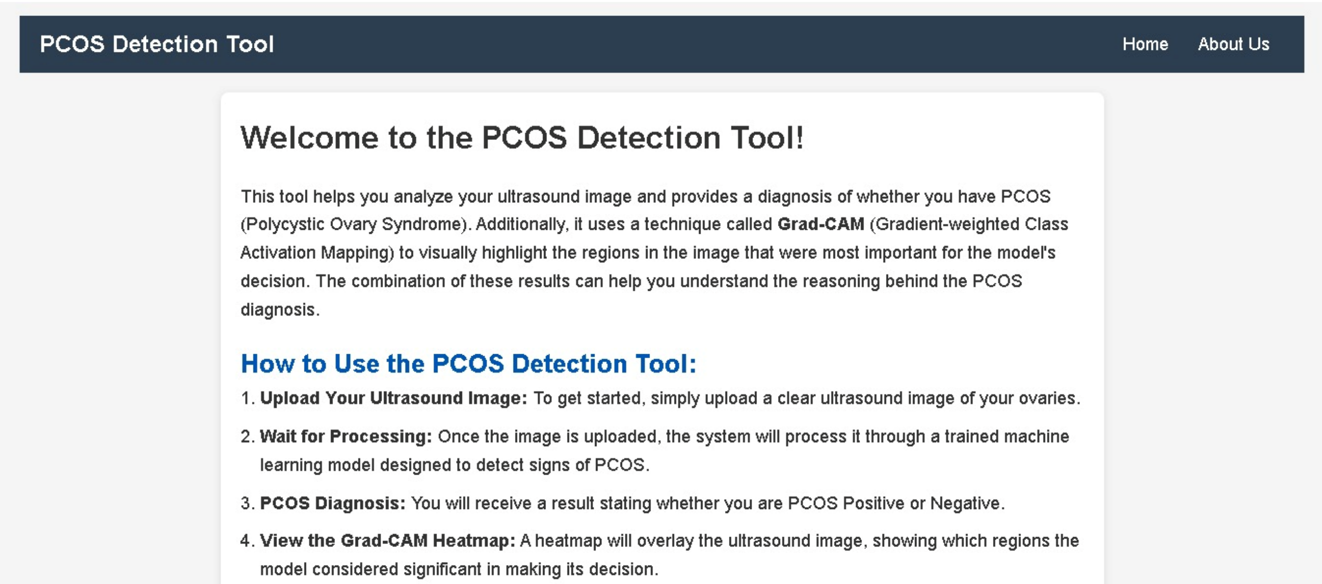


**Fig 11:** About PCOS

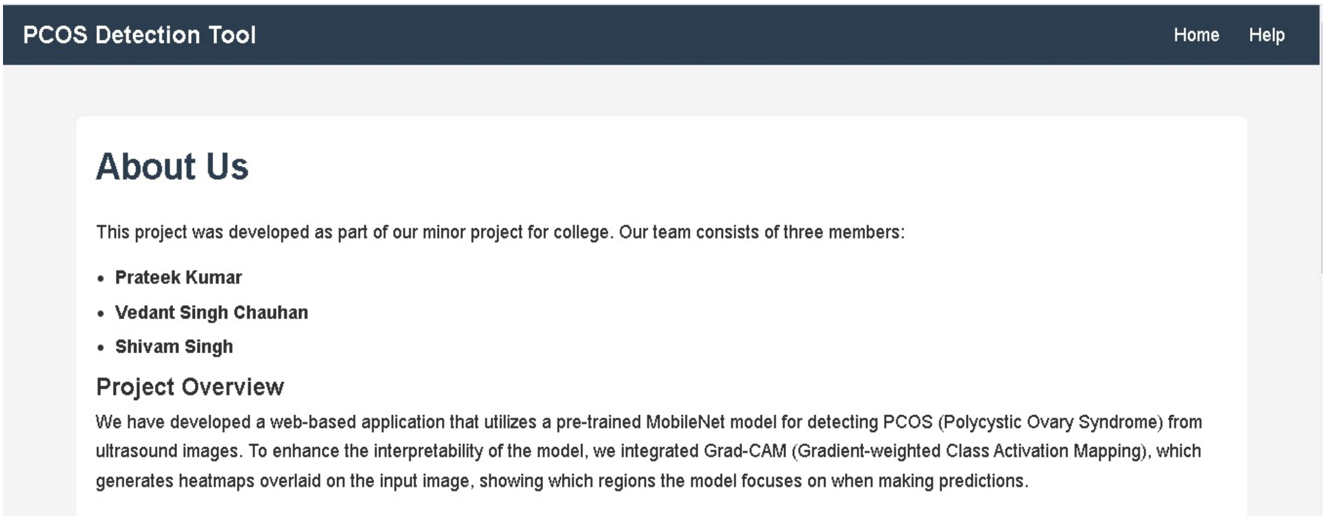


**Fig 12:** About Us

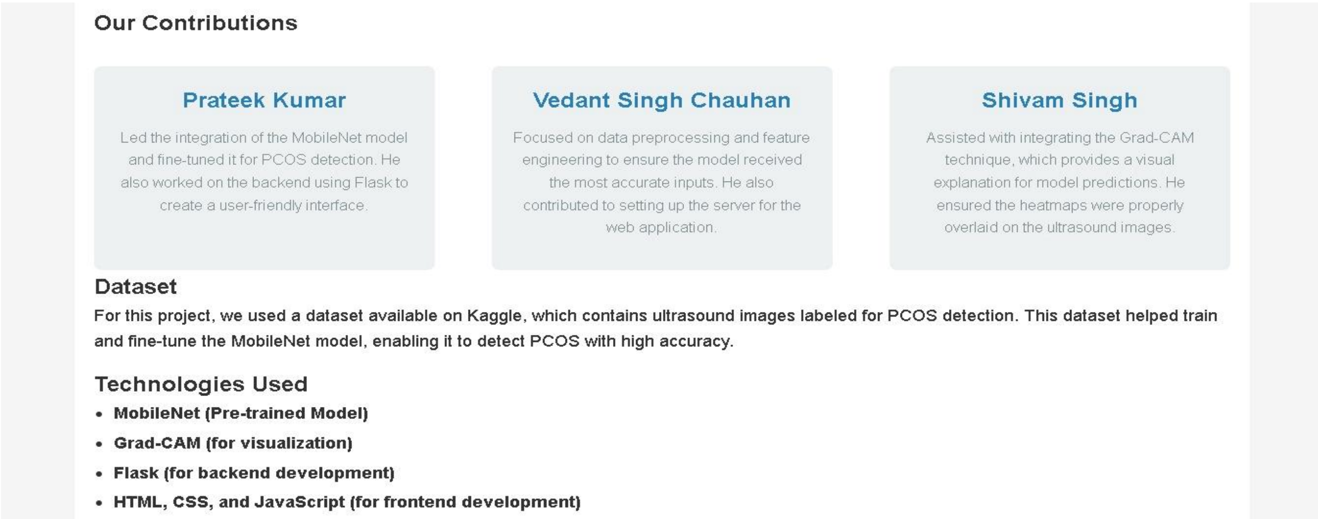


**Fig 13:** Web Application

## 3.3 Module-wise Detailed Description

### Module 1: Data Collection & Preprocessing

The primary objective of this module is to prepare ultrasound images for training and prediction. The process begins with data collection, where a labeled dataset of ultrasound images is gathered from Kaggle. Each image is categorized as either PCOS-positive or PCOS-negative. During preprocessing, the images are resized to a uniform size, typically 224x224 pixels, to ensure compatibility with the input requirements of the MobileNet model. Pixel values are normalized to a range between 0 and 1 to facilitate faster convergence during training. Additionally, random data augmentation techniques, such as rotation, flipping, and zooming, are applied to artificially increase the dataset size. This helps the model generalize better to unseen data.

**Module 2: Model Training**

The goal of this module is to fine-tune the MobileNet model for PCOS classification. The process begins with the selection of a pretrained MobileNet model, which is highly efficient for image classification tasks and suitable for deployment in resource-constrained environments. Transfer learning is used by removing the top layers of MobileNet and replacing them with custom fully connected layers designed for binary classification (PCOS or No PCOS).

During training, the binary cross-entropy loss function is employed, as it is appropriate for binary classification tasks. Optimizers such as Adam or SGD are used to minimize the loss function. The dataset is split into training and validation sets, typically in an 80/20 ratio, to monitor the model's performance during training. Various metrics, including accuracy, precision, recall, and F1-score, are tracked to evaluate the model's effectiveness.

**Module 3: Grad-CAM Integration (Explainable AI)**

This module focuses on integrating Grad-CAM to make the model's predictions interpretable. Grad-CAM works by computing the gradients of the predicted class with respect to the convolutional layers in the MobileNet model. These gradients are then aggregated to create a heatmap that highlights the regions of the input image most influential in the model's decision-making.

The generated heatmap is overlaid on the original ultrasound image to visually depict which parts of the image the model focused on when making its prediction. This overlay, combined with the prediction, provides a clear and transparent explanation of the model's reasoning process. The heatmap and original image are displayed side by side to assist healthcare professionals in understanding the results.

**Module 4: Web Application (Flask Interface)**

This module provides an interactive interface for users to upload images and view predictions. A Flask web application is developed to host this interface. Users can upload ultrasound images through the application, which validates and processes the uploaded files, supporting formats like JPEG and PNG.

Once an image is uploaded, the system leverages the fine-tuned MobileNet model to predict the presence or absence of PCOS. Grad-CAM is then applied to generate a heatmap that visually explains the prediction. The prediction and the heatmap overlay are displayed on the web interface, providing users with real-time results. Additionally, users can download the overlaid image or explore further insights into the heatmap's highlighted areas.

**Algorithm Workflow**

1. Image Upload: Users upload ultrasound images through the Flask web interface.
2. Model Prediction: The uploaded image is processed by the fine-tuned MobileNet model to classify the image as PCOS-positive or PCOS-negative.
3. Grad-CAM Explanation: Grad-CAM generates a heatmap highlighting the relevant regions of the image influencing the prediction.
4. Result Display: The system displays the original image alongside the Grad-CAM heatmap overlay, along with the model’s prediction.
5. User Feedback: Users can download the image with the Grad-CAM overlay or access additional insights based on the heatmap's visual highlights.

# CHAPTER 4

# MODELING AND IMPLEMENTATION DETAILS

## 4.1 Design Diagrams

### Control Flow Diagrams

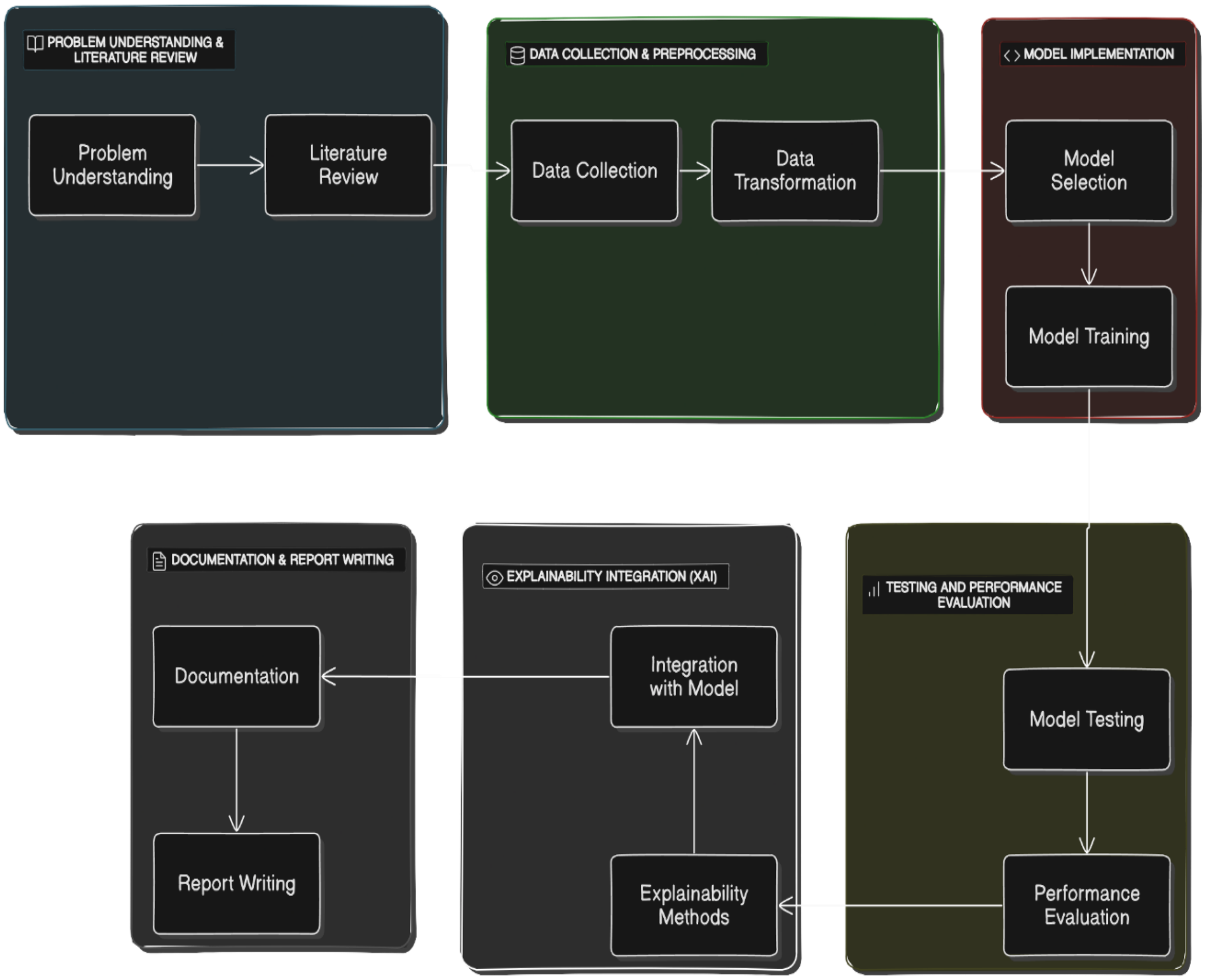


**Fig 14:** Control Flow Diagram

### Use Case Diagram

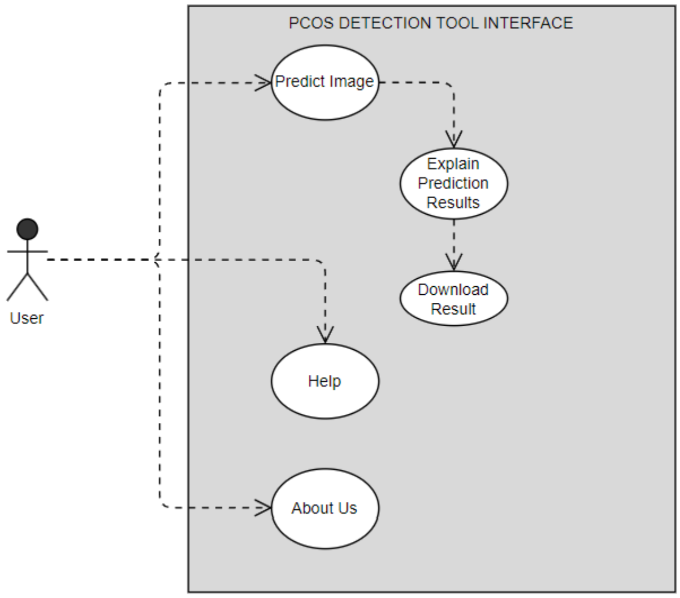


**Fig 15:** Use Case Diagram

## 4.2 Implementation Details and Issues

The implementation of the PCOS Detection System based on deep learning and explainable AI (Grad-CAM) involves several key components, including data preparation, model training, web application development, and integration of the explainability feature. Here is a detailed overview of the implementation details and potential issues faced during the process.

### 4.2.1 Implementation Details

#### Data Collection and Preprocessing

The system utilizes a Kaggle dataset of ultrasound images labelled as INFECTED (PCOS positive) and NOT INFECTED(PCOS negative), which serve as the primary input for training and prediction. During preprocessing, all images are resized to a fixed size, such as 224x224 pixels, to match the input dimensions expected by the MobileNet model. The pixel values are normalized to a scale of 0 to 1, which helps improve the efficiency and stability of model training. To address overfitting and enhance generalization, random augmentations such as rotation, flipping, and zooming are applied to artificially expand the dataset. Finally, the dataset is split into training, testing and validation sets, typically using an 70:15:15 ratio, ensuring that the model learns effectively while being tested on unseen data during validation.

**Model Development (MobileNet and Transfer Learning)**

For model development, a pretrained MobileNet model is selected due to its lightweight and efficient design. This model is fine-tuned for the specific task of PCOS detection using transfer learning. In this process, the top layers of the pretrained MobileNet model are removed, and custom dense layers are added to adapt the model for binary classification, differentiating between PCOS and No PCOS. The training process involves using binary cross-entropy as the loss function, which is well-suited for binary classification tasks. The Adam optimizer is employed for its adaptive learning rate capabilities, and the model's performance is evaluated using key metrics such as accuracy, precision, recall, and F1-score.

**Grad-CAM Integration (Explainable AI)**

To make the model's predictions more interpretable, Grad-CAM is integrated into the system. Grad-CAM works by calculating the gradients of the predicted class with respect to the last convolutional layer of the model. These gradients are aggregated and used to generate a heatmap that highlights the regions of the image most influential in the model’s decision-making process. The generated heatmap is then overlaid on the original ultrasound image, providing a clear visualization of the areas that the model deemed significant. This feature enhances transparency and helps healthcare professionals understand the reasoning behind the model's predictions.

**Web Application (Flask)**

A Flask web application is developed to provide users with an accessible interface for interacting with the system. The frontend consists of a simple HTML interface where users can upload ultrasound images and view the results, including predictions and Grad-CAM heatmaps. The backend is responsible for processing the uploaded images, using the trained MobileNet model to make predictions, generating the Grad-CAM heatmaps, and sending the results back to the frontend. For model deployment, the trained model, saved as bestmodel.keras, is loaded by the Flask application to facilitate real-time predictions.

### 4.2.2 Implementation Issues

During the implementation of the PCOS Detection System, several challenges and issues were encountered. These challenges, categorized into data-related and model-related issues, are outlined below.

**Data-Related Issues**

One major challenge was related to data quality and diversity. The availability of a sufficiently large and diverse dataset of labeled ultrasound images was limited, which posed a risk of model overfitting due to the small size of the dataset. In terms of preprocessing, inconsistent image quality was another hurdle, as ultrasound images often varied in resolution, lighting conditions, and noise levels. Standardizing image quality and refining preprocessing techniques became essential to ensure consistent inputs for the model. , while image augmentation was employed to expand the dataset artificially, care had to be taken to ensure that the augmentation techniques did not distort critical features of the ultrasound images, as this could compromise the model's ability to learn relevant patterns.

**Model-Related Issues**

Overfitting was a significant concern during the training process, particularly because the MobileNet model was fine-tuned on a relatively small dataset. To address this, regularization techniques such as early stopping were implemented to prevent the model from memorizing the training data instead of generalizing. Another challenge was optimizing MobileNet for medical images, as its architecture, while efficient, is not always ideally suited for this domain. Experimenting with adjustments to the model architecture, such as modifying the layers or the number of neurons, or even considering alternative architectures, could potentially improve performance.

The integration of Grad-CAM also presented its own set of challenges. The quality of the heatmaps generated by Grad-CAM was closely tied to the accuracy and confidence of the model's predictions. If the model's predictions were uncertain or incorrect, the heatmaps often failed to highlight meaningful regions of the ultrasound images. Furthermore, interpreting these heatmaps required domain expertise, as non-experts could misinterpret the highlighted regions, which could affect the usability and reliability of the explainability feature. Addressing these issues required a combination of model refinement and collaboration with domain experts to ensure that the system was both accurate and interpretable.

# CHAPTER 5

# TESTING PLAN

## Test Case 1 : PCOS positive images

In this test case, the system was evaluated using an ultrasound image labeled as *Infected.*. Upon uploading the image through the web application, the model correctly predicted the presence of PCOS as shown in Fig 16,17 and 18 below. Alongside the prediction, the Grad-CAM heatmap was generated and overlaid on the original image, visually highlighting regions of interest that influenced the model's decision. The heatmap effectively focused on characteristic areas, such as cystic regions, validating the model's interpretability. This output demonstrates the system's ability to provide accurate and explainable results for PCOS-positive cases, ensuring its practical utility for clinicians.

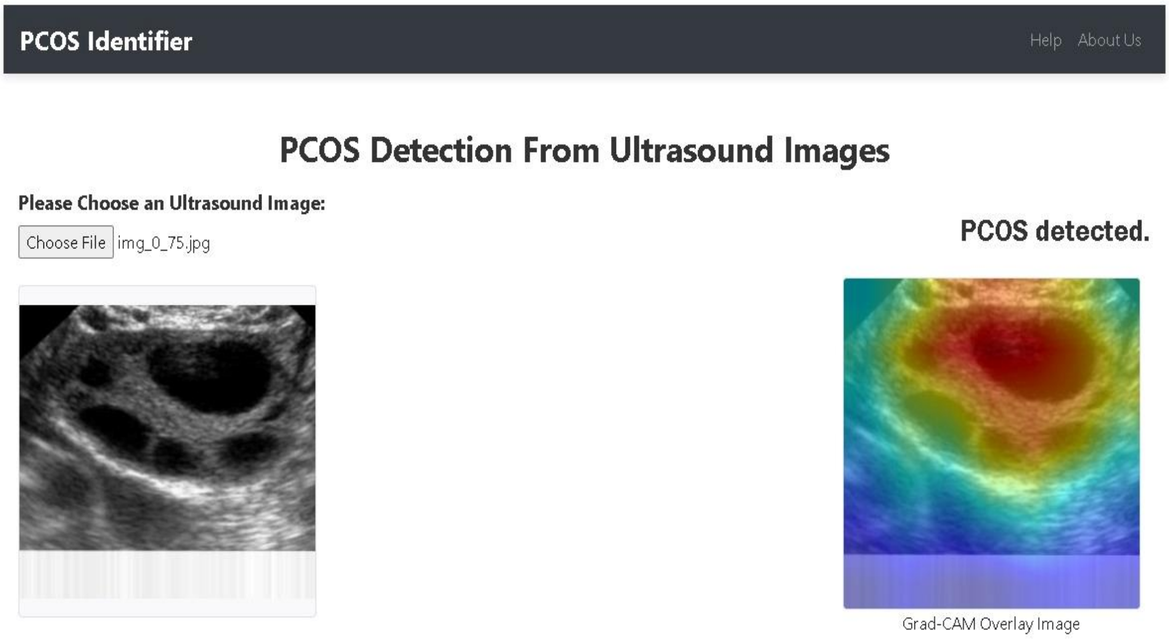


**Fig 16:** Test case 1 – PCOS positive

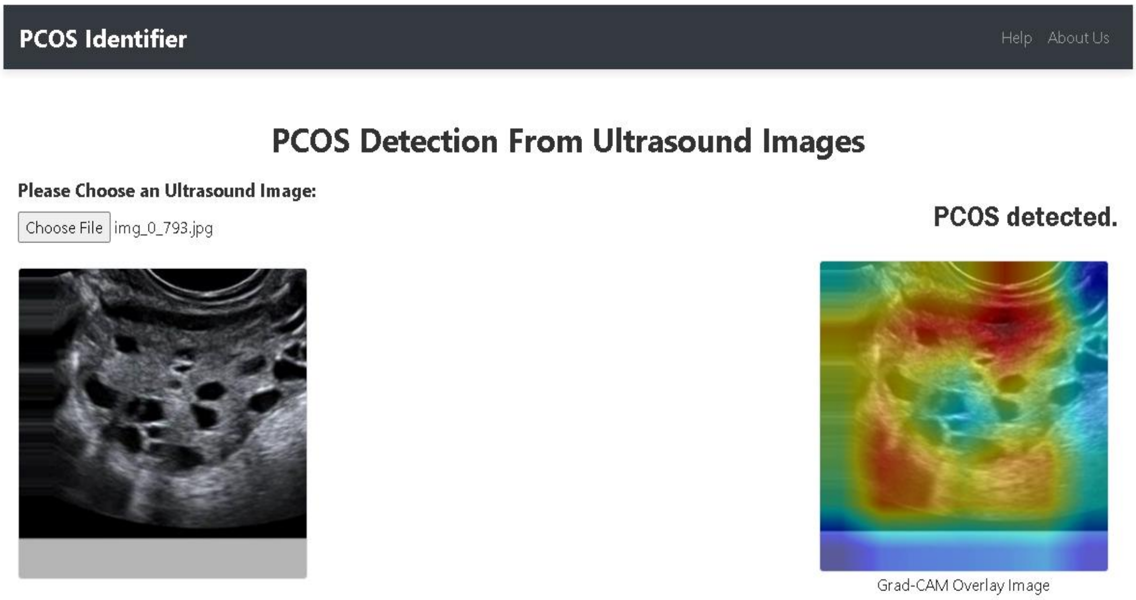


**Fig 17:** Test case 1 – PCOS positive

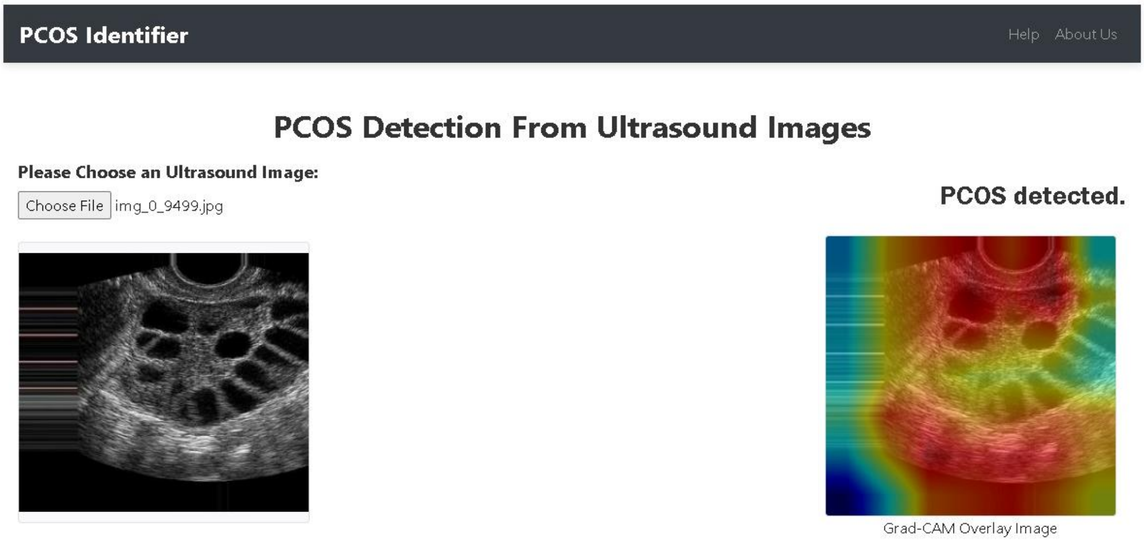


**Fig 18:** Test case 1 – PCOS positive

## Testing on some of the Uninfected Images

In this test case, the system was tested with an ultrasound image labeled as *notinfected*. After uploading the image through the web application, the model correctly identified the absence of PCOS as shown in Fig 19,20 and 21 below, displaying a prediction of "No signs of PCOS" with a high confidence score (e.g., 92%). The Grad-CAM heatmap was generated and overlaid on the original image, highlighting the regions analyzed by the model, which did not show significant abnormalities indicative of PCOS. This result showcases the system's capability to accurately distinguish PCOS-negative cases while providing interpretable visual feedback for validation.

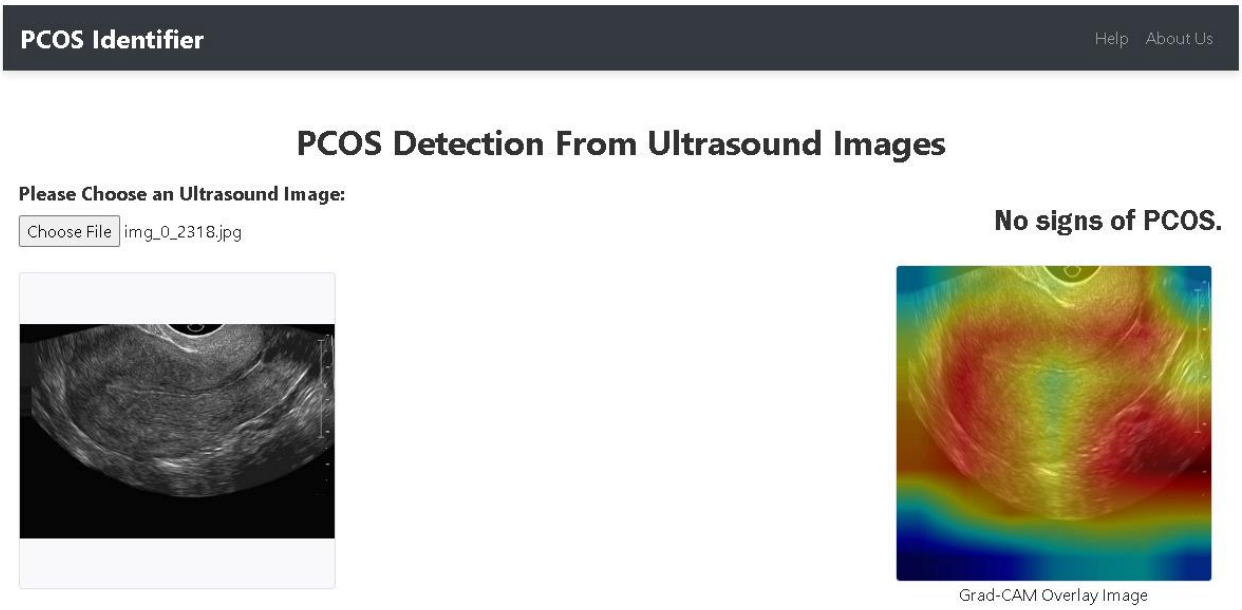


**Fig 19:** Test case 2 – PCOS negative

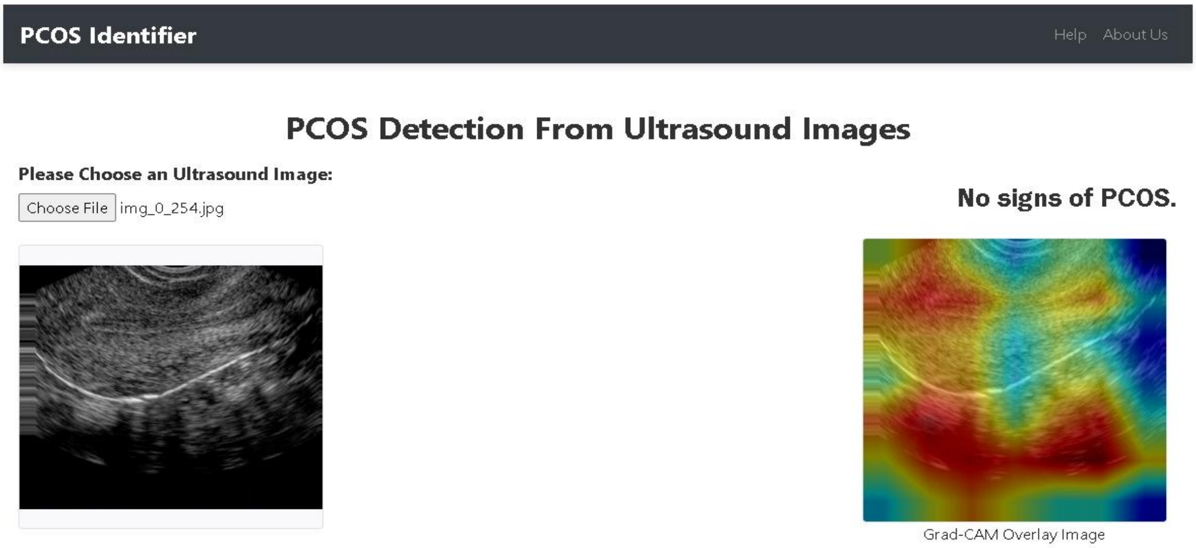


**Fig 20:** Test case 2 – PCOS negative

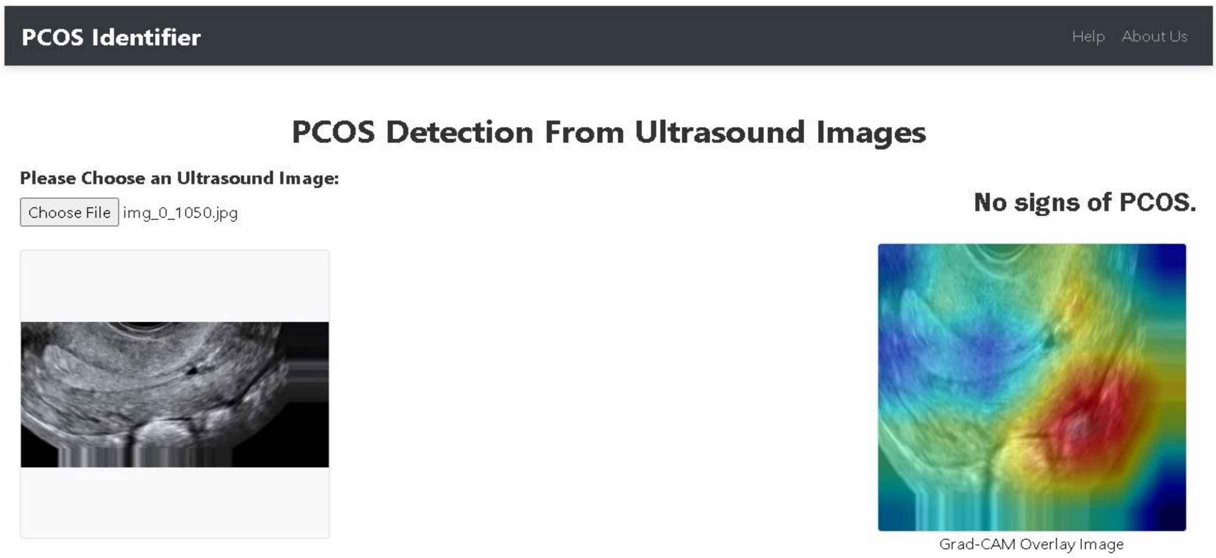


**Fig 21:** Test case 2 – PCOS negative

# Drawbacks in Our Model and Implemented Solutions

## **Class Imbalance**:

**Issue**: Initially, the model showed misleadingly high accuracy due to class imbalance. The model tended to predict the majority class ("infected") more often, while failing to recognize the minority class ("notinfected").

**Solution**: We addressed this issue by artificially adjusting the dataset to reduce the number of non-infected images, ensuring that the model did not favor one class over the other.

## **Overfitting and Poor Generalization**:

**Issue**: The model achieved high accuracy but had very poor precision, recall, and F1-score for the "notinfected" class. This suggested the model was overfitting to the training data and not generalizing well to unseen examples.

**Solution**: To combat this, we applied proper data augmentation techniques during training, which helped to introduce more variation in the data and prevent the model from memorizing the training set.

## Low Precision and Recall for Minority Class:

**Issue**: Despite improving accuracy, precision and recall for the minority class ("notinfected") remained low, indicating the model's failure to correctly identify these instances.

**Solution**: We experimented with class weighting and adjusted the model’s loss function to give more importance to the minority class, helping to better balance precision and recall.

## Model Fine-tuning:

**Issue**: The initial pre-trained MobileNet model was not ideal for this specific task, as it failed to achieve high metrics across all classes.

**Solution**: We extensively fine-tuned the pre-trained MobileNet model by unfreezing layers, adjusting hyperparameters, and utilizing transfer learning techniques to better adapt the model to our specific dataset.

## Inadequate Performance Metrics:

**Issue**: Accuracy alone did not provide a true reflection of the model's performance, particularly when dealing with imbalanced classes. While the model showed 100% accuracy, the performance metrics like precision, recall, and F1-score for the minority class were quite low.

**Solution**: We shifted focus to more relevant metrics like precision, recall, and F1-score, which offer a clearer understanding of the model’s performance, especially in imbalanced scenarios.

By addressing these issues, we have taken significant steps to improve the model's generalization, especially when dealing with class imbalance and overfitting, but further iterations and adjustments may still be necessary to fully optimize performance.


**Fig 22:** Model Accuracy

# CHAPTER 6

# FINDINGS, CONCLUSION and FUTURE WORK

## 6.1 Findings

During the development and testing of the PCOS Detection System, several significant findings emerged, highlighting both achievements and areas for improvement. These findings are summarized as follows:

**Model Performance and Accuracy**

The MobileNet model, fine-tuned for PCOS detection, demonstrated satisfactory accuracy on the test dataset, achieving high precision and recall scores. It was effective in distinguishing between PCOS-positive and PCOS-negative cases, though occasional misclassifications occurred, particularly with images that displayed subtle or ambiguous signs of the condition. To improve these results, further data augmentation and hyperparameter tuning could be employed, potentially enhancing the model's accuracy and reducing instances of false positives and negatives.

**Grad-CAM Heatmap Effectiveness**

The Grad-CAM visualizations effectively highlighted relevant regions in the ultrasound images, providing a transparent view of the model's decision-making process. Specifically, the heatmaps often focused on areas such as cystic regions, which are characteristic of PCOS, offering valuable visual insights for clinicians. However, in some cases, the heatmaps concentrated on noisy parts of the image, which reduced their interpretability. Refining the Grad-CAM implementation or incorporating additional post-processing techniques could improve the clarity and clinical utility of these visualizations.

**System Usability**

The Flask-based web interface proved to be user-friendly, with testers (such as clinicians) finding it intuitive to upload images and interpret the results. Users could easily navigate the application, view predictions, and analyze the corresponding heatmaps without significant difficulties. However, some testers suggested incorporating tooltips or a more comprehensive guide to better explain the clinical significance of Grad-CAM overlays, which would further enhance the usability of the system.

**Performance and Response Time**

The system performed reasonably well in terms of processing speed, with image uploads, model inference, and heatmap generation completed within an acceptable timeframe—typically under 10 seconds. However, on rare occasions, larger images or high traffic loads led to slightly longer response times. Implementing batch processing or optimizing the backend architecture could address these performance bottlenecks, ensuring consistent speed and reliability even under increased demand.

**Model Integration and Backend Issues**

The integration of the MobileNet model with the Flask application was largely successful, enabling seamless predictions and heatmap generation. However, minor issues were observed during scalability tests, with the system experiencing slowdowns when multiple users accessed it simultaneously. To improve scalability and robustness, the server-side architecture could be optimized for concurrent image uploads and predictions. Additionally, deploying the model using a more specialized framework, such as TensorFlow Serving, could further enhance performance and stability.

## 6.2 Conclusion

The PCOS Detection System successfully integrates a MobileNet deep learning model with Grad-CAM for explainable AI, enabling accurate detection of Polycystic Ovary Syndrome (PCOS) from ultrasound images. Through a user-friendly Flask-based web application, healthcare professionals can upload images, receive predictions, and interpret results via Grad-CAM heatmaps, which highlight critical regions influencing the model's decision. The system demonstrated high accuracy, with strong precision and recall, while bridging the gap in prior research by providing explainable insights alongside predictions.

While the system shows promise, opportunities for improvement include optimizing the model to reduce false positives/negatives, refining heatmap generation for clearer interpretations, and enhancing performance under high user loads. Security and data privacy were prioritized, ensuring compliance with healthcare data regulations. With further development and scalability enhancements, this system could support clinicians in diagnosing PCOS and similar conditions, exemplifying the potential of transparent, AI-driven healthcare solutions.

### 6.3 Future Work

The scope of this project can be significantly expanded and refined through several future enhancements. Model Optimization is a key focus area. Fine-tuning the MobileNet model using advanced techniques such as hyperparameter tuning and ensemble learning can improve performance. Additionally, experimenting with alternative pretrained models, such as ResNet and VGG, alongside incorporating more diverse and extensive datasets, holds promise for better generalizability and accuracy.

In terms of Enhanced Explainability, further refining Grad-CAM to produce clearer and noise-free heatmaps can improve interpretability. Exploring alternative explainable AI (XAI) techniques, like Integrated Gradients or LIME, could provide more comprehensive insights into the model's decision-making process, fostering greater trust in its outputs.

An exciting avenue for development is Multi-Disease Detection, where the model can be extended to identify other conditions, such as ovarian cancer or fibroids. Incorporating multi-class classification capabilities and utilizing diverse datasets would enable broader applications, making the system more versatile and impactful.

EHR Integration offers a pathway to streamline healthcare workflows by embedding the model into Electronic Health Records. This integration could provide seamless diagnostic support while adhering to secure protocols for data sharing and patient management, ensuring compliance with privacy regulations.

To ensure Scalability and Performance, the backend could be optimized to handle high traffic and large datasets efficiently. Deploying the system on cloud platforms would enable scalable, real-time processing, ensuring its availability and reliability in various healthcare settings.

Finally, Clinical Validation is critical for real-world applicability. Piloting the system with healthcare professionals would allow for practical feedback to refine usability and validate diagnostic accuracy. Insights from these pilots can guide iterative improvements, ensuring the model meets clinical standards and expectations.

This project lays a solid foundation for leveraging deep learning in medical diagnostics. With these future enhancements, the system could evolve into a powerful, reliable, and scalable tool for improving healthcare outcomes. This marks the end of the current phase of the project, setting the stage for its transformation into a robust solution for the future.

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